2022 한국개발정책학회
추계학술포럼

2022년 11월 18일(금요일) 12:00-18:10

서울대학교 국제대학원 국제회의실 (140-2동 401호)

주관: kadp 한국개발정책학회 후원: 기획재정부 한국수출입은행

온라인 참여 줌 링크: https://snu-ac-kr.zoom.us/j/96118008821

2022 한국개발정책학회 추계학술포럼

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12:00-13:00	운영이사회 오찬	
13:00-13:15	학회등록	
	개회사: 정혁(한국개발정책학회장)	
13:20-14:50	**제1세션: 거시경제 국제개발**	좌장: 최창용(서울대 행정대학원)
	Foreign Aid and Economic Development: A Firm-level Study of Korean Experience in the 1950-70s 발제: 홍석철(서울대 경제학부) | 토론: 이종관(이화여대 경제학과)	
	Measuring Interdependence of Inflation Uncertainty 발제: 이서현(KDI School) | 토론: 조덕상(KDI)	
	Empirical Quest for Development Effectiveness 발제: 정혁·이진이(서울대 국제대학원) | 토론: 강창희(중앙대 경제학부)	
	휴식	
15:00-16:30	**제2세션 : 환경과 국제개발**	좌장: 양희승(연세대 경제학부)
	Early-life Exposure to Cold Weather Shocks and Growth Stunting: Evidence from Tanzania 발제: 한유진(연세대 경제학과) | 토론: 윤정환(KIEP)	
	Good Governance and Household Resilience to Natural Disasters: Evidence from Vietnam 발제: 윤세미(서울대 국제대학원) | 토론: 정재현(이화여대 국제대학원)	
	Welfare Gains from Trade across Space with Transboundary Air Pollutants 발제: 임희현(KDI) | 토론: 정지원(KIEP)	
	휴식	
16:40-18:10	**제3세션 : 보건과 국제개발**	좌장: 오주환(서울대 의과대학)
	Costing the Implementation of Public Health Interventions in Resource-limited Settings 발제: 손호준(서울대 의과대학) | 토론: 이석원(서울대 행정대학원)	
	Strengthening Health Systems in Resource-constrained Settings: A Case of Health-based Health Information System Implementation in Ghana 발제: 김선영(서울대 보건대학원) | 토론: 신자은(KDI School)	
	Rough Assessments of Pandemic Responses and Preparedness in the Age of COVID-19 발제: 김태종(KDI School) | 토론: 오주환(서울대 의과대학)	
	폐회사	
18:30-20:00	만찬 호암교수회관 메이플룸	

문의: 한국개발정책학회 사무국 (02) 880-2921, 010-8990-3462, kadp2021@gmail.com

온라인 참여 줌 링크: https://snu-ac-kr.zoom.us/j/9611800821

목 차

세션1 거시경제 국제개발

- Foreign Aid and Economic Development:
  A Firm-level Study of Korean Experience in the 1950-70s
  발제: 홍석철(서울대 경제학부) | 토론: 이종관(이화여대 경제학과)

- Measuring Interdependence of Inflation Uncertainty
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- Empirical Quest for Development Effectiveness
  발제: 정혁·이진이(서울대 국제대학원) | 토론: 강창희(중앙대 경제학부)

제1세션 | 거시경제 국제개발

Foreign Aid and Economic Development: A Firm-level Study of Korean Experience in the 1950-70s

발제: 홍 석 철(서울대 경제학부)

토론: 이 종 관(이화여대 경제학과)

Foreign Aid and Economic Development:
A Firm-level Study of Korean Experience in the 1950-70s

Sok Chul Hong
Seoul National University

Sang-yun Ryu
University of Ulsan

Jongryong Park
Seoul National University

Korean Academy of Development Policy

November 18, 2022

Background

- Controversy over aid effectiveness
  - Sachs (2005) vs. Easterly (2006), Collier (2007), Moyo (2009)
  - Acemoglu and Robinson (2012): extractive institutions and failure of aid
  - Burnside and Dollars (2000 & 2004) : good policy environments
- Historical study
  - Eichengreen & Uzan (1992): Marshall Plan ➔ liberalization
- What lessons can we learn from Korean experience?
  - Corruption, inefficient rent seeking in the 1950s?
  - Not based on empirical evidence (Yoon 1991, Cho 1996), cotton industry as a typical case (Kim 1991, Lee 2001)
- Research Questions
  - Was the allocation of foreign aids in the 1950s competitive, fair, and efficient?
  - How much did the foreign aid in the 1950s contribute to the growth of Korean economy?

2

Foreign Aid for Korea in the 1940-60s

- GARIOA(Government Aid and Relief in Occupied Areas): 미국점령지역 행정구호원조 (1945-1948년)
  - 인도주의적 목적의 긴급구호 및 원조
  - 식량지원이 대부분. 재건을 위한 지원은 매우 적었음.
  - 원조규모: 4억 달러
- ECA(Economic Cooperation Administration): 경제협력처 (1949-1953년)
  - 재건, 산업개발, 경제부흥, 경제자립 목적
  - 식량, 비료, 석유 및 반제품, 공업시설, 기술원조
  - 한국전쟁 중 UNCACK(United Nations Civil Assistance Command in Korea)의 SEC(Supplies, Economic Cooperation) 원조로 이관.
  - 원조규모: 2억 백만 달러
- CRIK(Civil Relief in Korea): 한국민간구호계획 (1950-1956년)
  - UN의 군사적, 인도적 원조
  - 식료품, 의료, 의약품 지원
  - SKO: 미육군성 원조, SUN: UN 가맹국, 비가맹국, 민간단체 또는 개인
  - 원조규모: 4억 5,700만 달러

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Foreign Aid for Korea in the 1940-60s

- UNKRA(United Nations Korean Cooperation Administration: 국제연합한국재건단(1951-1960년)
  - 경제재건을 위한 원조 및 지원
  - 전쟁중 긴급구호, 전후 산업/교통/통신시설 복구, 주택/의료/교육 개선
  - 원조규모: 1억 2200만 달러
- FOA(Foreign Operations Administration, 1953-1955년) ➔ ICA(International Cooperation Administration, 1955-1961년) ➔ AID(Agency for International Development, 1962-1983년)
  - 경제안정 및 산업재건을 위한 지원
  - 지원규모: FOA(2억 610만 달러), ICA(15억 3,560억 달러), AID 이관 이후 증여형식의 원조를 지양하고 개발차관으로 전환.
- PL 480호에 의한 잉여농산물 원조(1956-1971년)
  - 1954년 미국농업교역 발전 및 원조법에 근거
  - 소맥, 원면, 우지 등 지원
  - 원조규모: 4억 5,700만 달러

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Foreign Aid for Korea by Type and Year, 1945-1983

Year	GARIOA	ECA/SEC	CRIK	UNKRA	FOA/ICA/AID	PL480	Total	FOA/ICA/AID(%)
1945	4,934						4,934	
1946	49,496						49,496	
1947	175,371						175,371	
1948	179,593						179,593	
1949	92,703	23,806					116,509	
1950		49,330	9,376				58,706	
1951		31,972	74,448	122			106,542	
1952		3,824	155,534	1,969			161,327	
1953		232	158,787	29,580	5,571		194,170	
1954			50,191	21,297	82,437		153,925	54
1955			8,711	22,181	205,815		236,707	87
1956			331	22,370	271,049	32,955	326,705	83
1957				14,103	323,268	45,522	382,893	84
1958				7,747	265,629	47,896	321,272	83
1959				2,471	208,297	11,436	222,204	94
1960				244	225,236	19,913	245,393	92
1961					154,319	44,926	199,245	77
1962					165,002	67,308	232,310	71
1963					119,659	96,787	216,446	55
1964					88,346	60,985	149,331	59
1965					71,904	59,537	131,441	55
1966					65,310	37,951	103,261	63
1967					52,640	44,378	97,018	54
1968					49,929	55,927	105,856	47
1969					32,434	74,830	107,264	30
1970					20,933	61,703	82,636	25
1971					17,566	33,651	51,217	34
1972					5,089		5,089	100
1973					2,146		2,146	100
1974					982		982	100
1975					1,155		1,155	100
1976					1,740		1,740	100
1977					948		948	100
1978					169		169	100
1979					224		224	100
1980					361		361	100
1981					236		236	100
1982					61		61	100
1983					30		30	100

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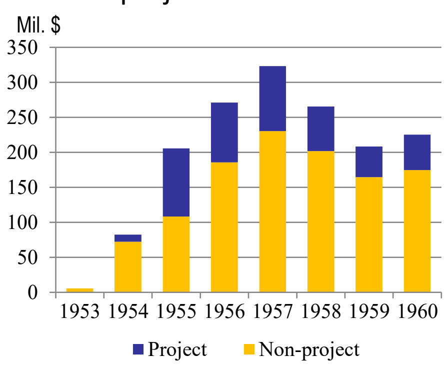
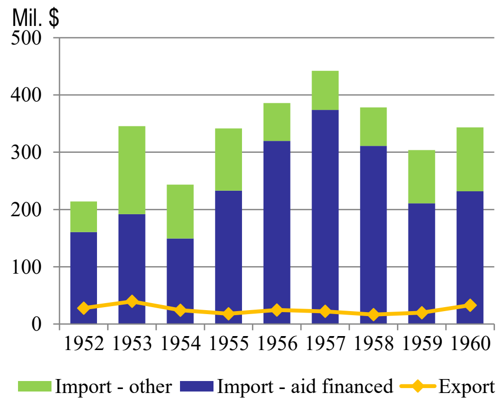
Foreign Aid for Korea in the 1950s

- More than 80% of foreign aid in the late 1950s after Korean War was provided through ICA, which aimed to help economic stabilization and reconstruction in Korea.
- FOA/ICA's foreign assistance had two types.
  - **Project assistance**: Provided construction materials and technology for reconstructing economic infrastructure destroyed by Korean War.
  - **Non-project assistance**: Provided raw materials and general consumer goods for operating industrial facilities.
  - Non-project assistance was dominant.





6

Allocation Process of Non-Project Assistance in the 1950s

- ICA’s non-project assistance was provided as a form that commercial firms or government purchased goods and materials provided by ICA.
- In particular, more than 50% of non-project assistance was purchased by commercial firms for civilian demand (52% in 1957).

Table. Allocation Process of ICA's Non-Project Foreign Assistance in Korea

Who purchased?	#	Purpose of purchase	Tyep of goods	Method of payment
Commercial firms through Bank of Korea	1	For general civilian demand	Raw materials	Paid at foreign exchange rate determined through competitive bidding among commerical firms
	2	For specified end users		Paid at official foreign exchange rate
Government	3	For Office of Supply	Goods for civilian use	
			Goods for public use	Paid by government expenditure
	4	For US agency in Korea	Communication equipment, oils, etc	

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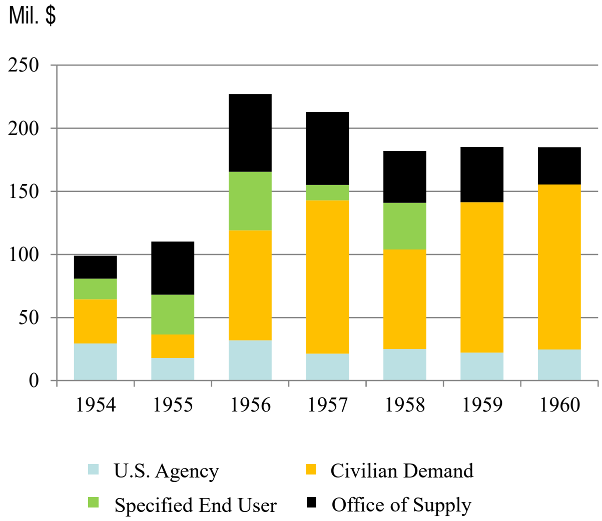
Allocation Process of Non-Project Assistance in the 1950s

- Type 1 aid (i.e., the purchase by commercial firms for general civil demand) needs more attention because it would more directly contribute to the growth of modern business and Korean economy.
- In the case, commercial firms purchased at lower prices than at market prices (price = foreign exchange rate).
- How was the exchange rate determined? How was the aid allocated?
  - 1954-55: competitive bidding
  - 1955-57: lottery
  - 1957-58: competitive bidding on government bond purchase
  - 1958-: competitive bidding on foreign exchange rate

8

Allocation Process of Non-Project Assistance in the 1950s

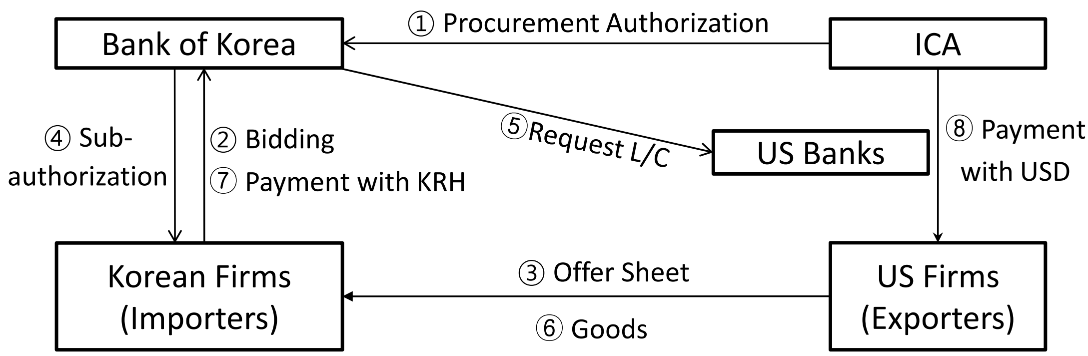
- Trend of non-project assistance by purpose



9

Allocation Process of Foreign Aid through Competitive Bidding

- Allocation process



- Where can we get the bidding information at the micro level?
  - ② → Daily Report on Allocation of ICA Funds
    Small Business Circular (1957~)
  - ④ → Weekly Report of Sub-authorization

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Notice of Competitive Bidding

ICA민수용 물자 구매자금의 배정공고

구매승인 번호	배정공고 번호	품목	구분	구매승인 금액	배정 금액	일인당최고신청액	일건당최저신청액	계약 기간	인도 기간	적출지	신청 기간
				$	$	$	$				
8266	8-95	인쇄용지	A	100,000	100,000	무제한	2,000	12/31 /58	4/30 /59	세계지역	6/ 2-6/ 5
8254	8-67B	기계공구	〃	52,085	52,085	〃	〃	8/31 /58	2/28 /59	〃	6/ 2-6/ 5
8246	8-60C	프라스틱원료	〃	85,600	85,600	〃	〃	9/30 /58	3/31 /59	〃	6/ 2-6/ 5
8018	8-96	원모	〃	400,000	400,000	80,000	〃	9/30 /58	3/31 /59	〃	6/ 5-6/ 9
8020	8-97	섬모및막모	〃	100,000	100,000	무제한	〃	9/30 /58	3/31 /59	〃	6/ 5-6/ 9
8156	8-49C	원피	〃	345,000	345,000	69,000	〃	7/31 /58	1/31 /59	미국	6/ 6-6/10
8250	8-90A	산업기계(수산자재)	DC	36,000	36,000	무제한	〃	8/31 /58	2/28 /59	세계지역	6/ 6-6/10
8240	8-62-4C	어업용화학품	D	50,000	50,000	〃	〃	9/30 /58	3/31 /59	〃	6/ 6-6/10
8233	8-63-1C	비금속광물(유황)	A	13,000	13,000	〃	〃	9/30 /58	3/31 /59	〃	6/ 7-6/11
8251	8-64C	발전기및모터	AC	37,987	37,987	〃	〃	8/31 /58	2/28 /59	〃	6/ 7-6/11
8257	8-69C	광산철도용부속품	〃	65,000	65,000	〃	〃	8/31 /58	2/28 /59	〃	6/ 7-6/11
8249	8-71C	농업기계	〃	92,000	92,000	〃	〃	8/31 /58	2/28 /59	〃	6/ 7-6/11
8017	8-98	농약	A	200,000	200,000	40,000	〃	9/30 /58	12/31 /58	〃	6/ 9-6/12
8259	8-61-1C	인견사(스프사원료)	〃	26,400	26,400	무제한	〃	9/30 /58	3/31 /59	〃	6/ 9-6/12
〃	8-61-2C	〃 (타이야코ー드)	〃	45,000	45,000	〃	〃	9/30 /58	3/31 /59	〃	6/ 9-6/12
8253	8-66B	광산기계	AC	124,020	124,020	24,000	1,000	8/31 /58	2/28 /59	〃	6/ 9-6/13
8255	8-68B	금속기계	C	24,400	24,400	무제한	2,000	8/31 /58	2/28 /59	〃	6/ 9-6/13
8016	8-93B	아마너실	A	196,000	196,000	39,000	〃	8/31 /58	10/31 /58	〃	6/ 9-6/13
8269	8-99	외국서적	A	100,000	100,000	무제한	〃	12/31 /58	4/30 /59	〃	6/12-6/16

(註) 1. A는 (1) 該當品目을 原資料로使用하여 完製品 또는 半製品을製造하거나 또는 製造할수있는 生産業者로 主務當局이認定한者와 (2) 該當品目의 取扱實績이有한 正常的인 貿易業者및 取扱專門家로 主務當局이 認定한者에 限하여 配定함
B는 資格制限없이 一般에게 配定함
C는 韓美合同審査委員會의 事前承認을 得한者에限하여 配定함
D는 海務廳長의 發給하는 適格證所持者에 限하여 配定함

2. 同購買承認申請은 ICA中小企業體에 對한 情報提供日부터 35日을 기다린後 30日以內에 申請하여야하고 情報提供이 不必要한境遇에는 資金配定日부터 30日以內에 申請하여야하되 契約期間內에하여야함

3. 本資金配定申請書에는 換價買入率(弗當30圜以上10圜單位)換價買入을 記載하고 該當圜貨를 서울特別市內所在 金融機關이 發行한 自己앞 保證手票(申請人의 裏書. 捺印을要함)로서 圜貨積立金과함께 同封申請하여야함
但 產業機械 金屬機械 機械工具 電氣器具 科學機械等은 圜貨積立率이 弗當500圜으로 割合이없을 境遇에는 圜貨追加徵收가免除됨

4. 本購買資金의 配定申請額은 一人當 一品目 一件에限함

5. 本資金配定申請書의 要記載事項및 要添付金額이 不明瞭. 誤記. 脫記. 金額不足 또는 申請書에 使用한 印鑑의 押印없이 訂正이있을境遇에는 無效로함

6. 本購買資金에 依한輸入은『美國國際協助處資金에依한 民需用物資購買事務取扱規程』에依함

7. 本資金配定申請(入札)은 申請期間中接受하고 期間最終日에 締切하여 當日 下午6時에 開函함

8. 其他詳細한內容은 當行外資部配定課에 問議하시압

檀紀4291年5月29日

韓國銀行

11

Daily Report: Bidding Outcomes

(CONTINUATION SHEET)

K-TC-AV-333A

DAILY REPORT ON ALLOCATION OF ICA FUNDS

Sheet 1 of 2 Sheets

PA No. 9072 9078
Terminal Contract Date Oct. 31, 59
PA Value ($) 500,000 (300,000)
Code No. 1801 Value ($) 500,000 (300,000)
Commodity Raw Wool
Allocation Period July 20, 59
Complete ☐ Partial ☐ x

Maximum Amount Applicable ($) 160,000
Minimum Amount Applicable ($) 2,000

Amount Offered ($) 800,000
Total Amount Bid ($) 1,147,070
Amount Allocated ($) 754,670
Amount Unallocated ($) 45,330

Date July 20, 1959
No. of Applicants 29
No. of Successful Bidders 17
No. of Unsuccessful Bidders 12

No. 146

Successful Bidder	Dollar Amount Awarded	Initial Deposit Hwan Rate	Total Amount of Initial Deposit In Hwan	Foreign Exchange Tax Rate In Hwan	Total Amount of Foreign Exchange Tax In Hwan	Remarks
Samsung Woolsan	94,000	300	28,200,000	500	47,000,000	
Yung Bo Industrail	50,000	300	15,000,000	520	26,000,000	
Kee Lung Industrial	20,000	300	6,000,000	450	9,000,000	
Hung Sung Ind.	62,000	300	18,600,000	510	31,620,000	
Shin Woo Silup	10,000	300	3,000,000	510	5,100,000	
Un Ryung Ind.	76,000	300	22,800,000	620	47,120,000	
Kim Yung Commercial	10,000	300	3,000,000	500	5,000,000	
Pacific Trading	30,000	300	9,000,000	580	17,400,000	
Heung An Silup	5,000	300	1,500,000	550	2,750,000	
Jung Poong Ind.	10,000	300	3,000,000	520	5,200,000	
Young Poong Shipping	50,000	300	15,000,000	490	24,500,000	
Korea Yakneung Trading	70,000	300	21,000,000	520	36,400,000	
Shin Min Ind.	35,000	300	10,500,000	540	18,900,000	
Nam Myung Ind.	5,000	300	1,500,000	550	2,750,000	
Cheil Woolen Textile	100,000	300	30,000,000	460	46,000,000	
Taihan Woolen Textile	120,000	300	36,000,000	480	57,600,000	
Yu Han Textile	7,670	300	2,301,000	580	4,448,600	
Total	754,670		226,401,000		386,788,600	
Unsuccessful Bidder	**Applied**					
Shin Il Trading Co., Ltd.	30,000	300	9,000,000	430	12,900,000	
Woon Kee Commercial Co., Ltd.	5,000	300	1,500,000	400	2,000,000	
Cheil Trading Co., Ltd.	10,000	300	3,000,000	400	4,000,000	
Han Kook Silk Textile Co., Ltd.	70,000	300	21,000,000	410	28,700,000	

Distribution
PE 2
PE-PD 4
CON 1
MOR 1
BOK 1

12

Small Business Circular (SBC): Information for Exporters

I C A Small Business Circular

Trade Opportunities for American Suppliers

Issued by The Office of Small Business, International Cooperation Administration
Washington 25, D. C. *STerling 3-6400, Ext. 2356*

SBC No. 58-9 | DATE January 14, 1958 | M/L 4-7-9-10-11-22

KOREA - SUPPLEMENT TO SBC No. 58-5, Item 14 . . . . ITEM 1
KOREA - SUPPLEMENT TO SBC No. 58-5, Item 15 . . . . ITEM 2
KOREA - SUPPLEMENT TO SBC No. 58-5, Item 8 . . . . ITEM 3
KOREA - Chemicals and Chemical Preparations . . . . ITEMS 4 thru 19

ITEMS 1 thru 20

Country: Korea
PA No: 89-390-99-L1-8213

ITEM 6

Commodity:
about 350,000 lbs. of Dicalcium Phosphate Dihydrate, Dentifrice Grade.
about 15,000 lbs. of Sodium Carboxy Methyl Cellulose, High Viscosity 1.0
about 20,000 lbs. of Foam Purified Powder, Sodium Lauryl Sulfate, Dentifrice Grade.
about 50,000 lbs. of Urea, Technical
about 150,000 lbs. of Formaldehyde, Aqueous Solution of 37% by weight

Buyer: Lucky Chemical Co., 363 Yunji-Kong, Pusan, Korea - Quotations should be forwarded to Room 504, Bando Hotel, Seoul, Korea - P. O. Box Kwang Hwa Moon 314 - Cable Address "YOURCLOVER"

Bid Deadline: January 31, 1958

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Weekly Report: Import Permit

SBA No. 57-28
June 19, 1957
(M/L: 24)

CAS/R- 017

WEEKLY REPORTS OF SUBAUTHORIZATIONS ISSUED BY THE BANK OF KOREA

FROM: April 29, 1957 TO: May 4, 1957

PA No.	SA No.	Name and Address of Importer	Commodity	Quantity	Amount (US$)	Name and Address of Supplier
7202	-377	Won Chang Trading Co., Ltd. 24, 1-ka, Chungmuro, Chung-ku Seoul	Viscose Rayon Yarn	33,000 lb	17,380.00	Italviscosa Sp.A. Italy.
"	-378	Federation of Korean Knittning Industry Assn. 21 Sokong-dong Chung-ku, Seoul	Twisted Nylon Yarn	9,900 lb	19,998.00	American Progress Corp. N.Y.
"	-379	Dae Un Textile Factory. 116, Taepyungro, 3ka, Taegu,	Woollie Nylon Yarn. etc.	64,397 lb	38,048.50	Sankei Trading Co., Ltd. Tokyo, Japan.
"	-380	Bu Chun Industrial Co., 155 Chun Rim Dong, Sudaimoon ku, Seoul	"	6,865 lb	19,998.75	"
"	-381	Tairyung Trading Co., Ltd. 111-6, Sokong-dong Chung-ku, Seoul	Rayon Yarn	20,000 lb	10,600.00	Comptior desTextile Artificeis. Paris.
7213	-92	Tai sung Industrial Co., Ltd. 123, Namdaimunro, Chung-ku, 2ka Seoul	Terramycin Intravanous	3,816 vial	4,998.96	Pfizer Corp., Hongkong.
"	-93	Samsung Moolsan Co., Ltd. 180, 1-ka, Ulchiro, Chung-ku, Seoul	"Squibb"	403,400 vial	89,674.00	U. S. Summit Corp. N.Y.
"	-94	Seoil Pharmaceutical Co., Ltd. 209, Rakwon-dong Chongro,-ku Seoul	Code 390 Sodium Salicylate	830 kilo	1,451.50	Karl Muller Uberseee Export W/G

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Data for Bidding Outcomes

- We collected SBC, Weekly Report, and Daily Report from National Archives (A2), University of Washington Library, and Hathi Trust Digital Library, and digitized all available documents.



- Each report has its own merit. We plan to vary the use of report considering research topics.

Table. Characteristics of SBC, Weekly Report, and Daily Report

	SBC	Weekly Report	Daily Report
Purpose	Inform U.S. exporters	Inform U.S. exporters	Reference for Aid Policy
Years	1956~60	1957 (19 W)	1957~60 (21 M)
Obs.	8,934	2,660	11,917 (S 6,427)
Variables	Name Address PA # Item description	Name Address PA # Amount Exporter	Name PA # Amount Bidding Rate
Remarks	Over $5,000	Incl. “C”	Incl. unsuccessful bidder

Research Framework

- Research questions:
  - Was the allocation of foreign aid in the 1950s competitive, fair, and efficient?
  - How much did the foreign aid in the 1950s contribute to firms’ survival and performance in later years?
- Among three reports on bidding information, Daily Report is the most useful.
  - Particularly, it contains the information on unsuccessful bidders.
- We focus on the bidding result in 1959.
  - Daily Report has complete information on 1959 biddings
- We merged Daily Report to DBs that contain firm’s initial condition and later performance.
  - 1959 Business Directory, which contains the information on only firms for which corporations tax was required.
  - 1973 Business Directory

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Data and Variables

Daily Report → **1973 Business Directory**

By firm and for 1959
- # of bid applications
- Success rate
  (= # of success / total applications)
- Average exchange tax
  (Actual bidding target)
- Average exchange gain
  (= Market Ex rate – Exchange Tax – 500)
- Expected exchange gain
  (= Average Ex gain * Success rate)
- Total aid amount received ($)
- Rent
  (=Total amount($) x Exchange gain)

1959 Business Directory → **1973 Business Directory**

Initial condition
- Paid-in capital
- Firm age
  (= 1959 – Year of established)

1973 Business Directory

Firm size
- Sales
- Equity
- # of workers

Rate of return
- Return on equity
- Sales on equity
- Return per worker
- Sales per worker
- Return (=net profit)
- Capital growth

Note: Sales, equity and return were measured as 1970-1972 average.

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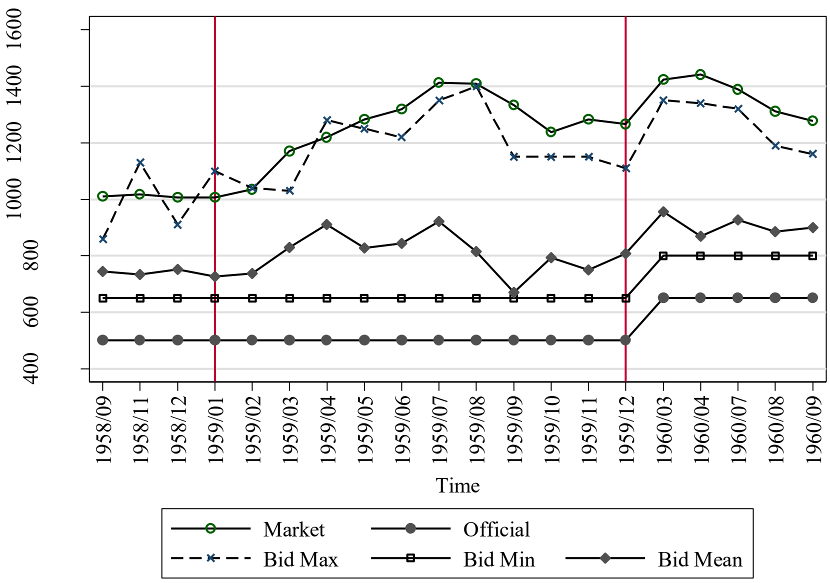
Descriptive Statistics

Table 3. Summary Statistics: Bidding Information in 1959, and Firm Performance in 1959 and 1973

Data linkage									
Daily Report in 1959	Y		Y		Y	Y	Y	N	N
1973 business directory	Y or N		Y		Y	N	N	Y	-
1959 business directory	Y or N		Y		N	Y	N	-	Y
Variables	Mean	SD	Mean	SD	Mean				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Num. of firms found	1,345		175		75	395	700	481	5,065
Aid and bidding information in 1959									
Number of bid applications	4.80	7.51	9.53	11.56	6.23	6.41	2.56	-	-
Success rate	0.54	0.39	0.62	0.32	0.58	0.56	0.50	-	-
Foreign exchange tax (hwan/dollar)	364.84	197.41	303.05	165.04	375.11	347.45	397.97	-	-
Foreign exchange gain (hwan/dollar)	400.88	196.34	459.56	176.65	384.83	413.24	373.38	-	-
Expected exchange gain (hwan/dollar)	298.56	219.57	338.70	228.19	268.83	286.71	297.44		
Aid amount received (mil. dollar)	0.09	0.25	0.26	0.48	0.11	0.10	0.03	-	-
Rent (mil. hwan)	45.48	145.37	129.23	284.45	43.32	42.27	12.18	-	-
Firm variables									
Firm size									
Sales (bil. KRW)	-	-	3.14	3.76	1.69	-	-	1.06	-
Equity (bil. KRW)	-	-	0.81	1.44	0.41	-	-	0.48	-
Number of workers (1,000)	-	-	1.17	1.79	0.62	-	-	0.37	-
Rate of return									
Return on equity	-	-	-0.01	2.12	0.19	-	-	0.24	-
Sales on equity	-	-	7.28	27.88	5.06	-	-	12.96	-
Return per worker (mil. KRW)	-	-	0.21	0.58	0.11	-	-	0.17	-
Sales per worker (mil. KRW)	-	-	4.35	5.52	2.25	-	-	4.82	-
Return (=net profit) (bil. KRW)	-	-	0.23	1.70	0.09	-	-	0.05	-
Capital growth (mil. KRW/1000 hwan)	-	-	6.01	42.09	-	-	-	-	-
Firm variables in 1959									
Paid-in capital (mil. hwan)	-	-	37.30	136.04	-	10.59	-	-	4.59
Firm age (years)	-	-	8.78	8.67	-	5.31	-	-	6.34

Trends of Bidding Exchange Rate

- Official rate: exchange rate for specified end-user allocation
- Market rate: sale of "export dollars"
- "Bid" exchange rate = Exchange tax rate + Official exchange rate
- Bid mean: weighted with foreign aid amount received



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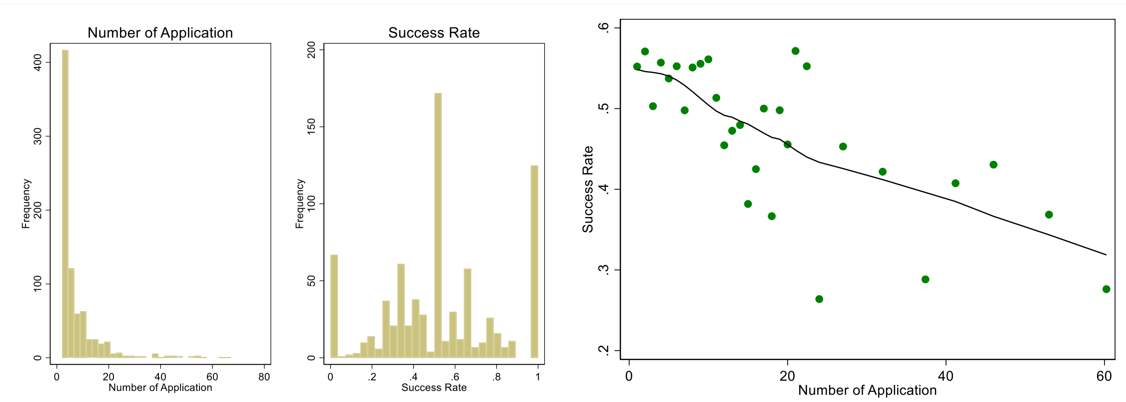
Q1: Fairness of Foreign Aid Allocation

- The distribution of application number and success rate, and the negative correlation between them suggest that firms frequently participated in bids, and that the allocation of foreign aid was very competitive.



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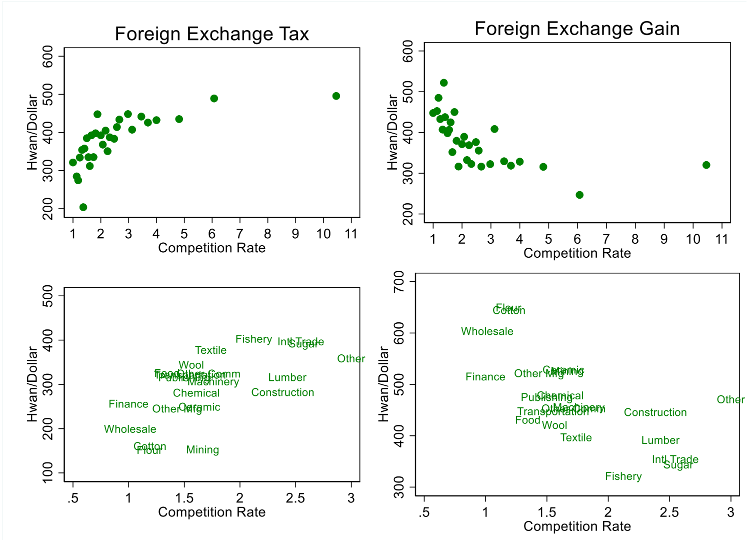
Q1: Fairness of Foreign Aid Allocation

- Did more competitive firms/industries bid higher exchange tax and obtain lower exchange gain on average?
  - Clustered firms with more than one success in 1959 into 30 groups by competition rate or 21 industries.
  - Measured bidding competition rate in each industry with a inverse of success rate.



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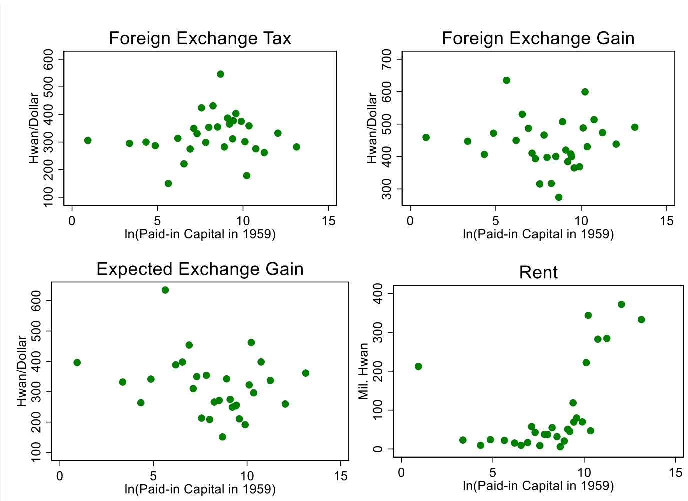
Q1: Fairness of Foreign Aid Allocation

- Did firms' initial conditions affect their bidding outcomes?
  - Sample: 496 firms found in both Daily Report and 1959 business directory with at least one successful bid in 1959.
  - Clustered the firms into 30 groups according to their paid-in capital in 1959 as a measure of initial condition, and plotted each group's average values of bidding outcomes.



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Q1: Fairness of Foreign Aid Allocation

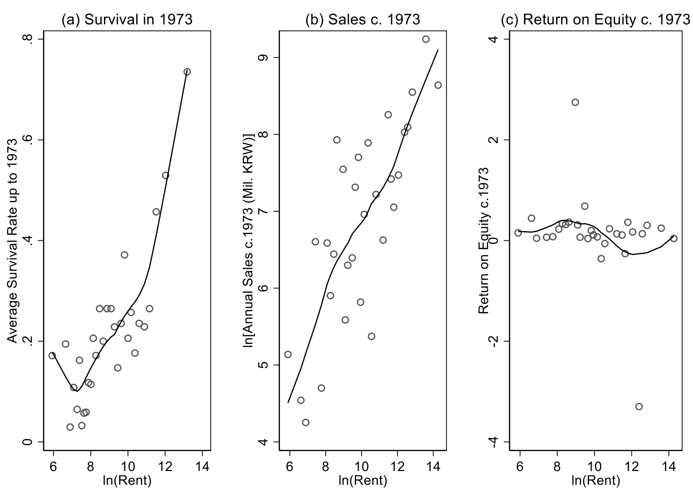
- Firm-level regressions:
  - Outcomes: success rate, exchange tax, exchange gain, expected gain, and rent
  - Measure of initial conditions: paid-in capital, firm age, industry
- Key results:
  - Firms' initial conditions seem to have not affected the level of exchange tax or gain. This suggests that the allocation and bidding process was fair.
  - But larger firms obtained more rent because they participated in a bid more frequently. This may suggest that the allocation was efficient.

Table 4. Estimated effects of firm paid-in capital in 1959 on bidding outcomes

Dependent variable	Success rate		ln(Exchange tax)		ln(Exchange gain)		ln(Expected gain)		ln(Rent)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls:										
ln(Paid-in capital 1959)	-0.0173**	-0.0096	0.0218*	0.0125	-0.0022	-0.0041	-0.0438**	-0.0299	0.2364***	0.0532
	(0.0073)	(0.0082)	(0.0128)	(0.0145)	(0.0119)	(0.0139)	(0.0220)	(0.0244)	(0.0401)	(0.0360)
Firm age in 1959		0.0011		-0.0068		0.0041		0.0078		0.0115
		(0.0024)		(0.0042)		(0.0041)		(0.0072)		(0.0106)
Number of bids		-0.0036**		0.0067**		0.0002		-0.0118***		0.0937***
		(0.0016)		(0.0027)		(0.0026)		(0.0045)		(0.0066)
Constant	0.7201***	0.5947***	5.4782***	4.9323***	5.9631***	6.2607***	5.7293***	6.2707***	7.5969***	7.9049***
	(0.0617)	(0.1859)	(0.1083)	(0.0337)	(0.1009)	(0.3241)	(0.0186)	(0.5687)	(0.3398)	(0.8390)
Industry FEs	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	558	555	496	493	496	493	496	493	469	493
R-squared	0.0099	0.1913	0.0059	0.2075	0.0001	0.1496	0.0080	0.2383	0.0658	0.5334

Q2: Long-Term Effect of Foreign Aid

- Did the size of rent obtained in 1959 increased the probability of being survived up to 1973, the size of firm, and the rate of return c. 1973?
  - Fig (a): clustered the firms found in Daily Report into 30 groups according to their rent obtained in 1959, and plotted each group's average survival rate. Survival = 1 if found in the 1973 business directory.
  - Fig (b) & (c): Compared b/t ln(rent in 1959) and outcomes in 1973 for all the firms found in both Daily Report and 1973 business directory clustered into 30 groups.



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Q2: Long-Term Effect of Foreign Aid

- Firm-level regressions:
  - Firms which obtained higher rent from 1959 foreign aids more likely survived up to 1973, and recorded significantly higher sales c. 1973.
  - But the size of rent did not affect the rate of return c. 1973.

Table 5. Estimated Effect of Foreign Aid in 1959 on Firms' Survival, Size and Return in the Early 1970s

Dependent variable	Survival dummy in 1973		ln(Annual sales c. 1973)			Return on equity c. 1973		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effect of Rent								
Controls:								
ln(Rent in 1959)	0.0678***	0.0671***	0.4895***	0.4516***	0.1355***	-0.0303	-0.1068	-0.0204
	(0.0072)	(0.0133)	(0.0696)	(0.1116)	(0.0174)	(0.0750)	(0.1733)	(0.0149)
ln(Paid-in capital in 1959)		0.0246**		0.0349			-0.0259	
		(0.0122)		(0.0841)			(0.1285)	
Firm age in 1959		0.0194***		0.0309			0.0105	
		(0.0036)		(0.0197)			(0.0308)	
Constant	-0.3902***	-0.3096	1.8574***	4.1250**	5.5197***	0.3396	0.8357	0.2375***
	(0.0658)	(0.3070)	(0.7055)	(1.7457)	(0.0962)	(0.7642)	(2.7485)	(0.0851)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	1,032	493	141	103	471	166	122	526
R-squared	0.0795	0.2076	0.2624	0.4608	0.1150	0.0010	0.0272	0.0036

Q2: Long-Term Effect of Foreign Aid

- Firm-level regressions:
  - Similarly, firms which enjoyed higher expected gain recorded significantly higher sales c. 1973.
  - But the survival rate and rate of return c. 1973. were not significantly affected.

(continued)

Dependent variable	Survival dummy in 1973		ln(Annual sales c. 1973)			Return on equity c. 1973		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Effect of Expected Gain								
Controls:								
ln(Expected gain in 1959)	0.0154	0.0078	0.5109***	0.2863	0.2216***	0.1105	0.3701	-0.0295
	(0.0136)	(0.0240)	(0.1557)	(0.2350)	(0.0320)	(0.1501)	(0.3316)	(0.0273)
ln(Paid-in capital in 1959)		0.0372***		0.1054			-0.0274	
		(0.0123)		(0.0906)			(0.1266)	
Firm age in 1959		0.0214***		0.0359*			0.0030	
		(0.0037)		(0.0214)			(0.0307)	
Constant	0.1365*	0.0831	3.9192***	5.7860**	5.5591***	-0.5671	-2.3753	0.2240
	(0.0740)	(0.3403)	(0.8674)	(2.2547)	(0.0976)	(0.8341)	(3.1888)	(0.0853)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	1,032	493	141	103	471	166	122	526
R-squared	0.0012	0.1642	0.0719	0.3635	0.0927	0.0033	0.0356	0.0022

Notes: Columns (1) and (2) estimate the effect of rent size or average expected gain on the probability of being survived up to 1973, which is measured by whether a firm is found from the 1973 business directory or not. Columns (3)-(5) utilize the log value of annual sales c. 1973 as a measure of firm size. We use firms found in both Daily Report in 1959 and business directory in 1973 for columns (3). In column (4), we use firms commonly found in both records and 1959 business directory. In column (5), we use any firm found in the 1973 business directory only if it could participate in aid allocaition in 1959, regardless of whether they are actully found in Daily Report in 1959 or not. In the analysis of column (5), we also assume that, if a firm in the 1973 business directory is not found in Daily Report in 1959, its rent and average expected gain are zero. Except that columns (6)-(8) use ROE (return on equity c. 1973) as dependent variable, their regression specifications are the same with those for columns (3)-(5), respectively. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

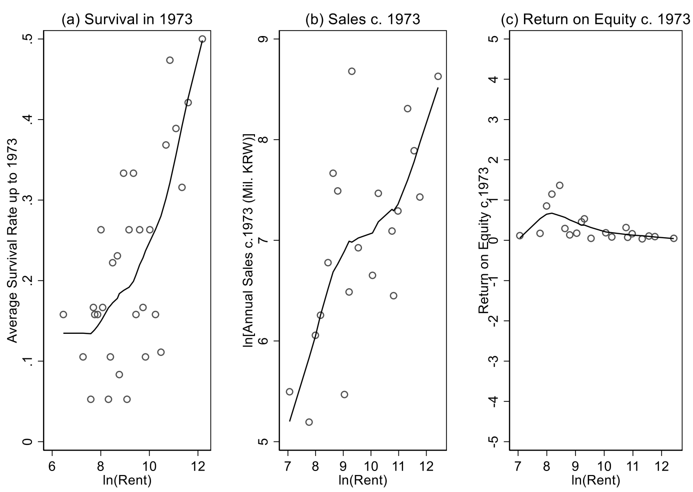
Q2: Long-Term Effect of Foreign Aid

Table 6. Estimated Effects with Alternative Bidding Outcomes and Firms' Performance c.1973

	Survival dummy	Firm size c.1973			Profitability c.1973					Capital growth in 1959-73
		ln(Sales)	ln(Equity)	ln(# of Workers)	Return on equity	Sales on equity	Return per worker	Sales per worker	ln(Return)	
Key controls:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Effects of Rent Size									
ln(Rent)	0.0671***	0.4516***	0.3484***	0.1588**	-0.1068	3.2856	0.0043	0.6905**	0.2723**	6.2240**
	(0.0133)	(0.1116)	(0.0834)	(0.0764)	(0.1733)	(2.5294)	(0.0474)	(0.3175)	(0.1288)	(2.4383)
Observations	493	103	124	146	122	93	117	97	108	143
R-squared	0.2076	0.4608	0.4365	0.3255	0.0272	0.0860	0.0896	0.6370	0.3528	0.3757
	Panel B: Effects of Average Expected Gain									
ln(Average expected gain)	0.0078	0.2863	0.4032**	-0.0156	0.3701	3.0591	0.1155	1.3002**	0.2139	-3.5132
	(0.0240)	(0.2350)	(0.1566)	(0.1351)	(0.3316)	(4.9953)	(0.0837)	(0.5769)	(0.2413)	(4.5129)
Observations	493	103	124	146	122	93	117	97	108	143
R-squared	0.1642	0.3635	0.3803	0.3018	0.0356	0.0692	0.0837	0.6386	0.3250	0.3451
	Panel C: Effects of Number of Bidding Applications									
# of bid applications	0.0106***	0.0393**	0.0246**	-0.0034	-0.0092	0.0250	0.0004	0.0665	0.0272	0.8171**
	(0.0022)	(0.0167)	(0.0116)	(0.0099)	(0.0211)	(0.3277)	(0.0059)	(0.0446)	(0.0173)	(0.3423)
Observations	555	110	135	155	133	100	125	103	116	156
R-squared	0.2005	0.4061	0.3844	0.3048	0.0235	0.0582	0.0765	0.5885	0.3357	0.3423
	Panel D: Effects of Success Rate									
Success rate	0.0280	-0.3323	0.2131	-0.2361	0.8982	1.1295	0.3067	1.0879	-0.3991	5.2626
	(0.0614)	(0.6008)	(0.4166)	(0.3617)	(0.7609)	(11.9756)	(0.2110)	(0.5796)	(0.5951)	(11.1842)
Observations	555	110	135	155	133	100	125	103	116	156
R-squared	0.1641	0.3707	0.3612	0.3617	0.0340	0.0582	0.0952	0.5796	0.3213	0.3119
	Panel E: Effects of Exchange Rate Gain									
ln(Exchange rate gain)	0.0264	0.3161	0.5392**	-0.2678	0.1362	4.4780	0.1886	1.1278	0.7768**	-11.4863
	(0.0430)	(0.3487)	(0.2541)	(0.2403)	(0.5191)	(7.1228)	(0.1446)	(0.9343)	(0.3808)	(7.7875)
Observations	493	103	124	146	122	93	117	97	108	143
R-squared	0.1647	0.3584	0.3679	0.3087	0.0242	0.0694	0.1057	0.6215	0.3506	0.3535

Q2: Long-Term Effect of Foreign Aid

- Did the lottery outcomes in 1957 have similar effects with bidding outcomes in 1959?
  - Fig (a): clustered the firms found in lottery records of Weekly Report into 30 groups according to their rent obtained in 1957, and plotted each group's average survival rate. Survival = 1 if found in the 1973 business directory.
  - Fig (b) & (c): Compared b/t ln(rent from lottery in 1957) and outcomes in 1973 for all the firms found in both Weekly Report and 1973 business directory.



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Q2: Long-Term Effect of Foreign Aid

- Firm-level regressions:
  - Firms which obtained higher rent or expected gain from lottery in 1957 more likely survived up to 1973, and recorded significantly higher sales c. 1973.
  - But the lottery outcomes did not significantly affect the rate of return c. 1973.

Table 7. Estimated Effects of Lottery Outcomes on Firms' Survival, Size and Return in the early 1970s

Dependent variable	Survival dummy in 1973		ln(Annual sales c. 1973)			Return on equity c. 1973		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Effect of Rent							
Controls:								
ln(Rent from lottery)	0.0602***	0.0793***	0.4654***	0.4497**	0.1202***	-0.0783*	0.0614	0.0103
	(0.0124)	(0.0206)	(0.1152)	(0.2105)	(0.0235)	(0.0453)	(0.0430)	(0.0191)
ln(# of workers in 1956)				0.7996***			-0.0224	
				(0.2768)			(0.0612)	
Constant	-0.3343***	-0.5766	2.3451**	0.0343	5.7362***	1.0367**	-0.2677	0.1558**
	(0.1159)	(0.3761)	(1.119)	(2.1215)	(0.0916)	(0.4452)	(0.4334)	(0.0780)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	561	294	76	38	471	91	32	526
R-squared	0.0403	0.1326	0.1807	0.6519	0.0530	0.0325	0.3960	0.5905

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Q2: Long-Term Effect of Foreign Aid

(continued)

Dependent variable	Survival dummy in 1973		ln(Annual sales c. 1973)			Return on equity c. 1973		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel B: Effect of Average Expected Gain							
Controls:								
ln(Expected gain from lottery)	0.0720***	0.0867**	0.5673**	1.0156	0.4082***	-0.1238	0.0778	0.0319
	(0.0250)	(0.0398)	(0.2615)	(0.5989)	(0.0820)	(0.0940)	(0.0949)	(0.0648)
ln(# of workers in 1956)				0.8475***			-0.0205	
				(0.2868)			(0.0633)	
Constant	0.0305	-0.0905	5.2900***	2.0222	5.7454***	0.6214	0.1202	0.1576**
	(0.0685)	(0.3494)	(0.7252)	(1.5780)	(0.0914)	(0.2711)	(0.2855)	(0.0777)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	561	294	76	28	471	91	32	526
R-squared	0.0146	0.1007	0.0598	0.6224	0.0502	0.0191	0.3541	0.0005

Notes: Columns (1) and (2) estimate the effect of rent size or average expected gain on the probability of being survived up to 1973, which is measured by whether a firm is found from the 1973 business directory or not. Columns (3)-(5) utilize the log value of annual sales c. 1973 as a measure of firm size. We use firms found in both Weekly Report in 1957 and business directory in 1973 for columns (3). In column (4), we use firms commonly found in both records and business directory in 1956, addtionally contraining the sample to manufacturers as the 1956 business directory as records the number of emploees only for manufacturers. In column (5), we also assume that, if a firm in the 1973 business directory is not found in Weekly Report in 1957, its rent and average expected gain are zero. Except that columns (6)-(8) use ROE (return on equity c. 1973) as a dependent variable, their regression specifications are the same with those for columns (3)-(5), respectively. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

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Summary

- Goal:
  - To investigate the fairness of foreign-assistance allocation in the 1950s and its long-term effect on the growth of Korean economy.
- Data:
  - Collected micro-level database on bidding information among commercial firms, and measured the size of rent and other gains from foreign aid.
- Main result:
  - The allocation of foreign aid among commercial firms was more competitive and fair than exiting studies have described.
  - We need more investigation to say about the efficiency of allocation.
  - The firms, which obtained higher rent (i.e., financial benefit from foreign aid) and expected gain significantly achieved larger firm size in 1973.
  - But the gains from foreign aid did not significantly affect the rate of return, which seem to have been more influenced by current economic conditions.

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Foreign Aid and Economic Development:
A Firm-level Study of Korean Experience in the 1950-70s

Sok Chul Hong*, Jongryong Park† and Sang-Yun Ryu‡

Abstract

This paper discusses fairness and growth effects of foreign aid given to South Korea in the late 1950s. Along with its almost 80-year history so far, foreign aid has brought about lasting debates on its effectiveness. In order to add to these disputes, we study the very early and successful example of foreign aid history, South Korea. We construct a unique firm-level data of allocation of aid funds and economic performance collected from historical administrative documents of aid agencies and business directories. From descriptive evidences and standard regression analyses, we find that enormous aid provided to South Korea was allocated to firms in a fair and competitive manner, and it also significantly contributed to long-run growth of recipient firms. The latter result is robust to using data of aid allocated by lottery to avoid latent endogeneity problem. These results support the consensus reached in the literature that institution which deal with the delivery and allocation of foreign aid is an important determinant of the success of foreign aid.

Keywords: Foreign aid, Subnational Allocation, Fairness, Aid effectiveness, Firm Growth
JEL Codes: F35, N15, O19

* Professor, Department of Economics, Seoul National University. Email: sokchul.hong@snu.ac.kr

† Ph.D. Student, Department of Economics. Seoul National University. Email: hitora@snu.ac.kr

‡ Assistant Professor, College of Social Sciences, University of Ulsan. Email: syryu@ulsan.ac.kr

1. Introduction

It has been almost 80 years since the first foreign aid projects began with the end of World War II in 1945. Even though a large scale of foreign assistance or aid has been provided mainly from developed to developing countries throughout the second-half of the 20th century and the first fifth of 21st century, only a few countries out of beneficiaries succeeded in economic development (Browne, 1997; Edwards, 2015; Goldin, 2018). This has provoked a controversy over on the effectiveness of foreign aid. Many researchers have argued that foreign aid has been useless or even harmful to economic growth (Bauer, 1976; Friedman, 1995; Hansen and Tarp, 2000; Remmer, 2004; Easterly, 2006; Collier, 2007; Rajan and Subramanian, 2005; 2007; 2008; Heckelman and Knack, 2008; Moyo, 2009; Acemoglu and Robinson, 2012). Political distortion of aid fund and induction of social conflicts are also pointed out as the dark side of foreign aid (Crost et al.,2014; Nunn and Qian 2014; Anaxagorou et al., 2020).

At the same time, new approaches have been raised to discover positive effects of foreign aid. One line of research has paid attention to the quality of policies of recipient and donor countries as dominant factor to shape effectiveness of aid (Browne, 1997; Burnside and Dollar, 2000; 2004; Hansen and Tarp, 2000; Martens et al., 2002; Lancaster, 2007; Bearce and Tirone, 2010; Dietrich, 2013; Edwards, 2015; Goldin, 2018). Another line has introduced importance of finer unit of observation. Especially, Dreher and Lohmann (2015) found that observed correlation of regional growth with foreign aid was positively associated with the smaller unit of region, which was interpreted that size of foreign aid had been small for its effects to be revealed in data aggregated at national level.

This paper focuses on the experience of South Korea, one of the early recipients of foreign aid, to deepen understanding of the historical and practical significance of foreign aid. The country has received lots of foreign aid for decades since its independence in 1945 and also achieved a rapid economic growth during the short period called as the *Miracle on the Han River*, which suggests a conjecture that South Korea is a representative example of success of foreign aid in the last century. However, South Korea could not avoid the negative views on aid so far. Some argued that foreign aid in the 1950s and 1960s distorted economic structure in the county and delayed economic independence (Hong 1962; Yi 1987). Others pointed out that the distribution of foreign aids was not effective (Krueger 1977; Cho 1996; Kim 1999).

We try to refute this established understanding by looking into foreign aid to South Korea in the late 1950s. Among $4.4 billion of aid funds given to the country from 1945 to 1983, $3 billion was provided no later than 1960. In particular, aid from FOA and ICA, U.S. foreign aid agencies, accounted for the largest share. FOA/ICA aid was divided into two types: project and non-project aid. While project aid was intended to improve social infrastructure, non-project aid was more related to industrialization because various kinds of economic resources, including fuel and raw material were distributed to domestic firms either through competitive bidding or lottery. Therefore, we analyze non-project aid of FOA/ICA aid in the late 1950s.

Our research questions are twofold. First, we inquire whether the allocation of foreign aid in the 1950s was competitive, fair, and efficient. This is intimately associated both with pros and cons of foreign aid as either side has stressed policies or institutions of the recipient countries (e.g. Burnside and Dollar, 2000; 2004; Acemoglu and Robinson, 2012). The second question is how much foreign aid in the 1950s contributed to firms' performance later. To answer them, we newly constructed firm-level micro datasets by merging administrative documents produced in the process of aid provision by relevant authorities with business directories published in the 1950s and 1970s. Our unique datasets provide both aid allocation outcomes and economic performance information at the firm-level.

Results suggest that foreign aid was justly allocated to domestic firms without any noticeable evidences of prejudiced favor and it also contributed to long-term survival and growth in size of recipient firms. Whether large and old or not, firms confronted above board competitions at every bid they applied. Although larger firms were able to obtain bigger amount of aid, they had to apply more times to do so suffering from lower marginal benefit and higher marginal cost. The rule of bidding was actually implemented, which greatly reduced the room for discretionary intervention by the government or collusion among firms. In addition, firms that earned more financial benefit from the allocation of aid, either by competitive bid or lottery, had a larger firm size in the early 1970s, as well as higher probability to survive until then, even when controlling for firm size in the late 1950s. This result suggests that aid had a positive impact on the growth of firms in South Korea, and the country itself considering the fact that only a few firms which played marked roles during its industrialization had colonial origins. Although aid outcomes were found to have few significant effects on rate or return, this is likely because the profitability of a firm at a certain point of time is affected primarily by the specific characteristics of industry it belongs or market situation rather than by its actual business competence.

Our study adds to the literature on the evaluation of foreign aid in four ways. First, this paper presents empirical analyses on the early example of foreign aid, which can shed light on theoretical and practical evaluations of history of the subject as recent studies contrate more on foreign aid after 2000 (Dreher and Lohmann, 2015; Chauvet and Ehrhart 2018; Dreher et al. 2021). Second, our paper is, to our knowledge, the first to take complete micro level approaches both on the allocation and effects of foreign aid.[4] Furthermore, we systemically combine the assessments on allocative procedure and on effectiveness of aid. Last but not least, we also newly figure out basic documents and historical details on South Korea's experience of foreign aid in the 1950s which will serve as the cornerstone for further research in this field.

This paper proceeds as follows: Section 2 reviews previous studies on the effectiveness of foreign aid. Section 3 summarizes South Korea's experience of foreign aid and evaluations of it raised so far. In section 4, we explain a series of data sources and describe our baseline dataset in advance of presenting our results in section 5 from descriptive correlations to more rigorous regression analyses. Section 6 concludes.

2. Evaluations of Foreign Aid in the Literature

Development aid is a unique phenomenon representing contemporary economic history of the world. It began with the Cold War, the wave of decolonization, and the birth of international organizations including United Nations at the aftermath of World War II. Since then, an increasingly large amount of aid has been provided usually to developing countries from the developed world. Core characteristics of aid also have changed from political and strategic to more humanitarian ones (Browne, 1997; Edwards, 2015; Goldin, 2018). As such, it can be argued that understanding aid effectiveness and its determinants is an important subject not only in economic history but also in development economics both in theoretical and practical aspects.

However, there have been few cases where the recipient countries have succeeded in achieving such a dramatic economic development as comparable with the size of aid provided. This seemingly unsatisfactory results have brought about long-lasting debates on the aid effectiveness issue. Above all, the criticism which can be referred to as the theory of fruitlessness of foreign aid

[4] Even though Chauvet and Ehrhart (2018) showed evidences of the positive effectiveness of aid from firm-level data of growth, their aid allocation variables were at country-level.

has continuously been raised, for example, by Bauer (1976), Friedman (1995), Easterly (2006), Collier (2007), Rajan and Subramanian (2008), and Moyo (2009). Some studies have even argued possibly adverse effects of aid on growth (Hansen and Tarp, 2000; Remmer, 2004; Rajan and Subramanian, 2005; 2007; Heckelman and Knack, 2008). Acemoglu and Robinson (2012) pointed out that most of foreign aid was wasted for decades in the inefficient execution and corruption owing to extractive institutions of recipient countries which themselves caused poverty at first. These negative assessments were also proposed from non-economic outcomes. Anaxagorou et al. (2020) found that allocation of aid from China within a county was led by electoral motives in sub-Saharan Africa after 2000. Nunn and Qian (2014) and Crost et al. (2014) verified positive causal effects of aid on social conflicts.

By contrast, positive points of view on aid have involved the quality of government and policy. For instance, Burnside and Dollar (2000; 2004) emphasized accountability of the recipient government as a key determinant of effectiveness of aid based on the analysis using the historical country-level panel data from 1970 to 1993. This view has been accepted by many countries and international organizations as a standard for the provision of foreign aid (Browne, 1997; Hansen and Tarp, 2000; Edwards, 2015; Goldin, 2018). Policy of donor country and specific methods of implementing aid have also been suggested to affect the aid effectiveness (Dollar and Svensson, 2000; Martens et al., 2002; Lancaster, 2007; Bearce and Tirone, 2010; Dietrich, 2013). Galiani et al. (2017) exploited International Development Association (IDA)'s eligibility criteria for aid provision to devise an instrumental variable, and found positive effects of aid in 35 countries from 1987 to 2010.

Another line of research with positive views has focused on subnational unit of observation to disclose effectiveness of aid after 2000. Dreher and Lohmann (2015) observed that a correlation between aid and growth became larger with the smaller regional unit of analysis, although causality was disapproved when they used regional fixed effects or instrumental variables. Dreher et al. (2021) reevaluated Chinese aid to African countries that it had causal contributions to regional development despite its political distortions in subnational allocation. They both instrumented regional allocation of aid with a multiplication of exogenous variation in aid supply and each region's actual probability to receive aid. Furthermore, Chauvet and Ehrhart (2018) adopted firm-level data to show that foreign aid had led to growth of firms in the recipient countries.

Adding to the debates on foreign aid, we contribute to the literature by investigating the aids to

South Korea in the 1950s which represents the very early stage and the greatest success of history of foreign aid. As foreign aid now has a history of more than 70 years, evaluation of its initial period would be necessary to understand its implications and long-run effects. Moreover, South Korea is a significant case in the discussions of foreign aid in that it is the exceptional country that transformed itself from a recipient to donor. Therefore, our paper may narrow the gap in the literature which concentrates more on recent aid projects where more data are available despite its long history. The next section describes foreign aid given to South Korea in the 1950s in detail.

3. Foreign Aid to South Korea in the 1950s

South Korea received large amount of foreign aid, mainly from the United States, by and large during its recovery from the damages of the Korean War which broke out in 1950. Foreign aid to South Korea began in 1945 with the establishment of US military government in Korea. Total of $4.4 billion foreign aid was injected between 1945 and 1983, while $3 billion of which was received by 1960. Although the United States provided aid before the Korean War, the amount was relatively small in size. The aid during the War was in the form of food and other necessities which was referred to as Civilian Relief in Korea (CRIK) then. It is not until 1954 when the aid for economic rehabilitation started in earnest.

In the US fiscal year of 1954 (from July 1953 to June 1954), the Foreign Operations Administration (FOA), the US foreign aid agency, commenced the aid operation, although actual provision did not begin until calendar year of 1954 due to delay in consultation with South Korean government. With the beginning of FOA aids, CRIK aid decreased sharply. The FOA and its successor, the International Cooperation Administration (ICA) provided more than $200 million USD of aid to South Korea annually in the late 1950s. The size of the aid reached its peak in 1957 when total of $380 million was provided to the county including UNKRA and PL 480 aids. The size of aid subsequently decreased to reach yearly average of $100 million in the 1960s. This is the reason why the South Korean economy in 1950s is often referred to as *the aid economy*.

FOA/ICA aid was divided into two types: project and non-project aids. In the project aid, imports and consulting services were provided to carry out specific projects. As can be seen in Table A2, this type of aid was of social overhead capital such as transportation, education and sanitation. Non-project aid, on the other hand, was provision of fixed amount of imports, including agricultural products, fuels, raw materials and semi-finished products, which were deemed necessary for the South Korean economy. At the initial negotiations for the aids, there were conflicts between the donor and recipient because the South Korean government demanded an increase in the proportion of project aid, which strongly involved capital accumulation while the US argued for non-project aid to achieve price stabilization. In the end, the aid got to largely consist of non-project aid as insisted by the US, as seen in Figure 1(a).

[Figure 1 Here]

While CRIK was provision of goods purchased by US military to the South Korean government or the private sector, FOA/ICA aids required more active participation of firms in South Korea. Particularly for non-project aid, domestic firms were responsible for the actual importation of aid goods although necessary funds were provided by the agency. Non-project aid was able to deliver considerable benefits to domestic firms because not only was it larger in size but it also allowed greater number of firms to participate in the allocation of the funds on more favorable exchange rate than the market.[5] On the contrary, impacts of the project aid on domestic firms were limited. It was relatively small in size and was for social overhead capital in nature. Only a few factories such as the Chungju Fertilizer and several small and medium size enterprises benefited from this type of aid.

For FOA/ICA non-project aid, there were four types of procurement methods: A. Procurement by the US agency; B. Procurement of goods for civilian demand; C. Procurement of goods for specified end-users and D. Procurement by the Office of Supply, South Korea. Composition of these four methods in each fiscal year is shown in Figure 1(b). Among them, we concentrate on the procurement of goods for civilian demand, as it allowed private firms to participate in regardless of their industrial classification and it accounted for the largest share. This openness enabled great number of firms to receive aid.

The allocation rule of goods for civilian demand have changed several times in accordance with

[5] Foreign exchange was managed exclusively by the Bank of Korea in the 1950s, and those who wanted to hold foreign currency were required to create an account at the Bank of Korea and deposit all of them. As the official exchange rate at that time overvalued the South Korean currency, *hwan*, firms that earned US dollars through exports preferred to deposit them into their accounts and sell them to other firms in need of US dollars than to change them to hwan at the official exchange rate. The price of the US dollar set by such a process was called ‘export dollar exchange rate’ and was the prevalent ‘market exchange rate’ at the time.

the government's foreign exchange and fiscal policy as well as the consultation with the US foreign aid authorities.[6] When the allocation was first implemented in 1954, a kind of exchange rate bidding method was adopted. Aid funds or import rights were distributed to the bidders which suggested highest hwan per dollar. It was to prevent inflation by absorb more Korean currencies and to collect more counterpart fund to lower fiscal deficit. However, since the introduction of so-called "single" official exchange rate of 500 hwan per dollar in August 1955, the single official rate was also applied to goods for civilian demand as a part of exchange rate policy. The government firstly adopted basically first-come-first serve method and lottery in case when the amount applied exceeded the amount offered in a day. However, a large number of participants were concentrated on popular items to acquire exchange rate gain. Since February 1956, the government changed its approach for quick and smooth collection of hwan: company with highest deposit could get aid funds, and lottery in case of competition among firms with same highest deposits.

In 1957, with a strong financial stabilization plan in place,[7] the government started to force firms that were allocated the funds to purchase national bonds in order to increase the fiscal revenue. In February 1957, the Treasury imposed 100 hwan of national bonds per dollar which translated to additional government revenue of 80-50 hwan per dollar as the bond was trading at 15-20% of issue price.[8] Then, in May 1957, the agreement between South Korea and the US introduced a bidding system called 'additive national bonds.' By allocating aid funds to firms that bought more government bonds, it was in essence an indirect exchange rate bidding.

The allocation criteria changed again in 1958 when the Temporary Special Foreign Exchange Tax was introduced in May of that year. The government replaced the bidding tool from national bonds to the exchange tax: firms which suggested to pay greater amount of foreign exchange tax in hwan per dollar were allocated with the funds. It was more direct method of increasing tax revenue. The actual exchange rate for winner of competitive bidding was suggested foreign exchange tax plus the official exchange rate, 500 hwan per dollar. This method continued until

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[6] Reference was made to newspapers and Monetary Policy Committee Resolution by the Bank of Korea which was responsible for the allocation methods.

[7] See Ryu (2012) for the influence of the "single" exchange rate, 500 hwan per dollar, to financial stabilization plans implemented in the late 1950s.

[8] Selling prices of government bonds at the time are found in the *Securities Statistics Yearbook*, 1963.

abolishment of the Temporary Special Foreign Exchange Tax in 1961. Those rules with additive national bonds and foreign exchange tax could be interpreted as measure to restrain speculative demand and promote budget capacity while maintaining the single exchange rate on the surface.[9] Table 1 summarizes types of FAO/ICA aid and change in the mode of allocation of funds for the purchase of goods for civilian demand.

[Table 1 Here]

In other words, goods for civilian demands were institutionally supposed to be allocated according to objective criteria such as lottery or bidding. Also, it is likely that bidding was competitive. Figure 2 shows that the monthly amount bid was approximately double the amount offered, according to the data we collected which are described in the following section.

[Figure 2 Here]

Firms which were allocated with goods for civilian demand had business opportunities to process or sell imported them, which itself would be profitable as the lack of foreign currencies were the bottle neck of the economy at the time. In addition, firms could benefit from exchange rate gain, because they could acquire import rights with more favorable official exchange rate compared to market rates. Figure 3 illustrates this exchange rate gain over time.[10] It compares the highest successful bidding price, lowest price, and average price by month to market and official exchange rates.[11]

[Figure 3 Here]

The highest price followed a similar trend as that of the market exchange rate, indicating that

[9] The counterpart fund could only be used through an agreement with the US aid agency; however, the government could use foreign exchange tax revenue independently.

[10] For the source and its time coverage, see the next section.

[11] Bidding price is the sum of official exchange rate – 500 hwan per dollar – and foreign exchange tax per dollar.

the bidders were closely aware of the market exchange rate. The lowest price was 650 hwan, namely 150 hwan above the official exchange rate since the government was collecting at least 150 hwan per dollar of foreign exchange tax in aid allocation, in order to increase its tax revenue. The average price formed between the market and official exchange rates. Therefore, firms that were allocated aid funds could gain profit in their imports compared to those that purchased the dollar in the market by a margin equivalent to the difference between the market exchange rate and the bidding price.

Along with foreign aid and through rapid growth from the 1960s, the country has become the world's 10th largest economy and now provides a considerable amount of foreign aid to other developing nations. Despite its importance, empirical study on the impact of aid on Korea's economic growth has been at a standstill. It is largely due to significant absence of data in the 1950s, which was the prime period of foreign aid to the country. At the same time, negative image of foreign aid has been promoted based on fragmented observations of corruption and rent-seeking behavior. The unimpressive macro-economic performance in the 1950s, which was in contrast to rapid growth in the 1960s, also added to negative impressions on foreign aid in the country. Studies in the period when theory of economic self-reliance was popular, for example Hong (1965) and Yi (1987), argued that foreign aid distorted the economic structure of South Korea. On the other hand, studies with growth-oriented perspectives, such as Krueger (1979), Cho (1996), and Kim (1999) pointed out that inefficiency of allocation of aid funds due to exchange rate distortions. Kim and Kim (2012) also followed this established assessment to focus on foreign aid in the 1960s.

Kim and Ryu (2014) compared the size of official development aid (ODA) between recipient countries to argue that foreign aids provided to South Korea were not of overwhelming amount relative to other countries considering their population or GDP. They also suggested that actual reason behind South Korea's success should be found in efficient use of the aid rather than its volume. Aid efficiency is deeply connected with aid allocation, because size and condition of the fund allocated to different industries and businesses influence their growth, and because corruption or collusion in the allocation processes can undermine the effects of the aid.

4. Data

4.1. Sources

The biggest obstacle to empirical evaluation on South Korea's experience of foreign aid has been the unavailability of detailed information about aid provision and economic outcomes at the micro level in the 1950s. To deal with this, we newly collected administrative documents reporting firm-level allocation results of the goods for civilian demand of non-project aid. In the 1950s, US foreign aid agencies were deeply involved in policymaking of South Korea through the Combined Economic Board of the US and Korea, which made the agencies produce or receive vast amount of data that included the details on allocation of each aid funds. Then we merged them with data on firms' performance in the 1950s and 1970s to construct datasets.

The documents of aid used in this paper are *Daily Report on Allocation of ICA Funds* and *Weekly Report of Sub-authorization*. In advance to introduction, allocation procedure of FOA/ICA aid funds where these documents were produced should be explained briefly to help understanding.[12] Based on the aid program for each fiscal year (FY) confirmed by the US Congress, South Korean government sent Firm Requests (FR) for items to the US aid agency headquarter in Washington. Washington then reviewed the FR and issued Procurement Authorizations (PA) to the government.[13]

PA was used as a unit in the allocation procedure of aid fund, such as bidding and lottery. Accordingly, the number assigned to PA has a very important role as a distinction code. PA number consists of four or five numbers. For example, one of the PA for cement in FY 1954 was assigned of 89-640-00-995-4238. The first two-digit number '89' was a code for South Korea and the second number '640' signified the product - cement in this case. The subsequent '00-995' indicated country and region from which it could be purchased respectively. The last four-digit number '4238' was a serial number that was actually used as a distinction code for that particular PA. The first digit '4' refers to the US fiscal year 1954 when the aid fund was authorized.[14] In cases where it was necessary to distribute the same items over multiple times, it was also required to produce multiple PAs.

Once the recipient firms for each PA were decided, the Bank of Korea issued Sub-Authorization

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[12] This is based on regulations republished in *Monthly Economic Bulletins* by the Bank of Korea.

[13] The first FR in FY 1954 was for raw rubber (FR 4-1, PA 4201) and the first PA was for raw cotton (FR 4-14, PA 4101).

[14] It does not necessarily mean that funds were spent in that period. For example, out of the $200 million funds by FOA for FY 1954, only $90 million was completed for contracts by June 1954 (the end of FY 1954) and it was $150 million by the end of calendar year 1954. Goods that were actually imported into Korea were only $30 million and $90 million by June 1954 and December 1954 respectively.

(SA) to the firms. The word 'sub' was used to indicate that there were multiple SAs under each PA. The recipient firms were given the right to import goods, while actual dollar was not transferred to them. The payment was made directly by the US authorities to the overseas exporters and the recipient firms deposited domestic currency with equivalent official value to the Bank of Korea. From the bidding to issuance of SA, this entire process following the issuance of PA for the purchase of goods for civilian demand was controlled by the Bank of Korea. We found and collected administrative documents produced in the above process in the record group of the US foreign assistance agencies in the US National Archives and Records Administration (NARA).[15]

Our baseline source for foreign aid is the *Daily Report on Allocation of ICA funds* (DR). DR is a record of every bidding outcome that was produced to grasp the distribution of exchange rates in competitive bidding, which was the primary interest of personnel responsible for foreign aid to South Korea in the US aid agencies. Therefore, the most important feature of the document is the inclusion of information on bidding prices - the amount of government bonds or foreign exchange tax. It also recorded bidder's name, amount of allocated funds, and other details of each PA regardless of whether the bidder was a winner or not.[16] DRs were produced by the Korean office of the US foreign aid agency and sent to the Washington headquarters monthly from September 1957 to September 1960,[17] meanwhile DRs for the period from December 1956 to August 1957 were also made and sent later.[18] Out of 46 months between December 1956 and September 1960, only 21 months' reports were found.[19] There are total of 1,082 bidding records during this period; 164 of them with no applicants. The number of applications is 11,917 among which 6,427 are

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[15] Some digital replicas were provided at the web site of the National Institute of Korean History (http://archive.history.go.kr).

[16] Information on the unsuccessful bidders began to be included in the DR produced after October 8. See CINCREP Seoul to ICA/W, TOICA No. A-1017, Oct. 8, 1957; Procurement – Saleables Review Committee Reports, 1957-1958; Central Subject Files, 1950-1956, Executive Office, Mission to Korea; RG 469.

[17] For the beginning of DR, see CINCREP Seoul to ICA/W, TOICA No. A-856, Sep. 20, 1957; Procurement – Saleables Review Committee Reports, 1957-1958; Central Subject Files, 1950-1956, Executive Office, Mission to Korea; RG 469. For the end, refer to Notice from Jong Bok Kim, Sep. 28, 1960; Funds – Allocations (1960); Central Subject Files, 1950-1956, Executive Office, Mission to Korea; RG 469, which stating that publication of DR would end on October 1.

[18] Considering the fact that the reports were reproduced, they would have included information on unsuccessful bidder as well.

[19] These are interspersed within entry UD 422 and UD 1276 of RG 469 in NARA. It appears that both the Korean office of the US aid agency and the Washington headquarter retained and preserved the documents.)

successful. DR for 1959 is the most complete with 6,669 applications of all 12 months remaining, and therefore we use as the baseline data.

One limitation of DR is that it does not cover allocation of aid by lottery which was applied from 20 Oct. 1955 to 17 May 1957. Hence, we additionally collected *Weekly Report of Sub-authorization* (WR) as supplementary data. WR records the name and address of the importer that received sub-authorization, in addition to the PA number, SA number, name, quantity and amount in dollar of the aid product, and name and address of the supplier, although unsuccessful applicants are not reported. It was originally written by the Bank of Korea, and copied and published in *Financed Awards*, a publication of the the Office of Small Business in Washington headquarters of foreign assistance agencies. Remaining reports were confirmed to be nineteen weeks of 1957, which covered mid-February to mid-October with one week, four weeks and eleven weeks of omission in March, April and June to August respectively. There are 2,660 SAs among which 2,144 are identified, by using PA number, to be of allocation by the procedure involving lottery. Figure 4 shows sequences in allocation procedure and where those two kinds of source materials, DR and WR, were produced.

[Figure 4 Here]

To examine foreign aid and firms' performance, we merged aid data above with business directories in the 1950s and 1970s at the firm-level. For the 1950s, we use *1959 List of Corporations* as a baseline firm data to merge with DR. It was published by the Ministry of Finance of South Korea in 1959 for the purpose of corporation tax collection. Along with name, address, representor, industrial classification, and date of establishment of 5,646 corporations,[20] *1959 List of Corporations* also records two types of business capital: nominal capital and paid-in capital. We use the latter for our analysis. A supplementary data to merge with WR is *1956 Directory of Commerce & Industry of Korea* published by the Korea Chamber of Commerce and Industry. This directory records name, address, representor, and industrial classification of 6,861 firms.[21] For manufacturers, it also documents number of employees which we use as the variable representing

[20] Duplications are excluded.

[21] Duplications are excluded.

firm’s size.

For the 1970s, we use *Comprehensive Survey of Korean Firms: 1973 edition* published by the Korea Productivity Center. It is the earliest available record that contains the detailed information on the assets, sales, and employment of 2,550 major firms,[22] which covers the period of three years from 1970 to 1972. We matched firms in these directories to firms in aid data using their names and addresses.[23] Table 2 illustrates how we constructed the baseline dataset by merging daily reports in 1959 and business directories along with key variables obtained from each source. See the next subsection for the details on variables.

[Table 2 Here]

4.2. Data description

Our baseline firm-level dataset consists of each firm’s aid allocation outcomes, performance, and other controls. Our baseline aid outcomes are calculated from bidding results of the purchase of goods for civilian demand in 1959 when information on bidding is complete. The bidding results are collected from the *Daily Reports on Allocation of ICA Funds* (DR) published by the aid agency.[24] We aggregated bidding outcomes in the DRs in 1959 at the firm-level to make aid variables, and matched firms in DR to business directories in 1959 and 1973 which reported firm-level performance variables.

Aid outcome variables are the number of bid applications, success rate, average foreign exchange tax, average foreign exchange gain, average expected exchange gain, total aid amount received, and total rent obtained. Number of bid application indicates how many times a firm applied to biddings in 1959. Success rate is the share of successful applications. In 1959, the biding price for fund for goods for civilian demand, which was allocated in dollar, was sum of official

[22] It also records name, address, representor, and industrial classification of each firm like other directories. Duplications are excluded.

[23] As DR (WR) recorded firm names (names and addresses) in English and sometimes used different orthography for the same firm, while business directories described above use Korean only, we referred to various Korean-language lists of firms in the 1950s and 1960s to identify and match firms.

[24] See the previous subsection for the details on daily report.

exchange rate and foreign exchange tax that a firm submitted.[25] Average foreign exchange tax is total amount of foreign exchange tax in hwan a firm paid in 1959 divided by total dollar amount of aid it received in the year.

Average foreign exchange gain is market value in hwan of aid received minus total hwan amount a firm paid for it divided by total dollar amount of aid in 1959. Average expected exchange gain has the same numerator as the previous variable, while the denominator is total dollar amount a firm applied for bids.[26] This is the conceptual combination of success rate and exchange gain which can be interpreted as the benefit a firm can expect when it bids one dollar. This is an average gain per dollar a firm enjoyed from the difference between marker exchange rate and price of aid dollar. By multiplying this average gain by total aid amount received, the sum of dollar amount of aid that a firm was allocated in 1959, a cumulative gain a firm obtained from foreign aid in the year can be evaluated. We define this cumulative gain as rent. Last five aid variables are only calculated for firm with one or more successful applications.

Among firm performance variables, sales, equity, and return of each firm c. 1973 are mean values of three years: 1970, 1971, and 1972. The prices are adjusted to 1972 level using CPI. Sales on equity and return on equity are also the mean values of the same three years. Number of workers is of 1973. Hence Sales per worker and Return per worker are the mean sales and return of the three years divided by number of workers in 1973, respectively. Capital growth is the mean equity c. 1973 divided by paid-in capital in 1959. Firm age in 1959 is calculated using date of establishment. If two directories report different dates for the same firm, we chose the earlier date.

Table 3 lists the descriptive statistics of the baseline database.[27] We divided the 1,345 firms found in the Daily Reports in 1959 into four groups depending on whether they can also be found in the *1959 List of Corporations* and *Comprehensive Survey of Korean Firms: 1973 edition*. 175

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[25] Unit of exchange rate and foreign tax is hwan per dollar.

[26] These can be expressed as a formula below. Market value of aid is a product of market exchange rate in the month when each bid was made and dollar amount of aid received by the bid.

(a) $Average\ foreign\ exchange\ gain\ = \frac{market\ value\ of\ aid\ (hwan) - acutal\ payment\ (hwan)}{total\ value\ of\ aid\ (dollar)}$

(b) $Expexted\ exchange\ gain\ = \frac{market\ value\ of\ aid\ (hwan) - acutal\ payment\ (hwan)}{total\ amount\ of\ application\ (dollar)}$

[27] See Table A## in Appendix ## (*to be added*) for summary of the supplementary dataset using lottery results in Weekly Report and *1956 Directory of Commerce & Industry of Korea* instead of bidding results in Daily Report in 1959 and *1959 List of Corporations*, respectively.

firms could be found in both directories; 395 were found only in the former, and 75 only in the latter.[28] For comparison, we presented the statistics for the total 5,065 firms recorded in the 1959 *List of Corporations* but not in the Daily Reports in 1959 as well as the 481 firms recorded in *Comprehensive Survey of Korean Firms: 1973 edition* but not in the Daily Report in 1959.[29] The figures for foreign exchange tax, foreign exchange gain, aid amount received, and rent shown in the Table are averaged only from successful bids, hence firms with only unsuccessful bids are not considered.[30]

[Table 3 Here]

The average number of bids made by the 1,345 firms that took part in the allocation of aid funds was 4.8 times in a year of 1959 with a success rate of 54%. In case of success, the average foreign exchange tax was 365 hwan per dollar, and the average exchange rate gain generated from its difference from the market exchange rate was 401 hwan per dollar. The average amount of the successful bid was 90,000 dollars, and the resulting rent 45 million Korean hwan. The 175 firms that are recorded both in Daily Reports in 1959 and two business directories made on average a significantly higher number of bids at 9.5 times but had only a slightly higher success rate at 62%. Firms in two groups also show similar levels of exchange tax and exchange gains on average, although they paid a little lower tax and had a little higher gain. In contrast, Firms found in all three records were bigger in size in both years, more profitable in 1973, and older in 1959 than firms only in one or two sources.

In other words, even though large firms were more likely to get more aid than small ones, their average performance in biddings for allocation of aid funds was not superb. They just tried more times to get more aid. Another interesting fact to note here is the difference in the average rent between firms that survived until 1973 in column (3) and (4), and those that did not in column (6):

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[28] We could find only 570 out of the entire 1,345 bidders recorded the Daily Report in 1959 since many of the latter were not corporations.

[29] Firms in *Comprehensive Survey of Korean Firms: 1973 edition* which were established after 1959 or does not appear in the aid data – Daily Reports in 1959 or Weekly Reports – are not included in the dataset. In addition, the linkage was not made for firms in two directories if they did not appear in the aid data.

[30] These firms are considered to have missing values for these four variables in the dataset.

the ones that did survive earned a much higher rent on average. This suggests that the allocation of aid funds may have positively affected the survival and persistence of firms.

5. Results

5.1. Fairness of Bidding Process

As Acemoglu and Robinson (2012) pointed out, alleged ineffectiveness and inefficient of foreign aid may come from misuse and waste of it. This argument would also go along with Burnside and Dollar (2000; 2004)'s stress on the policy of the recipient government to make foreign aid effective. In a similar vein, distortions and corruption were criticized for foreign aid to South Korea. Here we empirically examine whether allocation of aid funds in South Korea was distorted by corruption and prerogative, focusing on the fairness of bidding process for procurement of goods for civilian demand in 1959.

Among 1,345 firms that took part in bidding for the procurement of goods for civilian demand in 1959, 547 firms applied only once, and their average success rate was 0.55 that practically half of them received aid. Figure 5(a) shows the annual distribution of the number of bid applications and success rates for remaining 798 firms. As for the number of bid applications, there was a considerable difference among these firms. Although it was the most common for firms to apply just twice or three times, there were two firms that applied more than 60 times, showing that at least some firms were making applications very frequently. The mean and median number of applications were 7.4 and 4 times respectively, with standard deviation of 8.86. The success rate was concentrated around the 50 percent and showed a symmetrical distribution.[31] This is in accordance with the 2 to 1 competition shown in Figure 2, and demonstrates that the allocation of aid funds was quite competitive.

[Figure 5 Here]

Strong intensity in competition is more supported by negative relationship between two

[31] Mean, median, and standard deviation were 0.53, 0.5, and 0.29, respectively.

variables. Figure 5(b) illustrates the correlation between the number of bid applications and success rates for all 1,345 firms which are divided into 30 groups.[32] It is clear that more applications involved lower level of success rate, especially for firms applied more than 10 times. Firms had to take the risk of low success rate to bid many times as exposed to fierce competition. This suggests that the argument may not be supported that certain firms favored by the authorities had the advantage of unjustly higher success rate and applied to biddings more times to make use of it.

Another important indicator to look into is price. In competitive biddings for aid funds in 1959, the price was foreign exchange tax plus official exchange rate. Since official exchange rate was fixed at 500 hwan per dollar, variations in price a firm paid came from exchange tax. As shown in Figure 4, the average successful bidding price followed a similar trend as the market exchange rate, although at a lower level, suggesting that the successful bids were determined competitively. Difference between market exchange rate and bidding price was the unit benefit a firm could gain from successful bids.

Our firm-level data, a relatively micro-level data set, shows that prices were most likely set competitively. Figure 6 groups firms by their level of competition rate (a reciprocal of success rate) or industrial classification, and traces the relationship between the competition rate and the average foreign exchange tax or gain of successful bids.[33] In the first row, 1,033 firms that succeeded at least once at bids in 1959 are divided into 30 groups by competition rate. The second row divides 506 firms that succeeded in bids at least once and were found in 1959 business directory into 21 industries.[34] As expected, the competition rate was positively correlated with bidding price, while negatively with foreign exchange gain.

[Figure 6 Here]

[32] the number of bid applications and success rates are averaged without weighting.

[33] Variables of interest are averaged without weighting.

[34] Industrial classification follows that of business directories published by the Korea Chamber of Commerce and Industry, because classification of *1959 List of Corporations* is incomplete.

Next, we examine how initial paid-in capital affected bidding outcomes in order to check whether large firms may have engaged in unfair practices by using their power within the industry or connection to the government. Figure 7 divides the 496 firms that were found in both the 1959 Daily Report and 1959 List of Corporations, and made at least one successful bid into 30 groups according to the amount of capital and traces the relationship among average foreign exchange tax, average foreign exchange gain, average expected gain, and cumulated rent. Foreign exchange tax, representing average cost of successful bids, shows no significant relationship with the paid-in capital in 1959. Foreign exchange gain and expected gain, representing average ex-post realized and ex-ante expected benefit respectively, are also not significantly correlated with the paid-in capital. These indicates that firms with different initial conditions were facing a similar situation in their competition for aid rent. While it is true that larger firms earned more rent, this could be understood as the result of larger companies having made more bid applications.

[Figure 7 Here]

Based on the above observations, we turn to examining statistical significance and magnitude of aid fairness through OLS at the firm-level. The dependent variables are the five types of bidding outcomes we examined above: success rate, foreign exchange tax, foreign exchange gain, expected exchange gain, and rent.[35] The key explanatory variable is the natural logarithm of amount of paid-in capital in 1959. The outcomes are reported in Table 4. Column (1), (3), (5), (7), and (9) don’t use any additional control variables, while column (2), (4), (6), (8), and (10) use firm age, the number of successful bids, and industry as control variables. For dependent variables other than success rate, firms only with at least one successful bid are included in the sample.

[Table 4 Here]

Success rate had a negative relationship with the amount of capital in the absence of control variables in column (1). An increase in paid-in capital by one standard deviation lowers success

[35] Last four variables are used as natural logarithm.

rate by 0.1 standard deviation. In contrast, firms larger by one standard deviation had to higher average exchange tax by 0.08 standard deviation in column (3). These statistically significant correlations disappear when we control for firm age and number of bids. Especially the number of applications to bid for aid funds explains the observed correlation. This is consistent with our previous conjecture that larger companies made more bid applications even at the expense of stronger competitions, lower success rate, and higher higher price.

Effects of capital on average expected gain follows similar pattern with success rate, which seems actually result from success rate since foreign exchange gain doesn't display any significant correlation with capital and other controls. That is, low success rate that large firms suffered from as they applied more also gave rise to low average benefit they could expect ex-ante. Rent is the only benefit indicator that shows a positive causal relationship with the amount of capital; one standard deviation increases in capital leads to 0.3 standard deviation increases in the size of rent. However, even this relationship disappears when we introduce control variables. Rent was also affected by the number of successful bids because larger firms tended to make more bid applications.

The fact that the initial conditions of firms had no impact on success rate, foreign exchange tax, foreign exchange gain, expected exchange gain, and rent indicates that the allocation of aid and the relevant bidding process was fair. While larger companies earned more rent, this does not imply unfairness, rather they had to sacrifice average cost and benefit by making more applications. If firms with better initial conditions were the more competent ones, the above result may be interpreted that more rent was allocated to more competent firms.

5.2. Long-term Effects of Aid

The revaluation of procedural fairness of foreign aid in the previous subsection enables us to turn to effectiveness of aid on economic development. Here we examine how the allocation of foreign aid in the 1950s affected the long-term growth of firms. Figure 8 displays correlations between the size of rent in 1959 and long-term outcomes of firms. In the left panel, we categorized 1,032 firms that were found in Daily Report in 1959 with at least one successful bid into 30 groups by the size of rent,[36] and averaged natural logarithm of rent of each firm by group without

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[36] Among 1,033 firms satisfying these two conditions, one firm whose rent was not computable due to missing

weighting. In the middle and right penal, we repeated the same works for 120 firms that were found in both 1959 Daily Report and 1973 business directory, and made one or more successful bids, and whose amount of sales and return on equity (ROE) were recorded in 1973 business directory. Horizontal axes in three panels these mean values of natural logarithm of rent of each group.

[Figure 8 Here]

The left panel illustrates that survival probability of firms until the early 1970s is positively correlated with the size of rent they gained in 1959. The survival probability is defined as the share of number of firms in each group that are found in 1973 business directory. The mean size of sales of each firm group in the early 1970s is also positively correlated with the mean amount of rent earned in 1959. On the contrary, ROE which is a major indicator of the rate of return and also averaged by group is not correlated with rent in any way. These correlations suggest that foreign aid in the 1950s significantly contributed to long-term survival and growth of external size of domestic firms in South Korea.

Table 5 confirms these conjectures from Figure 8 using OLS regressions. The key explanatory variables are rent in panel A and average expected exchange gain in panel B. Column (1) and (2) report the effects of foreign aid on survival probability until 1973 of firms found in 1959 Daily Report with at least one successful bid. The dependent variable, survival dummy, has the value of one if a firm is recorded in 1973 business directory, and zero otherwise. In column (1) of panel A, it is shown that survival probability has a positive relationship with the amount of rent. 10% increases in rent size led to 0.7%p, about 2.3% of mean, increases in survival probability. This effect almost does not change after we control for additional characteristics, capital, firm age, region, and industry, in column (2).[37] In contrast, average expected exchange gain had no significant effects on survival probability in panel B.

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information is excluded.

[37] Industrial classification is the same as Figure 6. Region is taken from local tax administration that had jurisdiction over each firm in *1959 List of Corporations*. There were four local tax administrations in South Korea in 1959: Seoul, Busan, Daejeon, Gwangju. These additional controls constrain the sample to firms both found in 1959 Daily Report and 1959 business directory.

[Table 5 Here]

Column (3), (4), and (5) show that foreign aid had significant effects on annual sales of firms in the early 1970s. In column (3), firms both found in 1959 Daily Report and 1973 business directory made 5% larger sales circa 1973 if they had 10% more rent or expected exchange gain. These effects are still observed for rent after controlling for firms' capital, age, industry, and region in 1959, while effects of expected gain drop by half and lose statistical significance in column (4). In column (5), we additionally included all firms in 1973 directory which did not appear in 1959 Daily Report if they were established no later than 1959,[38] assuming that these extra firms had zero rent or zero expected gain. The results are still positive and significant, albeit small in magnitude.

On the contrary, ROE does not show any significant relationship with rent or expected gain. This is possibly because ROE at a certain point of time is determined primarily by the specific characteristics of the industry or market situation rather than the actual competence of the firm.[39]

In Table 6, we used different explanatory and dependent variables in order to check robustness. In addition to rent and expected exchange gain, we added number of bid applications, success rate, and foreign exchange gain as explanatory variables. As proxies for the dependent variables representing firm size or profitability, we added total amount of equity, number of workers, sales on equity, return per worker, sales per worker, net profit, and capital growth between 1959 and 1973. Among additional explanatory variables, the number of bid applications and foreign exchange gain show similar result with rent and expected gain respectively, while success rate did not show any statistically significant result.

[Table 6 Here]

In the case of using additional dependent variables, the use of neither the total amount of equity

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[38] Firms that appeared in 1959 Daily Report but did not make any successful bid are also included too.

[39] Regression specifications for ROE in column (6), (7), and (8) are the same as those of column (3), (4), and (5), respectively.

nor the number workers produces significantly different results from the original use of sales. Although positive and significant relationships are found in some alternative variables of the rate of return and capital growth, generally they do not show any strong and positive effects. But it is still worth note that no negative and significant relationship between foreign aid and profitability was found.

5.3. Effects of Lottery Outcomes

One possible limitation of our analysis on the long-term effects of foreign aid is that unobserved initial characteristics of firms may have affected both on bidding outcomes in 1959 and growth. Even though we verified that larger firms tended to apply to bid more times to receive more aid and larger rent at the expense of higher price and lower marginal benefit, and controlled for initial size of firms in growth analysis, there still remains a concern coming from the fact that biding for aid funds in 1959 itself was not random allocation. In order to deal with this concern, we here repeat analyses in section 5.2 using supplementary dataset which use 1957 Weekly Report and 1956 business directory instead of 1959 Daily Report and 1959 business directory, respectively. Weekly Report in 1957 that we collected, albeit not of full year data, records 2,144 SAs whose allocation procedure involved lottery. We use firms found in these lottery SAs as the sample.

Figure 9 reconfirms the correlations witnessed in Figure 8. The left panel classifies 561 firms recorded in lottery SAs in 1957 Weekly Report into 30 groups by size of rent obtained from these lottery allocations. As the same as rent from competitive biddings in 1959, rent from lottery is positively correlated with survival rate of firms until 1973. The middle and right panel, categorizing 66 firms found both in 1973 business directory and lottery SAs into 20 groups, also show the same result as Figure 8: more rent involves larger size of sales circa 1973 but is not correlated with ROE in the early 1970s.

[Figure 9 Here]

Table 7 shows that results in Table 5 also are valid with lottery both in quantitative and qualitative sense.[40] Similar to column (1) and (2) in panel A of Table 5, larger rent from lottery

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[40] Specifications of each column in Table 7 are the same as those of correspondents in Table 5. For some differences

led to higher survival probability of firms; 10% increase in rent size made survival probability get higher by 0.6 – 0.8%p. A little larger effects are also exhibited in average expected exchange gain. Effects of aid allocated in lottery on annual sales in the early 1970s are also similar to those of allocation thorough competitive biddings, both in magnitude and direction. One difference between Table 5 and 7 is in column (7) of panel A that rent from lottery is found to lower ROE of firms. But this sole negative effect not only has small statistical significance but also disappears when we control for initial conditions or introduce additional firms into the sample along with zero aid assumption.

[Table 7 Here]

6. Conclusion

This paper challenged the established understanding of the aid economy of South Korea in the 1950s with newly constructed data on the allocation of aid funds at the firm-level. Previous research argued that, in South Korea, allocation of aid in the 1950s was discretionary and inefficient. However, theses arguments usually were based on limited observations such as the textile industry that were accused of receiving preferential aid even at that time. This paper examined the fairness of aid in the 1950s and its long-term effect on the growth of the economy and firms.

The results revealed that allocation of aid funds through the purchase of good for civilian demand – the most important method of aid allocation in the 1950s – was more competitive and fairer than what was depicted by previous research. The rule of bidding was actually effective, which greatly reduced the room for discretionary intervention from outside. The fact that larger firms were allocated more rent does not need to be interpreted as indicative of allocative inefficiency since they paid corresponding costs, although a more rigorous analysis is required in order to be able to speak of the efficiency of aid with confidence. It was found out that firms that earned more rent and average gain, in other words, a larger amount of financial benefit from foreign aid had a larger firm size in and higher probability to survive until the early 1970s, which

in technical definitions of key variables, see appendix ## (to be added).

was robust to controlling for initial conditions in the late 1950s. We interpret this result to indicate that foreign aid had a positive impact not only on the growth of firms but also on the development of the country since there were only few firms with colonial origins that stood out during the industrialization.

Our study could contribute to the debates on aid effectiveness in four ways. While recent studies focus on today's foreign aid projects, we examined the experience of South Korea in the 1950s which would represent one of the the early examples of foreign aid history. We also manifested, to our knowledge, the first study to use complete microdata at the firm-level both of the allocation and effects of foreign aid. In addition, we merged together the inquire into allocation of aid and exploration of long-term effects of it. Our new aid data and the detailed elucidations on South Korea's foreign aid also could be the basis for further studies.

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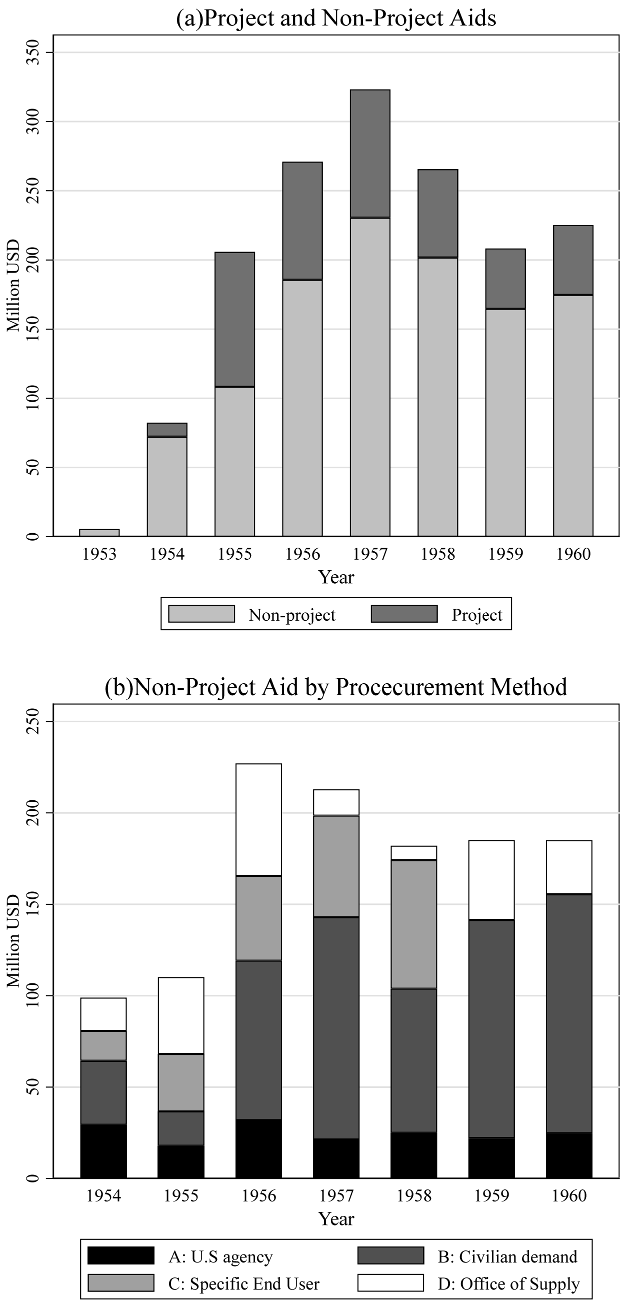
Figure 1. Trend of US FOA/ICA Aid to South Korea, 1953-1960



Sources: (a) Bank of Korea (BOK), *Economic Statistics Yearbook,* (b) *International Trade Yearbook* (each year's edition).

Table 1. Characteristics of FAO/ICA Aid to South Korea in the 1950s

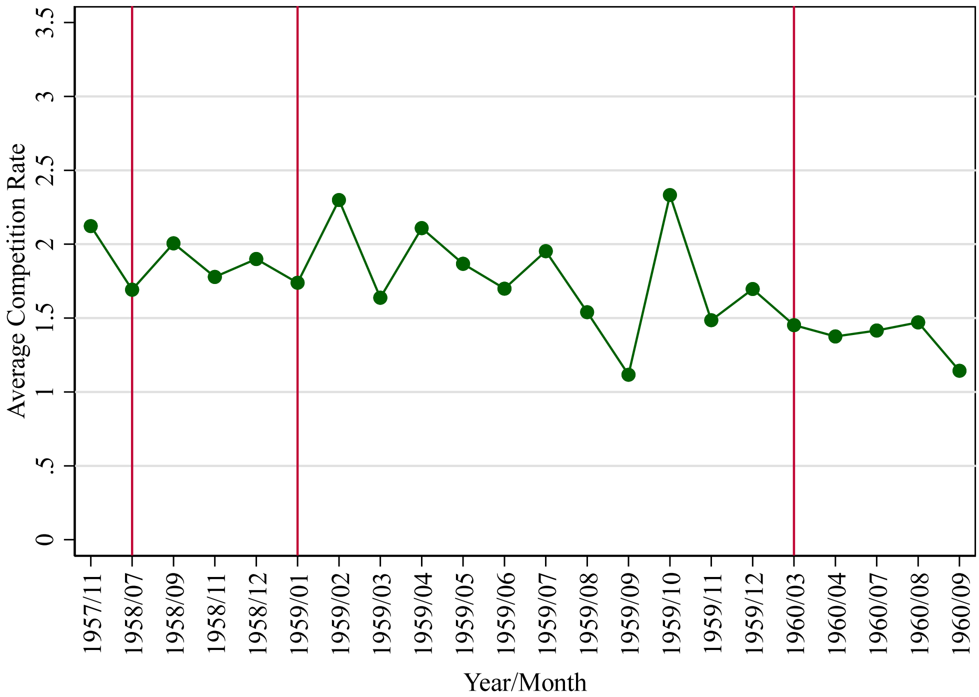
(a) Types of FAO/ICA Aid

Type		Description
Project Aid		To build social infrastructure.
Non-project Aid		To supply consumer goods, intermediate goods, and fuel and raw materials.
	U.S. Agency	Direct purchase and delivery by the US aid agency.
	Civilian Demand	Fund supply to domestic firms to import goods. Selection of firms by bidding or lottery. * Subject of analysis of this study.
	Specified End User	Fund supply to domestic firms to import goods. Selection of firms by the authorities based on attributes of goods.
	Office of Supply	Importation of good for direct use of the government.

(b) How to Allocate Aid Funds for Purchasing Civilian-Demand Goods by Period

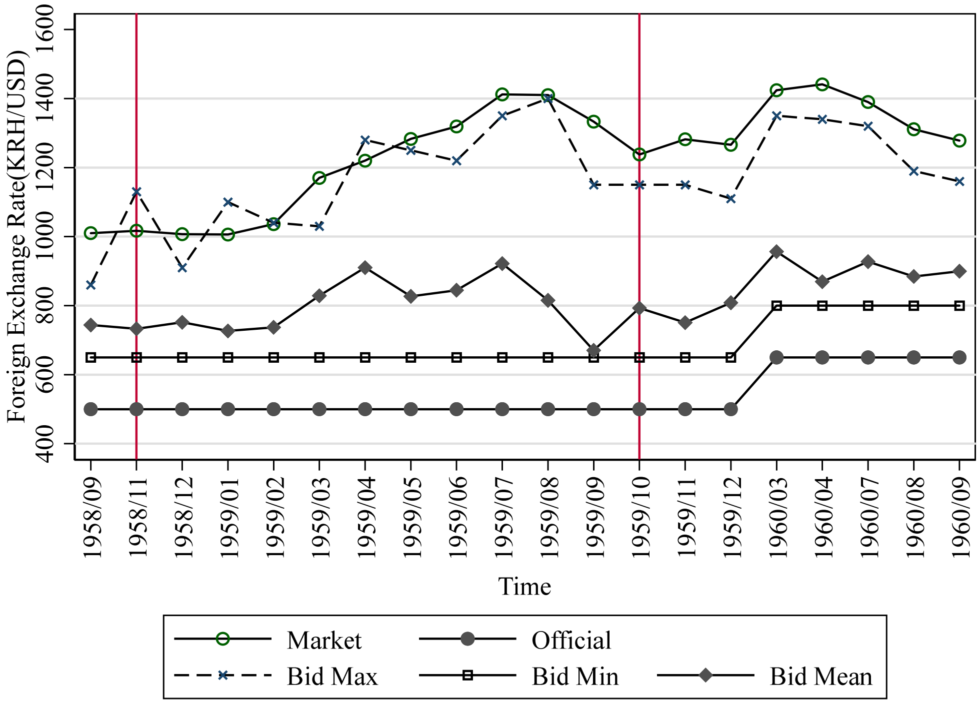
Period	Allocation method
Until 19. Otc. 1955	Exchange rate bidding.
20. Otc. 1955 – 5. Feb. 1956	First-come-first-serve basis. Lottery in case of over-application at the first day.
6. Feb. 1956 – 17. May. 1957	By the size of deposit. Lottery in case of tie and over-application.
18. May. 1957 – 8. Oct. 1958	By the size of deposit. By the size of purchase amount of government bond in case of over-application.
Since 9. Oct. 1958	By the size of foreign exchange tax. * Indirect exchange rate bidding

Figure 2. Average Monthly Competition Rate in Foreign Aid Allocation



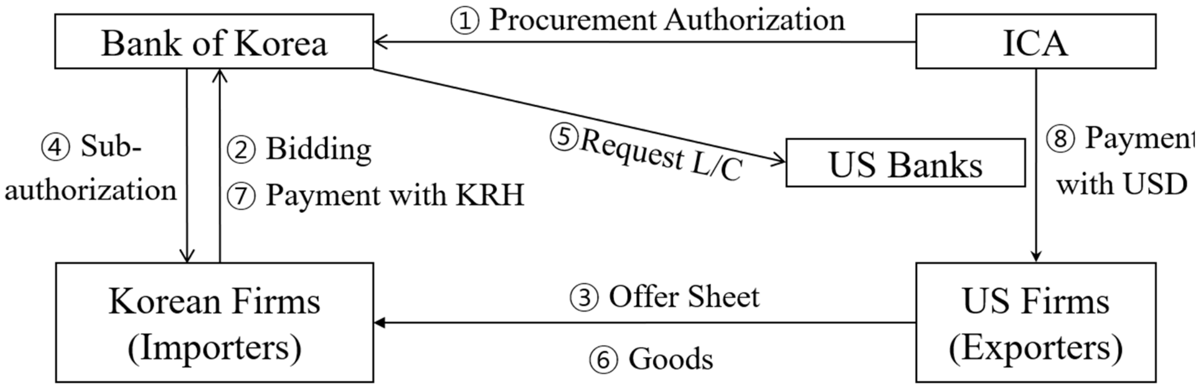
Note: competition rate = total amount bid / amount offered
Source: *Daily Reports on Allocation of ICA Funds*

Figure 3. Trends of Market Exchange Rates and Bidding Prices



Source: *Daily Reports on Allocation of ICA Funds* for bidding prices, and *International Trade Yearbook* (each year's edition) for exchange rates.
Note: Vertical lines distinguish the year of 1959 when our baseline analysis concentrates on.

Figure 4. Allocation Procedure



Note:

Table 2. Main Data Sources and Key Variables

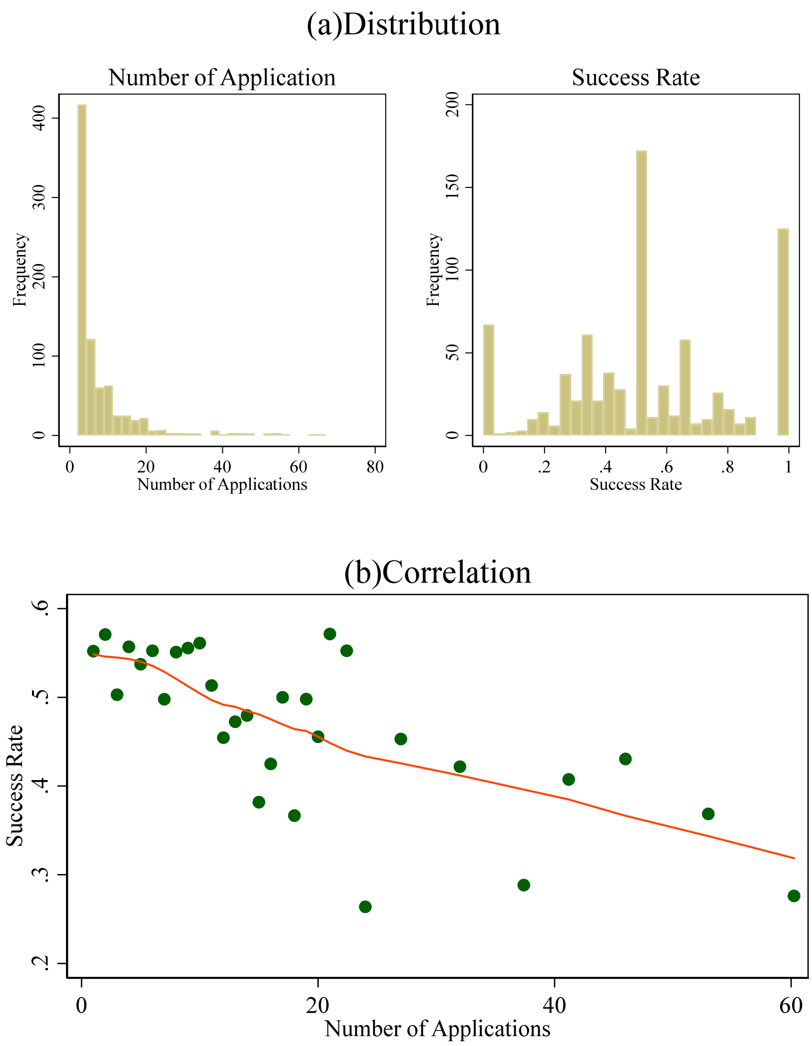
Data Source	Key variables (measured in firm-level)	Notes
Daily Report	– Number of bidding applications – Success rate – Average exchange tax – Average exchange gain – Expected exchange gain – Total aid amount received ($) – Rent	 Number of success / total applications Actual bidding target Market exchange rate – Exchange tax – 500 Average exchange gain * Success rate Total amount($) * Exchange gain
1959 Busincess Directory	– Paid-in capital – Firm age	 1959 – Year of established
1973 Business Directory	– Sales – Equity – Number of workers – Return on equity – Sales on equity – Return per worker – Sales per worker – Return (=net profit) – Capital growth	Sales, equity and return were measured as 1970-1972 average.

Table 3. Summary Statistics: Bidding Information in 1959, and Firm Performance in 1959 and 1973

Data linkage									
Daily Report in 1959	Y		Y		Y	Y	Y	N	N
1973 business directory	Y or N		Y		Y	N	N	Y	-
1959 business directory	Y or N		Y		N	Y	N	-	Y
Variables	Mean	SD	Mean	SD			Mean		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Num. of firms found	1,345		175		75	395	700	481	5,065
Aid and bidding information in 1959									
Number of bid applications	4.80	7.51	9.53	11.56	6.23	6.41	2.56	-	-
Success rate	0.54	0.39	0.62	0.32	0.58	0.56	0.50	-	-
Foreign exchange tax (hwan/dollar)	364.84	197.41	303.05	165.04	375.11	347.45	397.97	-	-
Foreign exchange gain (hwan/dollar)	400.88	196.34	459.56	176.65	384.83	413.24	373.38	-	-
Expected exchange gain (hwan/dollar)	298.56	219.57	338.70	228.19	268.83	286.71	297.44		
Aid amount received (mil. dollar)	0.09	0.25	0.26	0.48	0.11	0.10	0.03	-	-
Rent (mil. hwan)	45.48	145.37	129.23	284.45	43.32	42.27	12.18	-	-
Firm variables									
Firm size									
Sales (bil. KRW)	-	-	3.14	3.76	1.69	-	-	1.06	-
Equity (bil. KRW)	-	-	0.81	1.44	0.41	-	-	0.48	-
Number of workers (1,000)	-	-	1.17	1.79	0.62	-	-	0.37	-
Rate of return									
Return on equity	-	-	-0.01	2.12	0.19	-	-	0.24	-
Sales on equity	-	-	7.28	27.88	5.06	-	-	12.96	-
Return per worker (mil. KRW)	-	-	0.21	0.58	0.11	-	-	0.17	-
Sales per worker (mil. KRW)	-	-	4.35	5.52	2.25	-	-	4.82	-
Return (=net profit) (bil. KRW)	-	-	0.23	1.70	0.09	-	-	0.05	-
Capital growth (mil. KRW/1000 hwan)	-	-	6.01	42.09	-	-	-	-	-
Firm variables in 1959									
Paid-in capital (mil. hwan)	-	-	37.30	136.04	-	10.59	-	-	4.59
Firm age (years)	-	-	8.78	8.67	-	5.31	-	-	6.34

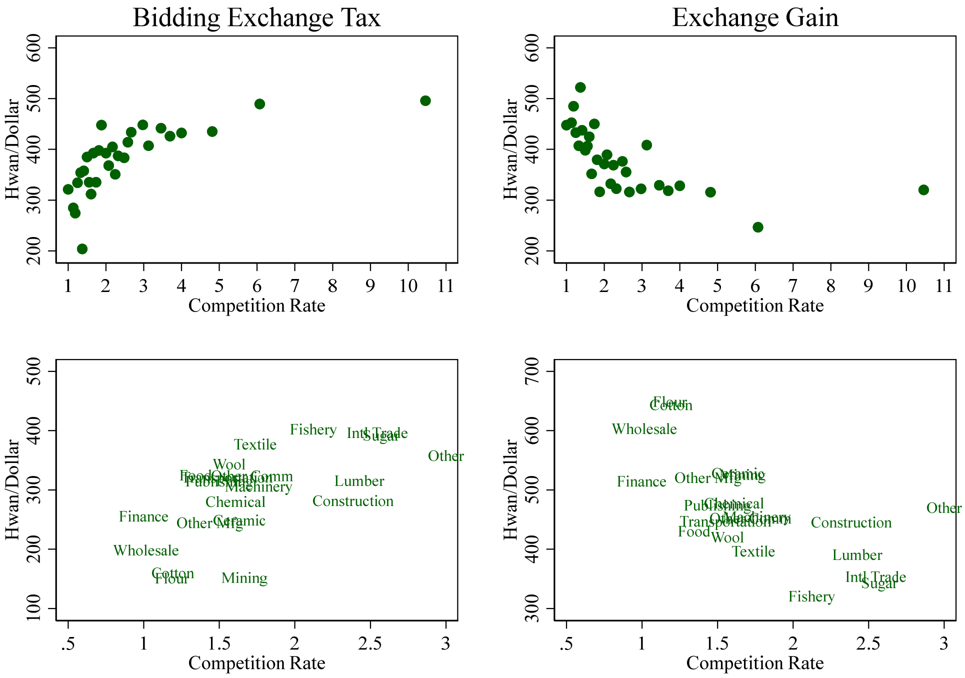
Notes: We calculated average aid and bidding information from the 1959 Daily Report for each firm, and merged them with the 1959 and 1973 business directory. In the calculation, we consider foreign exchange tax, foreign exchange gain, expected exchange gain, aid amount and rent only if the firm made one or more successful bids. Then, we classfied each firm into six groups according to whether it was found in Daily Report, 1973 business directory, and/or 1959 business directory. In the table, we report each variable's mean and standard deviation among firms in each group. For firms which do not appear in Daily Report, we did not execute matching between business directories. For firms in 1973 directory, we included in the dataset the firms only that were established in 1959 or before, or appear in aid data so that they were able to participate in aid allocation. Date of establishment in 1973 directory was also used to calculate firm age in 1959, in case of difference between directories we chose the earlier date.

Figure 5. Bidding Application Number and Success Rate



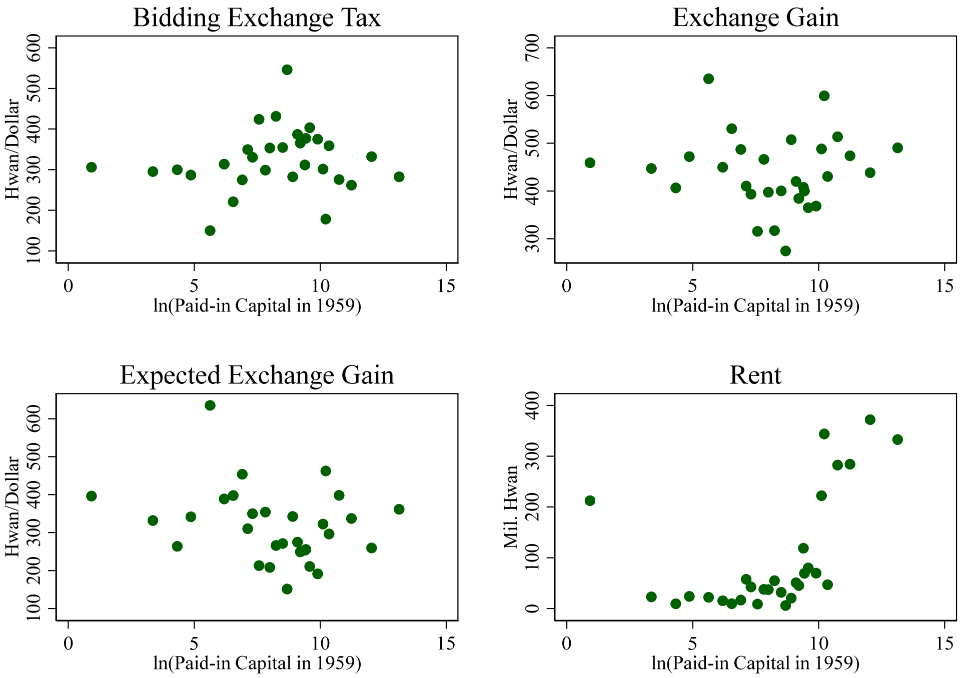
Note:

Figure 6. Bidding Exchange Rate and Exchange Gain by Competition Rate



Note:

Figure 7. Bidding Outcomes by Firm’s Initial Condition



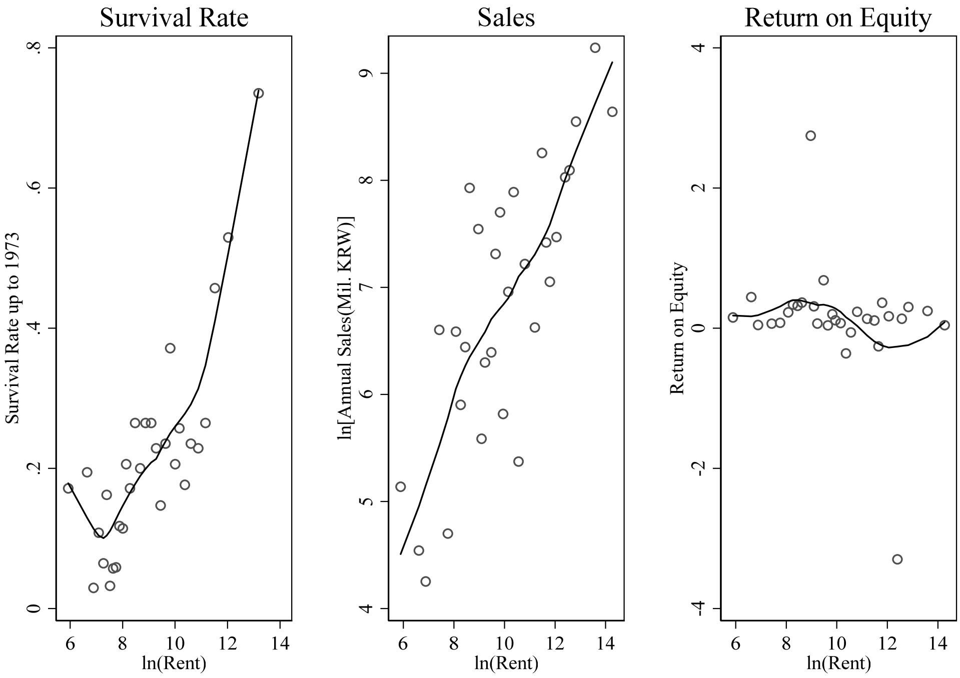
Note:

Table 4. Estimated effects of firm paid-in capital in 1959 on bidding outcomes

Dependent variable	Success rate		ln(Exchange tax)		ln(Exchange gain)		ln(Expected gain)		ln(Rent)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Controls:										
ln(Paid-in capital 1959)	-0.0173**	-0.0096	0.0218*	0.0125	-0.0022	-0.0041	-0.0438**	-0.0299	0.2364***	0.0532
	(0.0073)	(0.0082)	(0.0128)	(0.0145)	(0.0119)	(0.0139)	(0.0220)	(0.0244)	(0.0401)	(0.0360)
Firm age in 1959		0.0011		-0.0068		0.0041		0.0078		0.0115
		(0.0024)		(0.0042)		(0.0041)		(0.0072)		(0.0106)
Number of bids		-0.0036**		0.0067**		0.0002		-0.0118***		0.0937***
		(0.0016)		(0.0027)		(0.0026)		(0.0045)		(0.0066)
Constant	0.7201***	0.5947***	5.4782***	4.9323***	5.9631***	6.2607***	5.7293***	6.2707***	7.5969***	7.9049***
	(0.0617)	(0.1859)	(0.1083)	(0.0337)	(0.1009)	(0.3241)	(0.0186)	(0.5687)	(0.3398)	(0.8390)
Industry FEs	N	Y	N	Y	N	Y	N	Y	N	Y
Observations	558	555	496	493	496	493	496	493	469	493
R-squared	0.0099	0.1913	0.0059	0.2075	0.0001	0.1496	0.0080	0.2383	0.0658	0.5334

Note: We chose the firms found in both Daily Report in 1959 and 1959 business directory, and ran OLS regressions of their bidding outcomes on initial firm variables measured in 1959. Columns (1), (3), (5), (7), and (9) control for paid-in capital in 1959 only. Columns (2), (4), (6), (8), and (10) additionally include firm age, number of bids applied in 1959, and industry fixed effects. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Figure 8. Firm's Performance c.1973 by Rent from Bidding in 1959



Note:

Table 5. Estimated Effect of Foreign Aid in 1959 on Firms' Survival, Size and Return in the Early 1970s

Dependent variable	Survival dummy in 1973		ln(Annual sales c. 1973)			Return on equity c. 1973		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Effect of Rent								
Controls:								
ln(Rent in 1959)	0.0678***	0.0671***	0.4895***	0.4516***	0.1355***	-0.0303	-0.1068	-0.0204
	(0.0072)	(0.0133)	(0.0696)	(0.1116)	(0.0174)	(0.0750)	(0.1733)	(0.0149)
ln(Paid-in capital in 1959)		0.0246**		0.0349			-0.0259	
		(0.0122)		(0.0841)			(0.1285)	
Firm age in 1959		0.0194***		0.0309			0.0105	
		(0.0036)		(0.0197)			(0.0308)	
Constant	-0.3902***	-0.3096	1.8574***	4.1250**	5.5197***	0.3396	0.8357	0.2375***
	(0.0658)	(0.3070)	(0.7055)	(1.7457)	(0.0962)	(0.7642)	(2.7485)	(0.0851)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	1,032	493	141	103	471	166	122	526
R-squared	0.0795	0.2076	0.2624	0.4608	0.1150	0.0010	0.0272	0.0036
Panel B: Effect of Expected Gain								
Controls:								
ln(Expected gain in 1959)	0.0154	0.0078	0.5109***	0.2863	0.2216***	0.1105	0.3701	-0.0295
	(0.0136)	(0.0240)	(0.1557)	(0.2350)	(0.0320)	(0.1501)	(0.3316)	(0.0273)
ln(Paid-in capital in 1959)		0.0372***		0.1054			-0.0274	
		(0.0123)		(0.0906)			(0.1266)	
Firm age in 1959		0.0214***		0.0359*			0.0030	
		(0.0037)		(0.0214)			(0.0307)	
Constant	0.1365*	0.0831	3.9192***	5.7860**	5.5591***	-0.5671	-2.3753	0.2240
	(0.0740)	(0.3403)	(0.8674)	(2.2547)	(0.0976)	(0.8341)	(3.1888)	(0.0853)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	1,032	493	141	103	471	166	122	526
R-squared	0.0012	0.1642	0.0719	0.3635	0.0927	0.0033	0.0356	0.0022

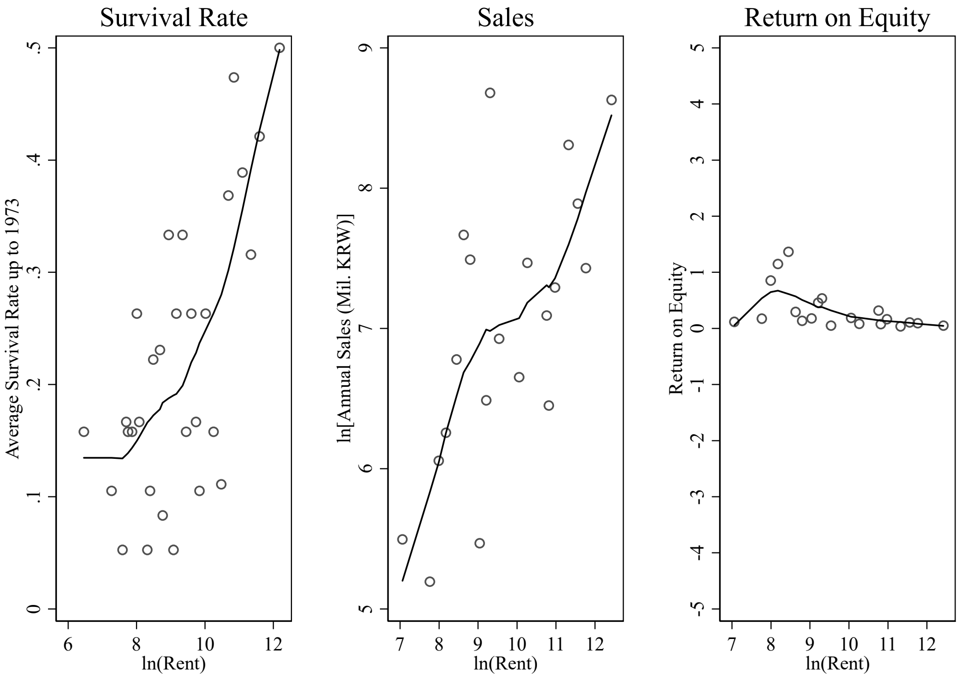
Notes: Columns (1) and (2) estimate the effect of rent size or average expected gain on the probability of being survived up to 1973, which is measured by whether a firm is found from the 1973 business directory or not. Columns (3)-(5) utilize the log value of annual sales c. 1973 as a measure of firm size. We use firms found in both Daily Report in 1959 and business directory in 1973 for columns (3). In column (4), we use firms commonly found in both records and 1959 business directory. In column (5), we use any firm found in the 1973 business directory only if it could participate in aid allocaition in 1959, regardless of whether they are actully found in Daily Report in 1959 or not. In the analysis of column (5), we also assume that, if a firm in the 1973 business directory is not found in Daily Report in 1959, its rent and average expected gain are zero. Except that columns (6)-(8) use ROE (return on equity c. 1973) as dependent variable, their regression specifications are the same with those for columns (3)-(5), respectively. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Table 6. Estimated Effects with Alternative Bidding Outcomes and Firms' Performance c.1973

	Survival dummy	Firm size c.1973			Profitability c.1973					Capital growth in 1959-73
		ln(Sales)	ln(Equity)	ln(# of Workers)	Return on equity	Sales on equity	Return per worker	Sales per worker	ln(Return)	
Key controls:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A: Effects of Rent Size									
ln(Rent)	0.0671***	0.4516***	0.3484***	0.1588**	-0.1068	3.2856	0.0043	0.6905**	0.2723**	6.2240**
	(0.0133)	(0.1116)	(0.0834)	(0.0764)	(0.1733)	(2.5294)	(0.0474)	(0.3175)	(0.1288)	(2.4383)
Observations	493	103	124	146	122	93	117	97	108	143
R-squared	0.2076	0.4608	0.4365	0.3255	0.0272	0.0860	0.0896	0.6370	0.3528	0.3757
	Panel B: Effects of Average Expected Gain									
ln(Average expected gain)	0.0078	0.2863	0.4032**	-0.0156	0.3701	3.0591	0.1155	1.3002**	0.2139	-3.5132
	(0.0240)	(0.2350)	(0.1566)	(0.1351)	(0.3316)	(4.9953)	(0.0837)	(0.5769)	(0.2413)	(4.5129)
Observations	493	103	124	146	122	93	117	97	108	143
R-squared	0.1642	0.3635	0.3803	0.3018	0.0356	0.0692	0.0837	0.6386	0.3250	0.3451
	Panel C: Effects of Number of Bidding Applications									
# of bid applications	0.0106***	0.0393**	0.0246**	-0.0034	-0.0092	0.0250	0.0004	0.0665	0.0272	0.8171**
	(0.0022)	(0.0167)	(0.0116)	(0.0099)	(0.0211)	(0.3277)	(0.0059)	(0.0446)	(0.0173)	(0.3423)
Observations	555	110	135	155	133	100	125	103	116	156
R-squared	0.2005	0.4061	0.3844	0.3048	0.0235	0.0582	0.0765	0.5885	0.3357	0.3423
	Panel D: Effects of Success Rate									
Success rate	0.0280	-0.3323	0.2131	-0.2361	0.8982	1.1295	0.3067	1.0879	-0.3991	5.2626
	(0.0614)	(0.6008)	(0.4166)	(0.3617)	(0.7609)	(11.9756)	(0.2110)	(0.5796)	(0.5951)	(11.1842)
Observations	555	110	135	155	133	100	125	103	116	156
R-squared	0.1641	0.3707	0.3612	0.3617	0.0340	0.0582	0.0952	0.5796	0.3213	0.3119
	Panel E: Effects of Exchange Rate Gain									
ln(Exchange rate gain)	0.0264	0.3161	0.5392**	-0.2678	0.1362	4.4780	0.1886	1.1278	0.7768**	-11.4863
	(0.0430)	(0.3487)	(0.2541)	(0.2403)	(0.5191)	(7.1228)	(0.1446)	(0.9343)	(0.3808)	(7.7875)
Observations	493	103	124	146	122	93	117	97	108	143
R-squared	0.1647	0.3584	0.3679	0.3087	0.0242	0.0694	0.1057	0.6215	0.3506	0.3535

Notes: We employ alternative dependent variables as listed the head of table, as well as alternative bid outcome controls as listed in the title of each panel. Column (1) estimates the effect of aid on the probability of being survived up to 1973, which is measured by whether the firm in Daily Report in 1959 is also found in the 1973 business directory or not. It additionally controls paid-in capital, firm age, and region and industry fixed effects in 1959. Accordingly, column (1) uses the sample firms found in both Daily Report and 1959 business directory. Columns (2)-(10) use the sample firms found in all three databases: Daily Report in 1959, 1973 business directory, 1959 business directory. The regression specification of column (1) is the same as that of column (2) in table 4, while specifications of other columns are the same as that of column (4) or (7) in table 4. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

Figure 9. Firm's Performance c.1973 by Rent from Lottery in 1957



Note:

Table 7. Estimated Effects of Lottery Outcomes on Firms' Survival, Size and Return in the early 1970s

Dependent variable	Survival dummy in 1973		ln(Annual sales c. 1973)			Return on equity c. 1973		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Effect of Rent							
Controls:								
ln(Rent from lottery)	0.0602***	0.0793***	0.4654***	0.4497**	0.1202***	-0.0783*	0.0614	0.0103
	(0.0124)	(0.0206)	(0.1152)	(0.2105)	(0.0235)	(0.0453)	(0.0430)	(0.0191)
ln(# of workers in 1956)				0.7996***			-0.0224	
				(0.2768)			(0.0612)	
Constant	-0.3343***	-0.5766	2.3451**	0.0343	5.7362***	1.0367**	-0.2677	0.1558**
	(0.1159)	(0.3761)	(1.119)	(2.1215)	(0.0916)	(0.4452)	(0.4334)	(0.0780)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	561	294	76	38	471	91	32	526
R-squared	0.0403	0.1326	0.1807	0.6519	0.0530	0.0325	0.3960	0.5905
	Panel B: Effect of Average Expected Gain							
Controls:								
ln(Expected gain from lottery)	0.0720***	0.0867**	0.5673**	1.0156	0.4082***	-0.1238	0.0778	0.0319
	(0.0250)	(0.0398)	(0.2615)	(0.5989)	(0.0820)	(0.0940)	(0.0949)	(0.0648)
ln(# of workers in 1956)				0.8475***			-0.0205	
				(0.2868)			(0.0633)	
Constant	0.0305	-0.0905	5.2900***	2.0222	5.7454***	0.6214	0.1202	0.1576**
	(0.0685)	(0.3494)	(0.7252)	(1.5780)	(0.0914)	(0.2711)	(0.2855)	(0.0777)
Region and Industry FEs	N	Y	N	Y	N	N	Y	N
Zero aid assumption	N	N	N	N	Y	N	N	Y
Observations	561	294	76	28	471	91	32	526
R-squared	0.0146	0.1007	0.0598	0.6224	0.0502	0.0191	0.3541	0.0005

Notes: Columns (1) and (2) estimate the effect of rent size or average expected gain on the probability of being survived up to 1973, which is measured by whether a firm is found from the 1973 business directory or not. Columns (3)-(5) utilize the log value of annual sales c. 1973 as a measure of firm size. We use firms found in both Weekly Report in 1957 and business directory in 1973 for columns (3). In column (4), we use firms commonly found in both records and business directory in 1956, addtionally contraining the sample to manufacturers as the 1956 business directory as records the number of emploees only for manufacturers. In column (5), we also assume that, if a firm in the 1973 business directory is not found in Weekly Report in 1957, its rent and average expected gain are zero. Except that columns (6)-(8) use ROE (return on equity c. 1973) as a dependent variable, their regression specifications are the same with those for columns (3)-(5), respectively. *, **, and *** denote statistical significance at the 90 percent, 95 percent, and 99 percent levels, respectively.

제1세션 | 거시경제 국제개발

Measuring Interdependence of Inflation Uncertainty

발제: 이 서 현(KDI School)

토론: 조 덕 상(KDI)

Measuring Interdependence of Inflation Uncertainty

Seohyun Lee[1]

November 9, 2022

Abstract

The unprecedented fiscal and monetary policy responses during the COVID-19 crisis have increased uncertainty about inflation. During crises periods, the strength of the transmission of inflation uncertainty shocks from one country to another tends to intensify. This paper examines empirical methodologies to measure the strength of the interdependence of inflation uncertainty between the UK and the euro area. We first estimate inflation uncertainty by *ex post* forecast errors from a bivariate VAR GARCH model. The interdependence of uncertainty is estimated using a probability model. The results imply that the spillover of uncertainty is stronger for uncertainty about distant future than near future. The evidence from quantile regressions shows that such empirical method could suffer from bias if endogeneity is not properly addressed. To identify structural parameters in an endogeneity representation of interdependence, we exploit heteroskedasticity in the data across different regimes determined by the ratio of variances. The results no longer exhibit stronger interdependence at longer horizons. Estimated by different sample periods, the strength of the propagation of inflation uncertainty intensifies during the Global Financial Crisis while the interdependence significantly weakens during the post-crisis period.

JEL Classification: E37, E52, F42

Keywords: inflation uncertainty, interdependence, GARCH, copulas, at-risk, conditional forecasting, identification through heteroskedasticity.

[1]KDI School of Public Policy and Management, 263 Namsejong-ro, Sejong, 30149, South Korea, email: slee6@kdis.ac.kr. I am grateful for helpful suggestions and insights from Barbara Rossi, Thomas Lubik, Roberto Rigobon, anonymous reviewers and participants of ASSA 2022 Annual Meeting, CEF (Computing and Economics and Finance) 2022 conference, and the Bank of Korea Economic Research Institute seminar.

I Introduction

The unprecedented fiscal and monetary policy responses to address the COVID-19 pandemic has prompted recent debates about the inflation prospects after the decades of low and stable inflation (e.g. Ball et al., 2021; Blanchard, 2021). The studies based on survey conducted in the early stages of the pandemic also suggest that uncertainty about inflation has rapidly risen since the pandemic (Armantier et al., 2021, Coibion et al., 2020). The heightened inflation uncertainty, along with the actual increases in inflation, has been seen globally and it is argued that multiple driving factors are relevant–including the uncertain path of the pandemic and economic recovery as well as the surge in commodity prices and its volatility followed by the pandemic-induced supply disruptions.

While it is well studied that inflation co-moves closely across countries (e.g. Monacelli and Sala, 2009; Ciccarelli and Mojon, 2010; Mumtaz and Surico, 2012; Bäurle et al., 2021), the research on the interdependence of inflation uncertainty are not well established. A large number of studies have analyzed the potential channels of the co-movement in inflation: common macroeconomic shocks (e.g. global commodity prices), trade, labor market channel through migration, exchange rate regimes, and financial integration.[1] Through similar mechanisms, uncertainty about inflation of a country can be transmitted to other countries and the transmission of inflation uncertainty shocks may exhibit different patterns over the various stages of global macro-financial cycles. The objective of this paper is to explore the various empirical methodologies to measure the strength of the interdependence of inflation uncertainty. In particular, this paper showcase the empirical framework by examining the case of the euro area and the United Kingdom (UK) with close economic, trade and financial integration.

This study extends a probabilistic model to characterize the entire distribution of inflation uncertainty in a two-country setting.[2] We first estimate inflation uncertainty by *ex post* forecast errors

[1] See, for example, Henriksen et al. (2013) (common macroeconomic shocks), Melitz and Ottaviano (2008) (trade openness), Bentolila et al. (2008) (migration channel), Calvo and Reinhart (2002) (foreign exchange regimes) and Rey (2016) (financial integration).

[2] Broadly speaking, the probabilistic model can also be referred as the ‘at risk’ approach following Adrian et al. (2019). While the empirical framework and estimation procedures of this paper differ substantially from the recent ’at risk’ literature, the idea of estimating entire conditional distributions assuming a specific parametric distribution is in line with the one in Adrian et al. (2019) and the following literature.

from a two-country bivariate VAR GARCH model. By defining the uncertainty measure as forecasts errors rescaled by their unconditional and conditional variance-covariance matrix, we allow the measure of inflation uncertainty to distinguish upside and downside surprises in inflation.

Next a two-step procedure for a probabilistic model is applied to evaluate the interdependence of inflation uncertainty between the UK and the euro area. The first step is to estimate the best-fit marginal density against two non-Gaussian distributions that could potentially account for heavy tail and skewness behavior of inflation uncertainty. As for the candidates, two piece normal distribution (TPN) and weighted skewed normal distribution (WSN) are considered. The use of TPN (Wallis, 2004) follows from the convention of central banks' fan chart to evaluate the balance of uncertainty. The alternative density, WSN (Makarova, 2018), is a synthetic distribution which is designed to reveal monetary policy responses to upside or downside inflation uncertainty. The results from fitting uncertainty to two different marginal distribution TPN suggest the possibility of long right tails in the distributions of the euro area inflation uncertainty. The results from WSN suggest monetary policy reactions by the ECB tend to be stronger to upside inflation surprises than downside surprises regardless of forecasting horizons. As oppose to the ECB's case, the BOE's monetary policy stance tends to be dovish to long term inflation surprises. But, for short term inflation surprises, the BOE's monetary policy responses are likely to be hawkish, as seen in the ECB's case.

The second step of the procedure is to estimate the conditional probability distribution of inflation uncertainty of two economies using copulas. Copulas is a flexible tool to construct a multivariate distribution by combining marginal densities estimated separately from the conditional probability distribution (see, e.g., Rodriguez, 2007; Smith and Vahey, 2016). Among various bivariate copulas, Frank copula is chosen to allow for asymmetric dependence structures without favoring either upper or lower tail dependence. The interdependence of inflation uncertainty of two economies can be summarized in the estimated copula parameters and the results unanimously point to higher dependence for the uncertainty about distant future than near future.

While the probabilistic model provides succinct estimates to measure interdependence, it could suffer from endogeneity problems (Rigobon, 2019). If there exists heteroskedasticity in the error terms of the structural model, the conditional density estimated by a probabilistic model can be biased. One typical example applicable to our empirical framework would be the case where the variance of inflation uncertainty shocks increases during the crisis period. To detect whether the estimates from the probabilistic model suffer from potential endogeneity bias, we run quantile regressions (Koenker and Bassett, 1978). The evidence from quantile regressions suggests potential biases in the copula estimates and the conditional distribution derived from the copula.

To identify structural parameters in an endogeneity representation of interdependence, we exploit heteroskedasticity in the data across different regimes determined by the ratio of variances as proposed in Rigobon (2019). The estimation is based on minimum distance criteria and statistical significance is bootstrapped. The results no longer exhibit stronger interdependence at longer horizons across all regimes. Instead, estimated by different sample periods, the strength of the propagation of inflation uncertainty intensifies during the Global Financial Crisis (GFS) while the interdependence is significantly muted during the post-crisis period.

Our paper contributes to a large literature on the measures of inflation uncertainty. Following Ball (1992), a long-standing practice in the literature is to examine the relationship between the level of inflation and inflation uncertainty measured by its volatility (see, for example, Grier and Perry, 2000; Kontonikas, 2004). Among many recent empirical studies, Caporale et al. (2012) examine the relationship between inflation uncertainty and inflation level in European countries by employing GARCH-type models. Survey-based disagreement measures of inflation have also been widely studied (see, e.g., Holland, 1995; Giordani and Söderlind, 2003; Clements and Harvey, 2011; Wright, 2011). Binder (2017) constructs micro-level inflation uncertainty measures by quantifying the uncertainty associated with round number responses in the survey data. Our approach departs from the existing literature by constructing an *ex post* unpredictability measure of inflation uncertainty that is close to the definition in Friedman (1977). Uncertainty, defined as the component that had not been predictable at the time of forecasting, is computed by pseudo out-of-sample forecasting errors as in Stock and Watson (2007). This framework provides a parsimonious way to construct a measure for inflation uncertainty from a multivariate GARCH model of two economies.

This paper is also related to the burgeoning literature on the ‘at risk’ approach which aims at estimating and evaluating conditional distributions of economic variables (see Adrian et al., 2019; López-Salido and Loria, 2020; Sokol, 2021, among many). Our approach differs from the existing ones in that it considers a two-country model rather than a variable conditional on other macroeconomic or financial variables to assess entire conditional distributions.

From an econometrics point of view in estimating the strength of interdependence, this paper is closely related to Pesaran and Pick (2007). They define contagion as a situation whereby a crisis in one country increases the probability of a crisis in another country over and above what would be implied by the interdependence in non-crisis periods. By illustrating a two-country framework, they show that the correlation-based tests of contagion could be biased due to endogeneity. Our empirical framework to identify structural parameters of a two-country setup in the presence of heteroskedasticity shares the similar idea of possible endogeneity issues. But we differ from their approach in that we exploit a broader definition of interdependence, that encompasses crises and non-crises periods alike, for identification through heteroskedasticity.

The rest of the paper is organized as follows. Section II explains inflation uncertainty computed by forecast errors from a bivariate VAR GARCH model. Section III estimates the interdependence of inflation uncertainty by a probability model. In Section IV, an endogenous model of interdependence is introduced to discuss potential biases of a probability model and the interdependence of inflation uncertainty is estimated by identification through heteroskedasticity. Section V concludes.

II Estimating inflation uncertainty

Inflation uncertainty is measured by *ex post* forecast errors from a bivariate VAR BEKK GARCH (1,1) model using inflation rates of the UK and the euro area. The main advantage of the forecasting model is that it is parsimonious while taking account for potential interdependence of two economies and time-varying volatility in inflation. Inflation uncertainty, denoted by $U_{t,h}$, is defined as below.

$$U_{t,h} = \Sigma_{t,h}^{1/2} \Sigma_{t|t-h}^{-1/2} e_{t|t-h} = \Sigma_{t,h}^{1/2} \Sigma_{t|t-h}^{-1/2} (\pi_t - \pi_{t|t-h}) \tag{1}$$

where $e_{t|t-h}$ is the forecast error conditional on the information available at the period of the prediction, i.e. the h-period ahead forecasts is made at time $t-h$. $\Sigma_{t,h}$ denotes the unconditional variance-covariance matrix of e_t and $\Sigma_{t|t-h}$ the conditional variance-covariance matrix of $e_{t|t-h}$. The forecast errors are computed by the differences between the realized inflation at t (π_t) and the h-step ahead forecast of inflation at t ($\pi_{t|t-h}$). To standardize the measure, the forecast errors are multiplied by the square root of the unconditional variance-covariance matrix and divided by the square root of the conditional variance-covariance matrix.

The monthly data for inflation is retrieved from the Eurostat database and the sample period is from January 1997 to March 2016. For both countries, inflation series are found to be I(1) and the first differences of the raw inflation series are used for the maximum likelihood estimation. Autoregressive order of VAR model is determined by Ljung-Box autocorrelation test for residuals. The minimal number of lags is chosen to ensure the residuals exhibit no autocorrelation at 5 percent significance level.

Based on the estimated VAR BEKK GARCH (1,1) model, the h-step ahead forecasts for $h = 1, 2, \ldots, 24$ months are estimated recursively with the initial recursion using the first 80 observations.[3] The resulting conditional and unconditional variance-covariance matrices are also obtained recursively. The h-step forecasts by maximum likelihood estimation can suffer from spurious dependence when $h > 1$. In order to tackle this issue, Vector Moving Average (VMA) decomposition is used for the estimation of the Mean Squared Error (MSE) matrix of the forecasts (see Lütkepohl, 2005).

Figure 1 plots inflation uncertainty of the UK and the euro area for the selected forecast horizons ($h = 3, 6, 12, 18, 24$). Inflation uncertainty rose rapidly after the Great Financial Crisis in

[3]The forecast yields 151 ($= 231 - 80$) *one-step-ahead* forecast errors, 150 *two-step-ahead* forecast errors, ... up to 128 *24-step-ahead* forecast errors.

2008 for both countries, followed by a significant decline below the average level. Positive values of inflation uncertainty imply that the realization of inflation had not been predicted at the time of forecasting and the unanticipated elements caused inflation to move upwardly. Similarly, negative values of inflation uncertainty measure indicate that the realized inflation rates were lower than the prediction by the two-country VAR-GARCH model. The descriptive statistics of inflation uncertainty (Table 1) suggest that inflation uncertainty may be better characterized with non-Gaussian density functions with non-zero skewness and/or heavy tails.

Correlation coefficients can be considered as a simple measure for interdependence of inflation uncertainty between the two economies. The Pearson's correlation coefficient captures only linear correlation and thereby is considered to be insufficient for a measure of dependence in the case of heavy tail or asymmetric dependence (Cont, 2001; Boyer et al., 1997). Therefore, rank correlation coefficients are computed in Figure 2. The average Spearman's correlation coefficient is 0.29 while Kendall's correlation coefficient is 0.21. The uncertainty measures with longer forecast horizons tend to exhibit higher correlations.

III Measuring interdependence by a probability model

This section illustrates a probability model to measure interdependence of inflation uncertainty of two economies. Probability models assume that a change in the probability of the two events occurring together reflects the strength of the dependence of those two events. In this paper, copulas, a tool widely used in finance for modeling extreme events, are applied to measure interdependence for non-Gaussian marginal densities. The main advantage of copulas is its flexibility in combining different parametric family univariate distributions. Also, the choice of a dependence model, a copula function, can be independent from the choice of the marginals. Following the Inference Function for Margins (IFM) method, as in Joe and Xu (1996), two steps of estimation procedures are sketched in this section. First, univariate marginal distributions are estimated by the simulated minimum distance criteria. Given the best-fit univariate distributions, a copula parameter is estimated by the maximum likelihood estimation.

A Marginal density function

Inflation uncertainty is estimated against two non-Gaussian univariate distributions from the same distribution family of skew normal distribution: Two Piece Normal (TPN; Wallis, 2004) and Weighted Skewed Normal (WSN; Makarova, 2018).

The choice of TPN density follows from the convention of central banks' fan chart. Starting from the Bank of England, fan chart is well-known and most widely used presentation of the probabilistic forecasts of inflation.[4] Fan chart considers both the degree of uncertainty and the balance of uncertainty around the forecast is assessed using TPN distribution (Britton et al., 1998). The *pdf* of TPN distribution is defined as follows (Wallis, 2004).

$$f_{TPN}(x;\sigma_1,\sigma_2,\mu) = \begin{cases} Aexp\{-(x-\mu)^2/2\sigma_1^2\} & \text{if } x \leq \mu \\ Aexp\{-(x-\mu)^2/2\sigma_2^2\} & \text{if } x > \mu \end{cases} \tag{2}$$

where $A = (\sqrt{2\pi}(\sigma_1+\sigma_2)/2)^{-1}$. If $\sigma_1 = \sigma_2$, it collapses to a Normal distribution. If $\sigma_1 < \sigma_2$, the distribution is positively skewed (long right tail).

The other candidate for univariate density is WSN. Derived from a combination of two normal distributions, WSN is a customised skew normal distribution which aims at decomposing uncertainty into epistemic and ontological components. Ontological uncertainty is assumed to be complete randomness formed by public knowledge whereas epistemic uncertainty indicates the uncertainty based on expert knowledge (Walker et al., 2003). To illustrate the distribution, we denote the inflation uncertainty measured by forecast errors as U, omitting the subscripts, t, h, for simplicity. It is assumed that U is decomposed by two components – the baseline forecast error (X) and the signal part based on the revised forecast error from expert knowledge (Y).

$$U = \underbrace{X}_{\text{baseline forecast error}} + \underbrace{\alpha \cdot Y \cdot I_{Y>m} + \beta \cdot Y \cdot I_{Y<k}}_{\text{Signal part based on revised forecast error}} \tag{3}$$

[4] A recent study using the TPN in examining price is Sokol (2021).

where $I_{Y>m}$ is an indication function that gives 1 if revised forecast errors are larger than a certain threshold, $m \geq 0$. Similarly, $I_{Y<k}$ is an indication function that gives 1 if revised forecast errors are smaller than a certain threshold, $k \leq 0$. Hence, the signal part will be switched on when either (i) $Y > m \geq 0$ or (ii) $Y < k \leq 0$ holds. X and Y are bivariate Normal distributions with mean zero, constant and identical variances (σ^2), and correlation coefficient, ρ. This implies that if $\alpha = \beta = 0$, WSN reduces to a Normal distribution.

The key assumption of the WSN distribution is that the *ex post* inflation uncertainty can be decomposed into the baseline forecast errors from public knowledge and the revised forecast errors based on expert knowledge given expected central bank's monetary policy decisions. Assume that the baseline forecast error (X) is initially established. Further assume that the forecast error based on expert knowledge is positive and larger than a certain threshold ($Y > m \geq 0$) and experts would know that a central bank with expert knowledge is expected to respond to this upside inflation surprise with hawkish policy actions, for example, by increasing the policy rate. Then the *realized* forecast error would be revised downwards ($\alpha Y < 0$ with $\alpha < 0$) from the initial baseline forecast errors. The magnitude of the effect of monetary policy tightening on inflation can be summarized in the parameter, α. Similarly, in the opposite case where the forecast error based on expert knowledge is negative and smaller than a certain threshold ($Y < k \leq 0$), β is assumed to be negative and depicts the magnitude of the effect of monetary policy easing to downside surprises ($\beta Y > 0$ with $\beta < 0$). The comparison between α and β in absolute value provides interesting intuition. If $|\alpha|$ is greater than $|\beta|$, it implies that the central bank tends to react more aggressively towards upside uncertainty than downside uncertainty.

The *pdf* of WSN distribution is as follows (Charemza et al., 2015).

$$\begin{aligned} f_{WSN}(x;\alpha,\beta,m,k,\rho) = {} & \frac{1}{\sqrt{A_\alpha}}\phi\left(\frac{x}{\sqrt{A_\alpha}}\right)\Phi\left(\frac{B_\alpha x - mA_\alpha}{\sqrt{A_\alpha(1-\rho^2)}}\right) \\ & + \frac{1}{\sqrt{A_\beta}}\phi\left(\frac{x}{\sqrt{A_\beta}}\right)\Phi\left(\frac{-B_\beta x + kA_\beta}{\sqrt{A_\beta(1-\rho^2)}}\right) \\ & + \phi(x)\cdot\left[\Phi\left(\frac{m-\rho x}{\sqrt{1-\rho^2}}\right) - \Phi\left(\frac{k-\rho x}{\sqrt{1-\rho^2}}\right)\right] \end{aligned} \quad (4)$$

where ϕ and Φ is the *pdf* and *cdf* of a standard normal distribution, respectively. $A_\tau = 1+2\tau\rho+\tau^2$ and $B_\tau = \tau + \rho$ for $\tau = \alpha, \beta$.

To find the best-fit marginal density for inflation uncertainty, the simulated minimum distance estimators method (SMDE) is applied.[5] The empirical histograms of inflation uncertainty estimated in Section I are fitted to the simulated density functions using a minimum distance criterion.

$$\hat{\theta}_{\text{SMDE}} = \arg\ \min_{\theta} \left[\xi \left(HD(d_n, f_{r,\theta}) \right)_{r=1}^{R} \right] \tag{5}$$

where d_n is the empirical histogram from the original data, $f_{r,\theta}$ is the simulated Monte Carlo approximation of theoretical densities with total R replications. ***HD*** is Hellinger distance measure[6] and ξ denotes the aggregating operator.

Since the number of parameters to be estimated in WSN $(\alpha, \beta, m, k, \rho)$ is larger than that of TPN $(\sigma_1, \sigma_2, \mu)$, it is necessary to impose restrictions on WSN parameters. Only α, β, σ in WSN are estimated by imposing restrictions on m, k, and ρ. It is assumed that $m = -k = \sigma$. In terms of the restriction on ρ, we consider two cases: constant ρ $(= 0.75)$ and ρ decaying exponentially from 0.75 to 0.25 as forecast horizon increases.[7] The second case is to reflect the tendency that the covariance between public and expert knowledge decreases along with the forecast horizons.

Table 2 shows the results of the estimation of two marginal distributions with the selected horizons ($h = 6, 12, 18, 24$) and under the assumption of exponentially decreasing ρ.[8] First, the estimated WSN parameters, α and β, can be considered as the experts' adjusters based on their expectation on monetary policy reactions to inflation surprises. In the UK case, the absolute value of α is greater than the absolute value of β for shorter horizons ($h = 6, 12$), implying the prevalence of stronger policy reactions to upside inflation surprises than downside surprises. For longer term horizons ($h = 18, 24$), the results indicate relatively stronger dovish monetary policy responses

[5]The estimation of skewed normal distributions by the maximum likelihood is known to be inefficient and numerically very complex (see, for example, Azzalini and Capitanio, 1999; Sartori, 2006; Franceschini and Loperfido, 2014).

[6]See Basu et al. (2002) for the definition of Hellinger distance measure.

[7]In particular, the computation is based on $\rho_h = 0.25 + \exp\left[\ln\left(0.75 - 0.25\right) \cdot h\right]$ where $h = 1, 2, \ldots, 24$.

[8]The results of other forecast horizons and different restrictions on ρ are available upon request.

to downside surprises. For the euro area, the estimation results show $|\alpha| > |\beta|$ for all forecast horizons. This suggests that the monetary reactions of the ECB tend to be stronger in response to upside inflation uncertainty than downside, namely a hawkish stance across all forecast horizons.

For the estimated parameters of TPN, the UK results show either $\sigma_1 < \sigma_2$ or $\sigma_1 > \sigma_2$ depending on the forecast horizons without any systematic trend. It is noticeable that σ_1 is much larger than σ_2 for $h = 18$, implying the long left tail. For the euro area, σ_1 is smaller than σ_2 for all horizons, indicating positively skewed (or long right tail) TPN distribution.

In order to select the best-fit marginal distributions, we first examine minimum distance statistics. For the UK case, WSN has smaller MD than TPN in the shorter horizons ($h = 6, 12$) while TPN is preferable for the longer horizons. For the euro area, WSN is selected for most horizons with an exception of the case of $h = 24$.

Next, the probability integral transforms (*pit's*) are computed to examine the goodness-of-fit with the estimated parameters of each marginal density. The *pit's* are the probability of observing the values of a random variable being not greater than its realization values. If the observed density is close to the true but unknown density, *pit's* would be uniform on the interval [0,1]. Figure 3 is the box plot of *pit's* for both WSN and TPN. Both the UK and the euro area inflation uncertainty are fitted better by WSN density across most horizons than by TPN.

To check the compatibility of the data with the uniform distribution, we conduct a simple goodness-of-fit test (the Cramér-von Mises test) using empirical *cdf*. Table 3 presents the test statistics for the selected forecast horizons ($h = 6, 12, 18, 24$).[9] The results support the robustness of parametric estimation. For both WSN and TPN at all horizons, the null hypothesis of uniformity cannot be rejected. By comparing the test statistics, it is also confirmed that WSN is a better fit over TPN for both economies at most of the forecast horizons.

To sum up, the empirical results, including minimum distance statistics, graphical diagnostics of *pit's*, and goodness-of-fit tests, support the choice of WSN against TPN for both the UK and the euro area.

[9]The complete results are available upon request.

B Conditional density function

Given the estimated parameters in the univariate densities, the copula parameter can be estimated by the maximum likelihood estimation. First, denote inflation uncertainty for the UK and the euro area as U_1 and U_2, respectively. The subscript t and h are omitted for simplicity. Consider continuous bivariate joint cumulative density function (*cdf*) of inflation uncertainties, $F(U_1, U_2)$. The univariate marginals for each inflation uncertainty are denoted as $F_1(U_1)$ and $F_2(U_2)$ with inverse quantile functions, ${F_1}^{-1}$ and ${F_2}^{-1}$. Applying the proposition of probability integral and quantile transformation, the joint *cdf* can be written as follows.[10]

$$\begin{aligned} F(U_1, U_2) &= F({F_1}^{-1}(y_1), {F_2}^{-1}(y_2)) \\ &= \Pr[Y_1 \leq y_1, Y_2 \leq y_2] \\ &= C(y_1, y_2) \end{aligned} \tag{6}$$

where $y_1 = F_1(U_1)$, $y_2 = F_2(U_2)$ with a uniform distribution, $\mathcal{U}(0, 1)$.[11] C($\cdot$) is a copula function that maps the two-dimension support $[0, 1]^2$ into the unit interval [0,1].[12] Rewriting the joint *cdf* of inflation uncertainty to obtain the resulting joint *pdf*,

$$F(U_1, U_2) = C(F_1(U_1), F_2(U_2)) \tag{7}$$

[10]Let X be a random variable with density F_X. Let F_X^{-1} be the inverse quantile function of F_X:

$$F_X^{-1}(\alpha) = \inf\{x | F_X(x) \geq \alpha\}$$

$\alpha \in (0, 1)$. Then,

(1) If F_X is continuous, the random variable Y, defined as $F_X(X)$, has a uniform distribution. ($F_X(X) \sim \mathcal{U}(0, 1)$).

(2) For any uniform distribution $Y \sim \mathcal{U}(0, 1)$, we have $F_X^{-1}(Y) \sim F_X$.

[11]This implies $U_1 = {F_1}^{-1}(y_1) \sim F_1$, $U_2 = {F_2}^{-1}(y_2) \sim F_2$.

[12]An *m*-dimensional copula is a function C($\cdot$): $[0, 1]^m \rightarrow$ [0,1] which satisfies the following conditions:

(1) $C(1, \ldots, 1, a_n, 1, \ldots, 1) = a_n$ for every $n \leq m$;

(2) $C(a_1, \ldots, a_m) = 0$ if $a_n = 0$ for any $n \leq m$;

(3) C is *m*-increasing.

then the joint density (*pdf*) of F is given by the following equation.

$$f(U_1, U_2) = c(F_1(U_1), F_2(U_2)) \cdot f_1(U_1) \cdot f_2(U_2) \tag{8}$$

where c is the density of the copula, partial derivative of $C(\cdot)$ with respect to y_1, y_2. Denote $\theta = (\theta_1, \theta_2, \alpha)$ be all the parameters of F_1, F_2 and C, respectively. Let $U = \{(U_{1t}, U_{2t})\}_{t=1}^{T}$ denote a sample. The log likelihood function can be written as follows.

$$l(\theta) = \sum_{t=1}^{T} \ln\left(c(F_1(U_1;\theta_1), F_2(U_2;\theta_2);\alpha)\right) + \sum_{t=1}^{T}\left[\ln\left(f_1(U_{1t};\theta_1)\right) + \ln\left(f_2(U_{2t};\theta_2)\right)\right] \tag{9}$$

Then the maximum likelihood estimator is

$$\hat{\theta}_{\text{MLE}} = \arg\ \max_{\theta}\ l(U_{1t}, U_{2t}; \theta) \tag{10}$$

In theory, the copula parameters can be estimated simultaneously with the parameters in marginal distribution by the maximum likelihood estimation. However, in multi-dimension cases, this might lead to high complexity in computation. Hence, the two-step estimation method or the Inference Function for Margins (IFM) method by Joe and Xu (1996) is applied.[13] With the estimated univariate marginal distributions, the copula parameter, γ, is estimated.

$$\hat{\theta}_1 = \arg\ \max_{\theta_1} \sum_{t=1}^{T} \ln\left(f_1(U_{1t};\theta_1)\right) \tag{11}$$

$$\hat{\theta}_2 = \arg\ \max_{\theta_2} \sum_{t=1}^{T} \ln\left(f_2(U_{2t};\theta_2)\right) \tag{12}$$

$$\hat{\gamma} = \arg\ \max_{\gamma} \sum_{t=1}^{T} \ln\left(c(F_1(U_1;\hat{\theta}_1), F_2(U_2;\hat{\theta}_2);\gamma)\right) \tag{13}$$

Among various bivariate parametric families of copulas, Frank copula is chosen. Frank copula

[13] The IFM estimator obtained by the two-step estimation, $\theta_{IFM} := (\hat{\theta}_1, \hat{\theta}_2, \hat{\gamma})$, is known to have a Normal distribution asymptotically (Joe and Xu, 1996).

is a symmetric Archimedean copula[14] and its *cdf* is given by

$$C(y_1, y_2; \gamma) = -\frac{1}{\gamma} \ln\left(1 + \frac{(e^{-\gamma y_1} - 1)(e^{-\gamma y_2} - 1)}{e^{-\gamma} - 1}\right) \tag{14}$$

where $\gamma \in (-\infty, +\infty)$. If $\gamma = 0$, the copula is independent.

γ is estimated positive if heightened uncertainty of one country is associated with higher uncertainty of the other. The copula parameters are estimated by either (i) plugging the marginals of the same forecast horizons or (ii) plugging the marginals that gives highest rank correlation. The dependence structure of the estimated copula can also be summarized by the rank correlations: Kendall's tau (τ) and Spearman's rho (ρ).[15]

Table 4 and Figure 4 shows the estimated γ parameter and the rank correlation coefficients using the marginals of the same forecasting horizons. The copula parameters for all horizons are estimated to be positive and mostly statistically significant. The estimated γ decreases at first and bounces back at around $h = 6$ before decreasing afterwards. However, for the horizons larger than $h = 12$, the estimated γ monotonically increases. The uniformity of the estimated joint distribution is confirmed by the Crémer-von Mises test. The rank correlation coefficients, τ and ρ, exhibit the same trend as the copula parameter. The results imply that the inflation uncertainty of the UK and the euro area contemporaneously affect one another and such spillover effect is stronger for uncertainty about the distant future than the near future.

Table 5 shows the estimation results of the forecast horizons of the euro area inflation uncertainty that have the highest rank correlation coefficients with given horizons of the UK inflation uncertainty. In terms of the Kendall's τ, the short term UK inflation uncertainty series (with fore-

[14] A copula C is Archimedean if there exists a convex, decreasing function $\varphi(\cdot) : (0, 1] \to [0, \infty)$ such that

$$C(y_1, y_2) = \varphi^{-1}(\varphi(y_1) + \varphi(y_2))$$

where $\varphi(\cdot)$ is copula generator and $\varphi(1) = 0$. The examples of Archimedean copulas are Gumbel, Frank, and Clayton. Frank copula is a symmetric Archimedean copula while other two are asymmetric Archimedean copulas. Gumbel copula exhibits greater dependence in the positive tail than in the negative tail while Clayton exhibits greater dependence in the negative tail than in the positive tail. Frank copula is chosen because it can identify the asymmetric dependence structure without favouring either upper or lower tail dependence.

[15] See Appendix A for the details of Frank copula.

cast horizons less than one year) have high correlation with the euro inflation uncertainty series of the forecast horizons from 12 to 14. One-year ahead inflation uncertainty in the UK has the highest correlation with approximately $1\frac{1}{2}$ year ahead uncertainty in the euro area. 16-months to 2-years ahead UK inflation uncertainty series have the highest correlation if paired with 23- to 24-months ahead uncertainty series of the euro area. Spearman's ρ criterion yields fairly similar results to the Kendall's τ criterion with a few exceptions in the short term horizons ($h = 1, 3$).

In Figure 5, the copula parameters are estimated with the pairs that give the highest correlation based on Kendall's τ. The estimated γ is larger for all forecasting horizons compared with the results where the copula function is fitted by the same horizons. $\hat{\gamma}$ increases as the horizon increases until $h = 10$. The strength of dependence of inflation uncertainty weakens until it reaches the local minimum at $h = 13$. The maximum value of the estimated γ occurs at $h = 20$. The rank correlation coefficients show similar patterns to the estimated copula parameter.

To showcase how the probability model by copulas can be interpreted in a similar fashion as in the 'at risk' approach in the literature, the conditional probability of the UK inflation being in a certain range conditional on the euro inflation uncertainty is illustrated in Appendix B.

IV Endogenous model of interdependence and measuring interdependence through heteroskedasticity

A Endogenous model of interdependence

The probability model to measure interdependence of inflation uncertainty could suffer from bias if endogeneity is not properly addressed. To illustrate the potential endogeneity bias in conventional empirical methods of measuring interdependence, an endogenous model of interdependence is assumed as in Rigobon (2019).

$$U_{1t} = \alpha U_{2t} + \eta_t \tag{15}$$

$$U_{2t} = \beta U_{1t} + \varepsilon_t \tag{16}$$

where U_{1t} is inflation uncertainty of the UK, U_{2t} is inflation uncertainty of euro area. The error terms, η_t and ε_t are assumed to be structural shocks, independent and have a Normal distribution. α and β are the coefficients capturing interdependence of uncertainty between two region. The variances of error terms are defined as σ_η^2 and σ_ε^2.

The reduced form equations of each country's uncertainty are as follows.

$$U_{1t} = \frac{1}{(1-\alpha\beta)}(\eta_t + \alpha\varepsilon_t) \tag{17}$$

$$U_{2t} = \frac{1}{(1-\alpha\beta)}(\beta\eta_t + \varepsilon_t) \tag{18}$$

The joint residuals in each of the above equations can be graphically represented by a rotated ellipse and the rotation can be summarized by the variance-covariance matrices.

$$\Omega = \begin{bmatrix} V_1 & C_{12} \\ C_{12} & V_2 \end{bmatrix} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \alpha^2\sigma_\varepsilon^2 + \sigma_\eta^2 & \alpha\sigma_\varepsilon^2 + \beta\sigma_\eta^2 \\ \alpha\sigma_\varepsilon^2 + \beta\sigma_\eta^2 & \sigma_\varepsilon^2 + \beta^2\sigma_\eta^2 \end{bmatrix} \tag{19}$$

where $V_1 = var(U_{1t})$, $V_2 = var(U_{2t})$, $C_{12} = cov(U_{1t}, U_{2t})$. The parameters representing the underlying information of the system are the slopes of structural equations (α, β) and the relative volatility of the structural shocks, ($\theta \equiv \sigma_\eta^2/\sigma_\varepsilon^2$). Therefore, if estimated by conventional methods, such as correlation or principal components of two series, the coefficients of interdependence may be biased. For instance, as illustrated in the endogenous model, linear regression of U_{1t} and U_{2t} results in simultaneity bias. The interdependence measured by probabilistic models using copula also suffers from endogeneity, even though the estimation procedure does not assume any econometric models. The conditional probability of a tail-event can be driven by the changes either in σ_ε^2 or σ_η^2 or any combination of the two, and thereby, cannot distinguish changes in interdependence from those in heteroskedasticity.[16]

[16]See Appendix C for quantile regressions to provide some empirical evidence of endogeneity bias.

B Measuring Interdependence by Identification through Heteroskedasticity

To identify the system of equations, we exploit the heteroskedasticity in the data across different regimes, proposed by Rigobon (2003), Rigobon and Sack (2004), and Rigobon (2019).[17]

Rewriting the endogenous model of equations (19)-(20) in a matrix representation with structural shocks as follows.

$$A \begin{bmatrix} U_1 \\ U_2 \end{bmatrix} = \begin{bmatrix} \eta \\ \varepsilon \end{bmatrix} \tag{20}$$

where

$$A = \begin{bmatrix} 1 & -\alpha \\ -\beta & 1 \end{bmatrix} \tag{21}$$

Define Ω to be variance-covariance matrix of $[U_1 U_2]'$.

$$\Omega = \begin{bmatrix} V_1 & C_{12} \\ C_{12} & V_2 \end{bmatrix} \tag{22}$$

Then, the variance-covariance matrix of the structural model can be expressed as follows:

$$A\Omega A^T = \begin{bmatrix} 1 & -\alpha \\ -\beta & 1 \end{bmatrix} \begin{bmatrix} V_1 & C_{12} \\ C_{12} & V_2 \end{bmatrix} \begin{bmatrix} 1 & -\beta \\ -\alpha & 1 \end{bmatrix} \tag{23}$$

$$= \begin{bmatrix} \cdot & -\beta V_1 - \alpha V_2 + C_{12}(1+\alpha\beta) \\ -\beta V_1 - \alpha V_2 + C_{12}(1+\alpha\beta) & \cdot \end{bmatrix} \tag{24}$$

By the assumption that η and ε are independent, the variance-covariance matrix of the structural model satisfies the following.

$$A\Omega A^T = \Sigma_{\eta\varepsilon} = \begin{bmatrix} \sigma_\eta^2 & 0 \\ 0 & \sigma_\varepsilon^2 \end{bmatrix} \tag{25}$$

The off-diagonal terms in Equation (30) need to be equal to zero, which defines the objective

[17] Recent applications includes Ehrmann et al. (2011) and Nakamura and Steinsson (2018).

function of the optimization problem.

$$\min_{\alpha,\beta} f(\alpha, \beta; V_1, V_2, C_{12}) = -\beta V_1 - \alpha V_2 + C_{12}(1 + \alpha\beta) \tag{26}$$

The estimation strategy using the identification through heteroskedasticity is to solve the system for two unknowns, α, β. In order to solve the problem, we impose additional assumptions that the parameter values in matrix A are stable over time and that the data have heteroskedasticity. We define two regimes that are determined by the ratio of variances, θ: RH if $\theta > median(\theta)$ and RL otherwise. The ratio (θ) of the variance of U_1 to the variance of U_2 is computed using different sample periods (p), forecast horizons (h), and rolling windows (rw).

$$\theta = \frac{V_1}{V_2} = m(p; h, rw) \tag{27}$$

where $p \in \{1, 2, 3\}$ while defining 1 is pre-crisis period, 2 Global Financial Crisis period, 3 post-crisis period. $h = 1, 2, \ldots, 24$ and $rw = 12$.[18] Then V_1, V_2, and C_{12} for each regime are computed to obtain minimum distance estimates of α and β.[19] The estimation model is just identified as we have two equations with two unknowns.

The significance of the estimates is computed by bootstrap. We bootstrap every regime, but not across the regimes, so that only the observations within each regime with replacement. Bootstrap is drawn from uniform distribution for 500 times.

Figure 6 presents the point estimates of the parameters, α and β, in Equation (19)-(20) against the forecast horizons ($h = 1, \cdots, 24$). The results from the pre-crisis period (top panel) show that both α and β are estimated to be closer to zero for $h < 12$, suggesting the interdependence of near term inflation uncertainty is statistically insignificant. For the longer horizons, the signs of coefficients alternate within the range of [-1, 1]. The pattern of opposite signs between α and β is also shown for $h > 12$.

[18] Pre-crisis periods: September 2003 - December 2007, Crisis period: January 2008 - December 2012, Post-crisis period: January 2013 - March 2016. We check robustness by changing p and rw.

[19] We allow positive and negative values for α and β by imposing sign restrictions $-1 \leq \alpha \leq 5, -1 \leq \beta \leq 5$.

The results for the crisis period (middle panel) show that the estimates of β from the crisis period exceed 1, in particular for longer term horizons. This could indicate potential amplifying effects of the surprises in the UK inflation on the euro area inflation during the GFC period. However, the crisis period estimates of α remain near zero for longer term forecast horizons, implying that the spillover of inflation uncertainty from the euro area to the UK is almost insignificant. For the near-term uncertainty (3-9 months ahead), the estimates of interdependence range between -1 and 1 and the signs of dependence measures are in the opposite direction: $\alpha > 0$ and $\beta < 0$.

For the post-crisis period (bottom panel), the range of the estimates lies between -1 and 1, mostly close to zero. For $h > 15$, β is estimated to be negative, implying that the upside (downside) inflation surprises in the UK are translated into the downside (upside) inflation uncertainty in the euro area. A negative sign of the estimated structural parameters may suggest that the underlying drivers of inflation uncertainty shocks do not stem from common factors such as high volatility in commodity prices affecting both economies in a same way.

Tables 6-8 show the point estimates of α or β as well as bootstrap results. At the 1 percent significance level, only the crisis-period estimates of β for $h = 11, 12, 20, 21, 22, 24$ are statistically significant and positive. At the 5 percent significance level, the crisis-period estimates of α for $h = 9, 10$ are significantly positive but less than 1, suggesting that the upside (downside) inflation uncertainty of the euro area is translated into the upside (downside) uncertainty of the UK but with a lesser extent.

V Conclusions

This paper explores various empirical methodologies to measure the strength of the interdependence of inflation uncertainty between the euro area and the UK. We first estimate inflation uncertainty by *ex post* forecast errors from a bivariate VAR GARCH model. It is shown that the estimated uncertainty is well characterised by non-Gaussian density with skewed, heavy tail properties–Two Piece Normal (TPN) and Weighted Skewed Normal (WSN) and the goodness-of-fit tests support the choice of WSN against TPN for both the UK and the euro area inflation uncertainty.

The estimated parameters in WSN suggests that the UK monetary policy reactions in the short run have been relatively hawkish while in the longer term the responses are rather dovish, focusing more on economic growth. For the euro area, the estimation results suggest that the ECB tends to be hawkish in response of upside risk of inflation uncertainty regardless of the forecast horizons.

The interdependence of uncertainty is estimated using a probability model. The results imply that the simultaneous spillover of inflation uncertainty is stronger for uncertainty about distant future than near future.

However, the evidence from quantile regressions indicates that such empirical method could suffer from endogeneity biases. To identify structural parameters in an endogeneity representation of interdependence, we exploit heteroskedasticity in the data across different regimes: pre-crisis, GFS crisis, and post-crisis periods. The results no longer exhibit stronger interdependence at longer horizons. The strength of the propagation of inflation uncertainty intensifies during the GFS period while the interdependence significantly dampens during the post-crisis period.

The main policy implications of this research is the importance of the monetary policy credibility in the presence of increased interdependence of inflation uncertainty during the crises periods. Heightened inflation uncertainty of a country may amplify uncertainty of the other country with strong economic and financial linkages, resulting in de-anchoring of inflation expectation. Monetary policy credibility becomes more crucial in times of great uncertainty with high degrees of contagion.

There are a number of gaps in the research that would benefit from further study. It includes the extension of the sample through Brexit, a crucial moments for the UK and EU relationships, as well as through the COVID-19 pandemic, a time where inflation uncertainty is among the highest over history. In addition, it would be helpful to understand the potential multiple relationships including the US.

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Tables and Figures

FIGURE 1 Inflation uncertainty

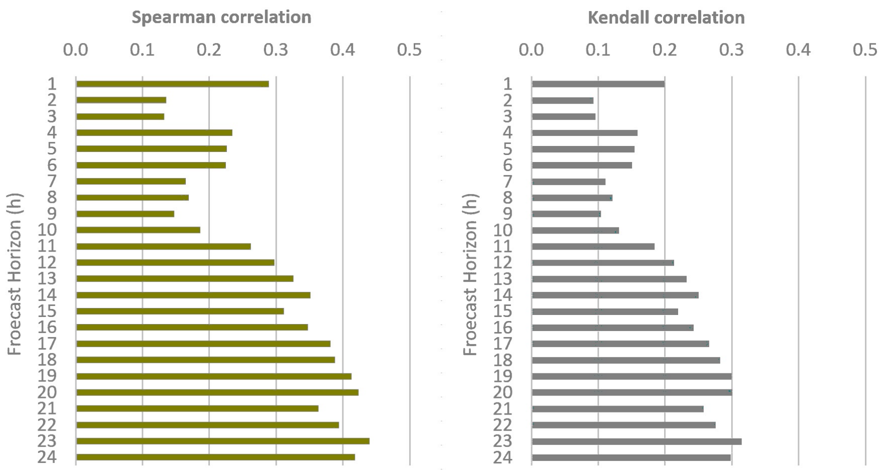
Notes: The figures are the estimated coefficients in Equation (1) by VAR BEKK GARCH (1,1) model.The top panel shows estimated inflation uncertainty of the UK for the selected forecast horizons, $h = 3, 6, 12, 18, 24$. The bottom panel shows estimated inflation uncertianty of the euro area for the same selected forecast horizons.

TABLE 1 Summary statistics of inflation uncertainty

	UK				Euro			
Horizon	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis
1	-0.05	0.43	-0.19	0.35	-0.02	0.41	-0.25	0.42
2	-0.09	0.69	-0.06	0.61	-0.10	0.52	-0.01	0.41
3	-0.06	1.00	-0.13	1.12	-0.15	0.69	-0.24	1.82
4	-0.02	1.20	-0.08	1.24	-0.16	0.90	-0.81	2.95
5	-0.06	1.43	-0.06	1.21	-0.28	1.23	-1.10	4.06
6	-0.13	1.58	-0.02	1.63	-0.26	1.51	-1.13	4.66
7	-0.13	1.75	-0.01	2.22	-0.33	1.81	-1.23	4.99
8	-0.09	1.89	0.09	2.58	-0.45	2.14	-1.17	4.75
9	-0.10	1.97	0.25	3.53	-0.51	2.45	-1.15	5.13
10	-0.13	1.99	0.10	2.84	-0.59	2.68	-1.22	5.14
11	-0.16	2.03	0.09	2.86	-0.63	2.82	-1.32	5.33
12	-0.09	2.00	0.29	3.48	-0.51	2.95	-1.10	4.98
13	-0.14	1.93	0.23	2.81	-0.59	2.97	-1.07	4.66
14	-0.13	1.81	0.45	2.88	-0.73	2.98	-0.96	3.72
15	-0.09	1.70	0.48	3.23	-0.80	2.88	-0.78	3.50
16	-0.06	1.57	0.39	1.77	-0.81	2.76	-0.72	2.79
17	-0.08	1.45	0.40	1.12	-0.90	2.67	-0.59	1.94
18	-0.10	1.28	0.36	0.00	-0.83	2.54	-0.35	1.44
19	-0.08	1.21	0.43	-0.20	-0.85	2.45	-0.12	1.29
20	-0.03	1.24	0.65	0.84	-0.89	2.46	0.24	1.59
21	-0.03	1.24	0.65	1.15	-0.90	2.45	0.30	1.83
22	-0.02	1.33	0.94	2.19	-0.92	2.52	0.51	2.21
23	-0.03	1.37	0.95	1.75	-0.91	2.51	0.57	1.67
24	0.03	1.44	1.19	2.97	-0.76	2.47	0.60	1.63

Notes: Inflation uncertainty is measured by *ex post* forecast errors from a bivariate VAR BEKK GARCH using monthly inflation (January 1997-March 2016). To standardize, the forecast errors are multiplied by the square root of the unconditional variance-covariance matrix and divided by the square root of the conditional variance-covariance matrix of error terms.

FIGURE 2 Interdependece of inflation uncertainty: rank correlation coefficients



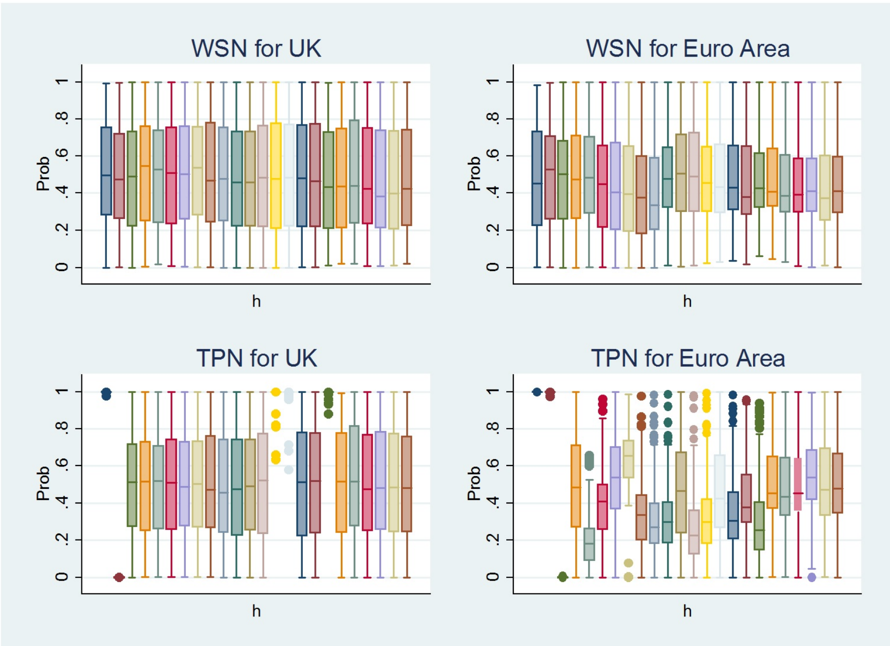
Notes: Spearman's rank correlation can be defined as $\rho_S(X,Y) = \rho(F_1(X), F_2(Y))$. Kendall's rank correlation is defined as $\rho_\tau(X,Y) = \Pr[(X_1 - X_2)(Y_1 - Y_2) > 0] - \Pr[(X_1 - X_2)(Y_1 - Y_2) < 0]$.

TABLE 2 The estimated parameters of marginal densities

		h=6		h=12		h=18		h=24	
		UK	Euro	UK	Euro	UK	Euro	UK	Euro
WSN	α	-1.81	-3.61	-1.47	-3.19	-0.84	-3.19	-1.00	-0.96
		(0.36)	(1.29)	(0.42)	(0.54)	(0.90)	(0.49)	(0.37)	(0.01)
	β	-0.98	-2.72	-1.38	-0.21	-0.95	0.00	-1.10	-0.01
		(0.46)	(1.01)	(0.69)	(0.17)	(1.54)	(0.00)	(1.09)	(0.02)
	σ	0.99	0.56	1.22	1.47	1.13	1.74	1.07	2.28
		(0.08)	(0.29)	(0.29)	(0.08)	(0.51)	(0.10)	(0.31)	(0.12)
	MD	**1.99**	**13.56**	**14.13**	**22.70**	12.64	**46.18**	6.65	24.86
TPN	σ_1	1.70	0.56	1.58	1.61	3.91	1.07	0.54	1.84
		(0.71)	(0.27)	(0.42)	(1.51)	(0.27)	(0.31)	(0.67)	(0.75)
	σ_2	1.03	2.76	1.78	1.83	0.23	3.99	1.78	2.60
		(0.21)	(1.12)	(0.47)	(0.71)	(0.20)	(0.03)	(0.03)	(0.89)
	μ	0.35	-1.12	-0.26	-0.32	-2.59	-1.18	-0.96	-1.38
		(0.40)	(2.02)	(0.70)	(1.51)	(0.62)	(0.83)	(0.51)	(1.20)
	MD	4.64	39.19	15.37	39.97	**6.56**	55.71	**3.05**	**18.38**
Sample size		146		140		134		128	

Notes: MD denotes the minimum distance statistics for the equiprobable null hypothesis against the alternative hypothesis of bumps or dips in the probability. Under the null hypothesis, the MD statistic has an asymptotic χ^2 distribution (Cressie and Read, 1984).

FIGURE 3 Box plot of probability integral transformation



Notes: h is horizon of uncertainty index, ranging from 1 to 24. The boxes of each plot indicate IQR (interquantile range) with median. The whiskers are stretched in both sides to 1.5 IQR and the outliers are presented in dots.

TABLE 3 Cramér-von Mises statistics for testing uniformity of *pit's*

	h=6		h=12		h=18		h=24	
	UK	Euro	UK	Euro	UK	Euro	UK	Euro
WSN	0.173	0.134	0.194	0.139	0.212	0.140	0.224	0.147
TPN	0.198	0.127	0.223	0.158	0.331	0.177	0.278	0.166

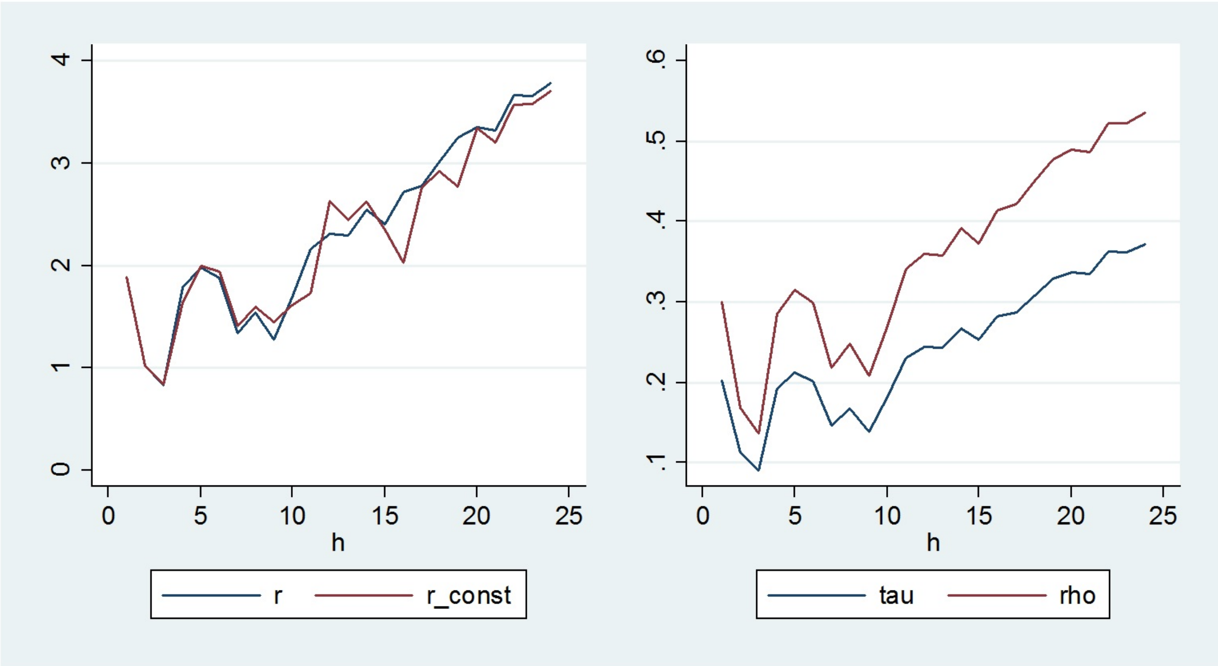
Notes: Asymptotic critical values for the Cramér-von Mises statistics are 0.347 at 10% significance level, 0.461 at 5% significance level.

TABLE 4 The estimated parameters of Frank copula: same horizon

h	γ	se(γ)	CvM	τ	ρ
1	1.886	0.783	0.091	0.203	0.300
2	1.022	0.784	0.094	0.112	0.168
3	0.823	0.751	0.083	0.091	0.136
4	1.783	0.800	0.120	0.192	0.285
5	1.984	0.837	0.219	0.212	0.315
6	1.878	0.830	0.193	0.202	0.299
7	1.341	0.820	0.151	0.146	0.218
8	1.539	0.848	0.201	0.167	0.249
9	1.273	0.830	0.332	0.139	0.208
10	1.684	0.858	0.425	0.182	0.271
11	2.167	0.874	0.311	0.230	0.340
12	2.307	0.876	0.202	0.244	0.360
13	2.297	0.838	0.194	0.243	0.358
14	2.552	0.849	0.210	0.267	0.392
15	2.401	0.833	0.253	0.253	0.372
16	2.713	0.841	0.286	0.282	0.413
17	2.777	0.819	0.333	0.287	0.421
18	3.017	0.856	0.395	0.309	0.451
19	3.252	0.860	0.374	0.329	0.478
20	3.354	0.868	0.460	0.337	0.490
21	3.326	0.873	0.354	0.335	0.487
22	3.665	0.893	0.419	0.362	0.523
23	3.654	0.872	0.463	0.362	0.522
24	3.784	0.913	0.256	0.372	0.536

Notes: The parameters are estimated under the assumption that ρ in WSN distribution decays exponentially as forecast horizon increases.

FIGURE 4 The estimated copula parameters and rank correlations: same horizon



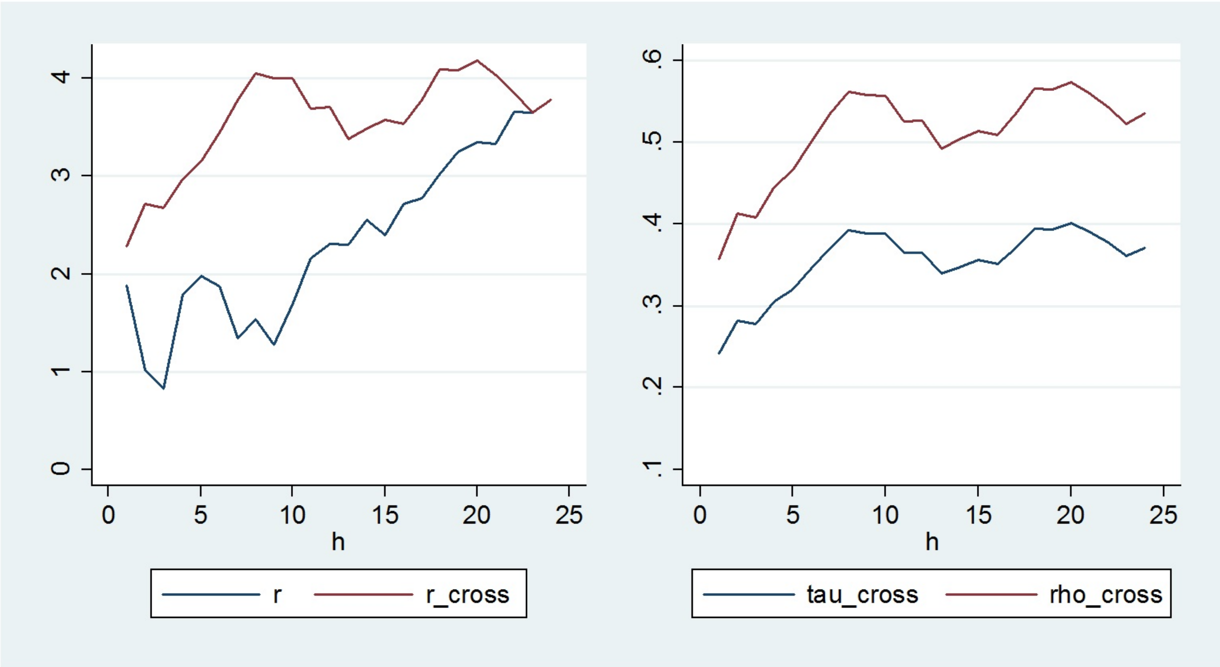
Notes: *r* denotes γ parameter of Frank copula estimated under the assumption of decaying ρ in WSN marginal densities. *r_const* denotes γ parameter of Frank copula assuming constant ρ (=0.75) for WSN marginal densities. *tau* and *rho* are the estimated rank correlation coefficients computed by the analytical form (Equations 32 and 33) in Appendix A.

TABLE 5 The estimated rank correlations: matching horizons

h_{uk}	$h_{eu,1}$	τ	$h_{eu,2}$	ρ	h_{uk}	$h_{eu,1}$	τ	$h_{eu,2}$	ρ
1	12	0.223	6	0.316	13	19	(0.307)	20	(0.436)
2	12	0.261	12	0.358	14	20	(0.324)	20	(0.457)
3	12	0.259	8	0.369	15	20	(0.331)	20	(0.474)
4	13	0.268	13	0.378	16	23	(0.330)	23	(0.472)
5	14	0.273	14	0.384	17	23	(0.349)	23	(0.492)
6	14	0.303	14	0.418	18	23	(0.364)	23	(0.520)
7	14	0.322	14	0.450	19	23	(0.370)	24	(0.515)
8	14	0.326	14	0.448	20	24	(0.356)	24	(0.492)
9	14	0.321	14	0.435	21	24	(0.328)	24	(0.457)
10	14	0.306	16	0.430	22	24	(0.311)	24	(0.432)
11	14	0.307	17	0.435	23	23	(0.315)	23	(0.440)
12	17	0.299	17	0.424	24	24	(0.298)	24	(0.418)

Note: h_{uk} denotes the horizons for the UK inflation uncertainty. $h_{eu,1}$ denotes the horizons of the euro inflation uncertainty that give the highest Kendall's τ correlation given each horizon of the UK inflation uncertainty (h_{uk}). $h_{eu,2}$ refers to the horizons of the euro inflation uncertainty that give the highest Spearman's ρ correlation given each horizon of the UK inflation uncertainty (h_{uk}).

FIGURE 5 The estimated copula parameters and rank correlations: matching horizons



Notes: Given each forecast horizon of the UK inflation uncertainty, the forecast horizons of the euro area inflation uncertainty are selected to have the highest correlation. *r* denotes γ parameter of Frank copula estimated under the assumption of decaying ρ in WSN marginal densities and combining the same horizon. *r_cross* denotes γ parameter of Frank copula assuming decaying ρ in WSN marginal densities and combining different horizons that give the highest correlation. *tau_cross* and *rho_cross* are the estimated rank correlation coefficients that correspond to r_cross computed by the analytical form (Equations 32 and 33) in Appendix A.

FIGURE 6 Interdependece of inflation uncertainty: identification through heteroskedasticity

Notes: The figure shows the point estimates of α and β computed from Equation (27) using pre-crisis, crisis, and post-crisis periods, respectively. UK denotes the estimates of α in Equation (15) and EU denotes the estimated of β in Equation (16).

TABLE 6 The parameter estimates and bootstrap results: pre-crisis period

	α				β			
	Point estimate	Bootstrap			Point estimate	Bootstrap		
		Mean	SD	Prob ($\alpha < 0$)		Mean	SD	Prob ($\beta < 0$)
h=1	0.278	0.253	0.253	0.124	0.077	0.075	0.350	0.309
h=2	0.171	0.106	0.510	0.401	0.075	0.092	0.356	0.363
h=3	0.301	0.141	0.543	0.381	-0.105	-0.003	0.338	0.537
h=4	-0.058	0.022	0.571	0.495	0.051	-0.004	0.326	0.471
h=5	0.290	0.235	0.489	0.240	-0.187	-0.160	0.287	0.766
h=6	0.271	0.230	0.541	0.337	-0.297	-0.261	0.252	0.914*
h=7	0.010	0.012	0.414	0.527	-0.300	-0.288	0.201	0.950**
h=8	-0.143	-0.098	0.357	0.645	-0.292	-0.303	0.198	0.954**
h=9	-0.338	-0.235	0.473	0.739	-0.224	-0.239	0.375	0.743
h=10	-0.131	-0.236	0.614	0.671	-0.295	-0.142	0.435	0.593
h=11	-0.497	-0.162	0.614	0.629	0.035	-0.118	0.372	0.625
h=12	0.123	-0.077	0.603	0.555	-0.238	-0.059	0.441	0.563
h=13	0.555	0.023	0.556	0.401	-0.617	-0.131	0.517	0.637
h=14	0.732	-0.162	0.430	0.661	-0.984	0.103	0.566	0.425
h=15	0.165	0.161	0.300	0.234	-0.333	-0.296	0.372	0.788
h=16	0.242	0.209	0.200	0.106	-0.336	-0.310	0.281	0.844
h=17	0.076	0.049	0.491	0.439	-0.142	-0.101	0.344	0.605
h=18	-0.749	-0.568	0.462	0.908*	0.742	0.630	0.321	0.042++
h=19	-0.588	-0.529	0.321	0.958**	0.689	0.655	0.234	0.014++
h=20	-0.133	-0.016	0.315	0.719	0.170	0.153	0.133	0.136
h=21	0.107	0.312	0.471	0.305	-0.159	-0.206	0.241	0.844
h=22	0.450	0.444	0.398	0.034++	-0.417	-0.394	0.257	0.952**
h=23	0.117	0.102	0.255	0.307	-0.351	-0.350	0.324	0.932*
h=24	-0.215	-0.202	0.173	0.880	-0.310	-0.324	0.291	0.926*

Notes: The within-regime bootstrapped estimates are drawn from uniform distribution for 500 times. Then the probability of the estimated α, β to be below zero is computed for each regime and horizon.

TABLE 7 The parameter estimates and bootstrap results: crisis period

	α				β			
	Point estimate	Bootstrap			Point estimate	Bootstrap		
		Mean	SD	Prob ($\alpha < 0$)		Mean	SD	Prob ($\beta < 0$)
h=1	-0.539	-0.103	0.673	0.605	0.502	0.211	0.459	0.275
h=2	0.002	-0.005	0.536	0.501	0.196	0.160	0.207	0.178
h=3	0.825	0.350	0.737	0.277	-0.093	0.080	0.370	0.441
h=4	0.898	0.560	0.749	0.186	-0.269	0.015	0.510	0.607
h=5	0.783	0.613	0.653	0.136	-0.425	-0.136	0.703	0.750
h=6	0.705	0.564	0.543	0.134	-0.674	-0.301	0.735	0.808
h=7	0.657	0.532	0.482	0.132	-0.657	-0.240	0.853	0.770
h=8	0.616	0.541	0.536	0.118	-0.755	-0.360	0.791	0.818
h=9	0.315	0.599	0.538	0.044++	0.635	1.401	1.468	0.036++
h=10	0.268	0.468	0.417	0.034++	0.732	1.415	1.492	0.016++
h=11	0.238	0.385	0.380	0.082+	0.844	1.420	1.375	0.008+++
h=12	0.190	0.284	0.319	0.114	0.958	1.346	1.183	0.006+++
h=13	0.210	0.255	0.256	0.104	0.953	1.043	0.948	0.036++
h=14	0.172	0.170	0.151	0.110	1.044	1.019	0.428	0.012++
h=15	0.185	0.173	0.129	0.090+	0.989	0.928	0.428	0.032++
h=16	-0.020	0.030	0.178	0.507	1.473	1.208	0.715	0.082+
h=17	-0.012	0.039	0.168	0.457	1.552	1.243	0.773	0.096+
h=18	-0.140	0.056	0.237	0.585	1.921	0.963	1.282	0.293
h=19	-0.019	0.002	0.129	0.557	1.749	1.546	0.715	0.066+
h=20	0.042	0.040	0.057	0.214	1.608	1.600	0.175	0.000+++
h=21	0.065	0.062	0.049	0.100+	1.638	1.630	0.137	0.000+++
h=22	0.053	0.053	0.056	0.176	1.622	1.614	0.110	0.000+++
h=23	0.350	0.262	0.171	0.096+	-0.022	0.274	1.028	0.447
h=24	0.078	0.083	0.095	0.174	1.438	1.422	0.266	0.000+++

Notes: The within-regime bootstrapped estimates are drawn from uniform distribution for 500 times. Then the probability of the estimated α, β to be below zero is computed for each regime and horizon.

TABLE 8 The parameter estimates and bootstrap results: post-crisis period

	α				β			
	Point estimate	Bootstrap			Point estimate	Bootstrap		
		Mean	SD	Prob ($\alpha < 0$)		Mean	SD	Prob ($\beta < 0$)
h=1	0.079	0.060	0.353	0.477	0.307	0.251	0.652	0.309
h=2	-0.406	-0.273	0.340	0.838	0.737	0.493	0.643	0.196
h=3	-0.170	-0.135	0.376	0.661	0.144	0.082	0.519	0.363
h=4	-0.396	-0.240	0.398	0.838	0.707	0.489	0.576	0.146
h=5	-0.278	-0.218	0.405	0.826	-0.046	-0.050	0.216	0.607
h=6	0.597	0.165	0.654	0.349	-0.563	-0.221	0.516	0.747
h=7	-0.179	-0.150	0.323	0.705	-0.050	-0.055	0.316	0.563
h=8	-0.410	-0.367	0.326	0.916*	0.269	0.237	0.338	0.192
h=9	0.530	0.455	0.508	0.096+	-0.175	-0.143	0.367	0.733
h=10	0.516	0.458	0.374	0.064+	-0.287	-0.230	0.384	0.800
h=11	0.615	0.477	0.519	0.104	-0.306	-0.209	0.372	0.818
h=12	0.566	0.409	0.487	0.138	-0.240	-0.112	0.447	0.747
h=13	0.287	0.279	0.275	0.136	-0.012	-0.005	0.292	0.525
h=14	-0.089	-0.119	0.211	0.741	0.252	0.303	0.273	0.132
h=15	0.319	0.291	0.200	0.062+	-0.613	-0.569	0.317	0.974**
h=16	0.275	0.231	0.262	0.136	-0.525	-0.443	0.450	0.886
h=17	0.297	0.099	0.348	0.265	-0.728	-0.318	0.683	0.768
h=18	0.267	0.147	0.281	0.166	-0.850	-0.560	0.636	0.874
h=19	0.139	0.118	0.165	0.152	-0.637	-0.582	0.396	0.952**
h=20	0.138	0.151	0.157	0.102	-0.715	-0.694	0.295	0.986**
h=21	0.050	0.060	0.122	0.363	-0.515	-0.516	0.233	0.984**
h=22	-0.028	-0.022	0.119	0.603	-0.352	-0.333	0.274	0.918*
h=23	0.053	0.055	0.114	0.309	-0.467	-0.462	0.241	0.984**
h=24	-0.027	-0.055	0.215	0.593	-0.266	-0.104	0.688	0.685

Notes: The within-regime bootstrapped estimates are drawn from uniform distribution for 500 times. Then the probability of the estimated α, β to be below zero is computed for each regime and horizon.

Appendix

A Frank copula

The *cdf* of Frank copula is given by

$$C(y_1, y_2; \gamma) = -\frac{1}{\gamma} \ln \left(1 + \frac{(e^{-\gamma y_1} - 1)(e^{-\gamma y_2} - 1)}{e^{-\gamma} - 1}\right) \tag{28}$$

where $\gamma \in (-\infty, +\infty)$. If $\gamma = 0$, the copula is independent.

The copula generator for Frank copula, $\varphi(\cdot)$, is

$$\varphi_\gamma(t) = -\ln \left(\frac{e^{-\gamma t} - 1}{e^{-\gamma} - 1}\right) \tag{29}$$

The *pdf* of Frank copula is

$$c(y_1, y_2; \gamma) = \frac{-\gamma(e^{-\gamma} - 1)e^{-\gamma(y_1+y_2)}}{((e^{-\gamma y_1} - 1)(e^{-\gamma y_2} - 1) + (e^{\gamma} - 1))^2} \tag{30}$$

The analytical closed forms of these rank correlations, which depend on the parameter value, γ, are as follows.

$$g_\tau(\gamma) = 1 - \frac{4(1 - D_1(\gamma))}{\gamma} \tag{31}$$

$$g_\rho(\gamma) = 1 - \frac{12(D_1(\gamma) - D_2(\gamma))}{\gamma} \tag{32}$$

where $D_k = kx^{-k} \int_0^x t^k (e^t - 1)^{-1} dt$ is the Debye function.

B Conditional probability

Based on the estimated marginal and joint densities of inflation uncertainty, the conditional probability of certain scenarios of inflation outcomes can be computed. The subscript for the density functions (f and F) and uncertainty index (U) indicates each region: 1 for the UK and 2 for the euro area. Then, the unconditional probability for the UK inflation being inside [a,b] can be represented as follows.

$$\int_a^b \hat{f}_1(U_1)\, dU_1 \tag{33}$$

The probability of the UK inflation inside the interval [a,b] conditional on the euro inflation being inside the same interval is given below.

$$\frac{\int_a^b \int_a^b c(\hat{F}_1, \hat{F}_2; \hat{\alpha})\ \hat{f}_1 \cdot \hat{f}_2\ dU_1 dU_2}{\int_a^b \hat{f}_2(U_2)\ dU_2} \tag{34}$$

Table B1 and Figure B1 show two different scenarios, (i) the inflation below 1% and (ii) the inflation within [1%, 3%] for both economies based on the post-crisis sample period.

The downward sloping lines in the left panel of Figure B1 suggest that both unconditional and conditional probability of the UK inflation below 1% decreases as forecasting horizon increases. The unconditional probability is lower than the conditional probability for all horizons in the first scenario. For example, the probability of the UK inflation below 1% in two years without considering the dependence structure is approximately 0.24 while this increases to 0.31 if it is known that the euro area inflation will also become below 1% in two years. This implies that the left tail events of inflation are positively correlated between the two regions.

The second scenario of the UK inflation within the target band tells a different story (Figure B1 right panel). The probabilities do not decrease in a monotonic sense when forecast horizon increases. The unconditional probability appears to be flat across all forecast horizons, roughly between 0.4 and 0.5. The conditional probabilities are either flat (copula estimated with marginals of the same horizons) or increasing (copula estimated with marginals of the different horizons) for the short forecast horizons. For the longer horizons, the conditional probabilities tend to decline as the forecast horizon increases. Comparing the unconditional and conditional probabilities, unconditional probability of the UK inflation inside the target band is significantly lower than the conditional probability in the short and medium term. However, the long term unconditional probability is larger than the conditional probability.

TABLE B1 The unconditional and conditional probability of the UK inflation

I. The probability of the UK inflation below 1%

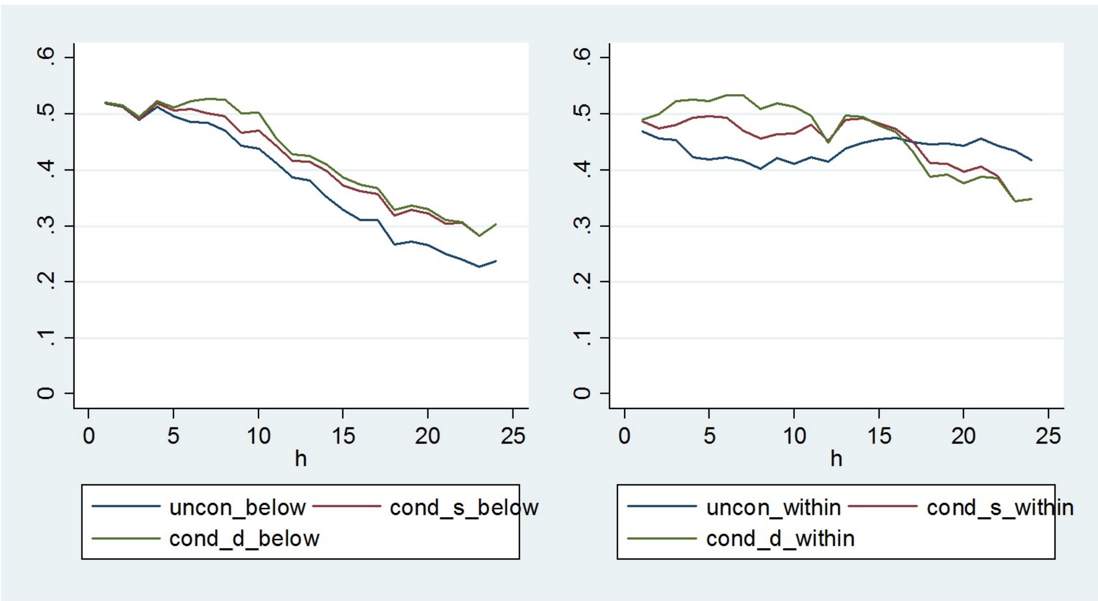
	Unconditional	Conditional (same h)	Conditional (different h)	$[h_{eu}]$
$h_{uk}=6$	0.4867	0.5095	0.5238	14
$h_{uk}=12$	0.3863	0.4163	0.4281	17
$h_{uk}=18$	0.2663	0.3184	0.3289	23
$h_{uk}=24$	0.2387	0.3036	0.3036	24

II. The probability of the UK inflation within [1%, 3%]

	Unconditional	Conditional (same h)	Conditional (different h)	$[h_{eu}]$
$h_{uk}=6$	0.4224	0.4942	0.5337	14
$h_{uk}=12$	0.4150	0.4523	0.4488	17
$h_{uk}=18$	0.4457	0.4127	0.3884	23
$h_{uk}=24$	0.4179	0.3483	0.3483	24

Notes: The conditional probability is computed from the copula estimation results in Section III. B. *Conditional (same h)* indicates the conditional probability calculated using the estimated joint distribution combined by the same horizon univariate densities of the UK and the euro inflation uncertainty. *Conditional (different h)* indicates the conditional probability calculated using the estimated joint distribution combined by the matching univariate densities of the UK and the euro inflation uncertainty which give the highest Kendall's τ rank correlation given the horizon of the UK inflation uncertainty (h_{uk}). h_{eu} denotes the selected horizons for the euro inflation uncertainty that gives the highest Kendall's τ correlation.

FIGURE B1 The unconditional and conditional probabilities of the UK inflation



Notes: The left panel shows the results when the UK inflation is below 1%, and the right panel shows the results when the UK inflation is within target [1%, 3%]. The blue lines are unconditional probability and the red lines are conditional probability computed for the same horizons. The green lines are conditional probability computed for the different horizons when when pairing the two marginal densities.

C Empirical evidence of endogeneity bias: Quantile regressions

Quantile regressions (28) can provide empirical evidence of endogeneity. The model for the τ-th conditional quantile of Y, Q_τ, can be written as follows.

$$Q_\tau = X\beta(\tau) \tag{35}$$

where X is a vector of explanatory variables. The estimation of $\beta(\tau)$ is based on a sample of n observations in Y. If the estimates of $\beta(\tau)$ differ across τ's, it suggests that the marginal effect of X is heterogeneous across different quantiles of the conditional distribution of Y. Therefore, non-flat quantile treatment effects indicate whether there is any potential non-linearity in the data conditional on the quantile.

To detect potential bias due to endogeneity, we estimate the coefficients of quantile regressions of U_{1t} on U_{2t}, and vice versa. Figure C1 plots the estimated slope coefficients, $\beta(\tau)$, of the quantile regressions of U_{1t} on U_{2t} for each forecast horizon ($h = 1, \cdots, 24$). Different patterns among different groups of forecasting horizons were found in the results. The estimates from the regressions of uncertainty at short horizons exhibit large variations, while the estimates are likely to be flatter for the regressions of uncertainty at longer horizons. For the inflation uncertainty at short horizons ($h = 1, \cdots, 4$), the quantile slope estimates are U-shaped, suggesting the changes in skewness. For longer horizons ($h = 5, \cdots, 10$), the quantile slopes are flat up to 40-60 percentile and then U-shaped in the right tail. The estimates from uncertainty about one-year-ahead to 19-month-ahead inflation exhibit modest increases, with some irregularities as reaching the far right tail. The quantile regression coefficients tend to be flat for $h = 20, \cdots, 24$.

Figure C2 plot the quantile estimates of U_{2t} on U_{1t} for each forecast horizon. The plots are quite different from the previous results in many aspects. First, the quantile slope coefficients are much larger than those from the regressions of the UK uncertainty on the euro uncertainty.[20] Second, heterogeneity in the strength of interdependence is more pronounced in the case of uncertainty at longer horizons compared to the previous results. The variability of the estimated coefficients across quantiles tends to be greater as h gets larger. Third, we observe pick-ups in the estimated coefficients in the left tails except for very short ($h = 1, 2$) or very long horizons ($h = 23, 24$).

Next, we conduct simulations of quantile regressions with iid errors to confirm whether the quantile slope coefficients are flat across τ's when there is no endogeneity. First, we assume a model of random variables X and Y: $Y = 0.5X + \epsilon$, where the relationship between X and Y is uniquely defined by an iid error term, exogenous to X. Second, we assume a random variable X and an error term ϵ have following distributions. For each combination, we allow for different symmetric and asymmetric distributions while maintaining iid assumptions for ϵ's.

[20]Please note that y-axis is modified, ranging from 0 to 2. For $h = 19$, y-axis ranges from 0 to 2.2.

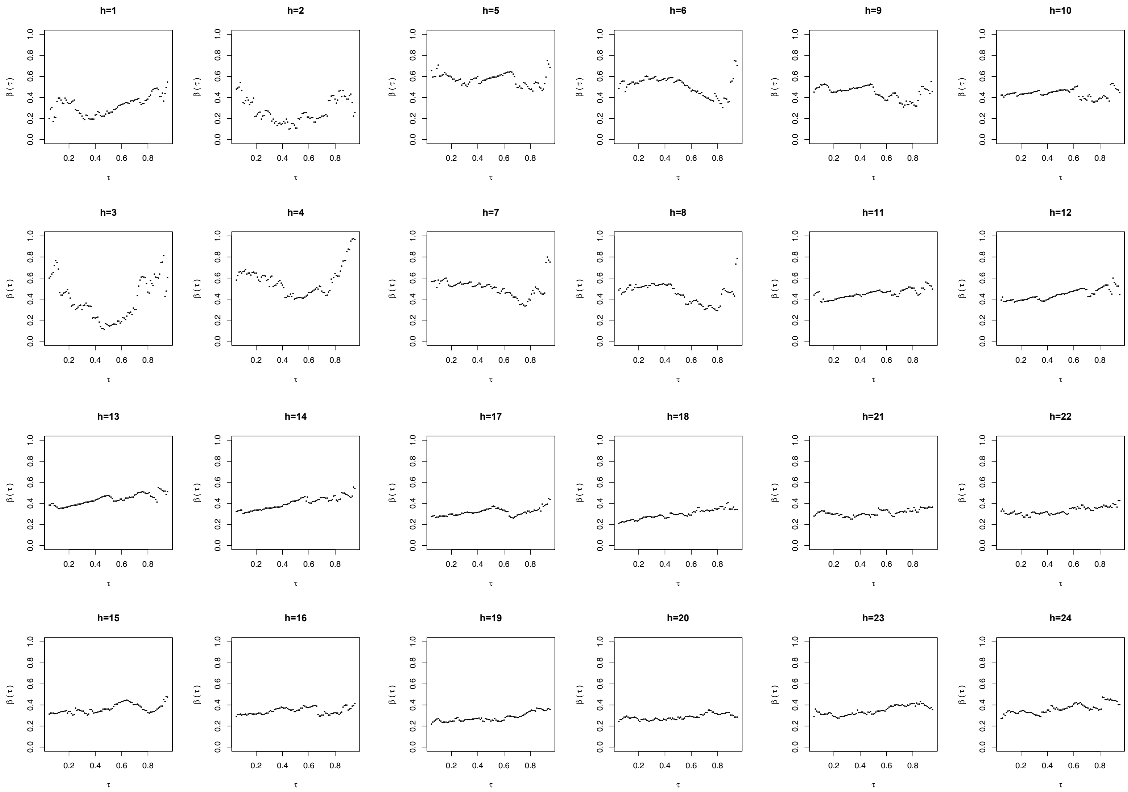
1. $X \sim N(2,1); \epsilon \sim iidN(0,1)$.
2. $X \sim t(5); \epsilon \sim iidN(0,1)$.
3. $X \sim t(5); \epsilon \sim iidt(5)$.
4. $X \sim N(2,1) + \chi^2(4); \epsilon \sim iidN(0,1)$.
5. $X \sim N(2,1); \epsilon \sim iidt(5)$.
6. $X \sim N(2,1); \epsilon \sim iidN(2,1) + \chi^2(4)$.

Third, we draw a sample of size $n = 1001$ for X, which is fixed over replications. Fourth, we draw error terms for $r = 100$ times and compute Y for each replication. Lastly, for every replication, we compute $\widehat{\beta(\tau)}$ and average $\widehat{\beta(\tau)}$ over replications.

Figure C3 present the estimated $\beta(\tau)$ from a sample draw (left panel) and from the average of all estimates across 100 repetitions (right panel). As expected, the slope coefficients are flat across quantiles when there is no endogeneity.

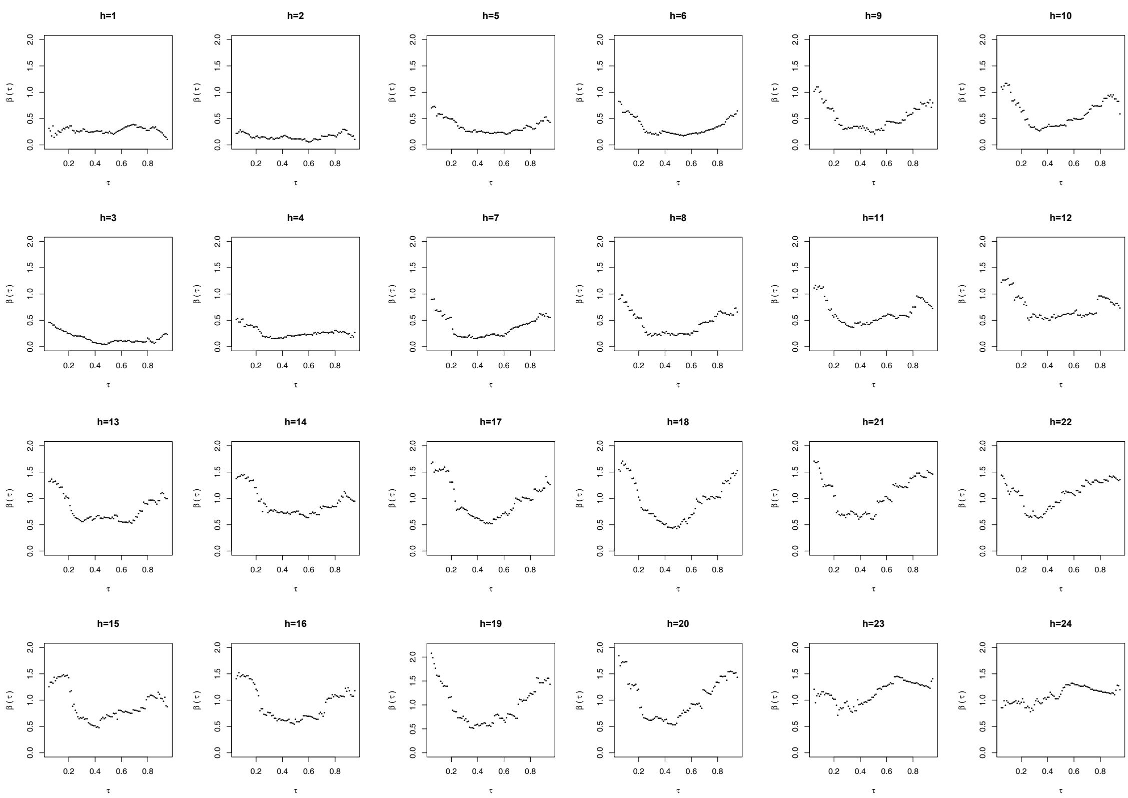
Overall, the results confirm that the conventional strategies for estimating interdependence could be biased in the presence of endogeneity problem.

Figure C1 The estimated slope coefficients of linear quantile regressions (I)



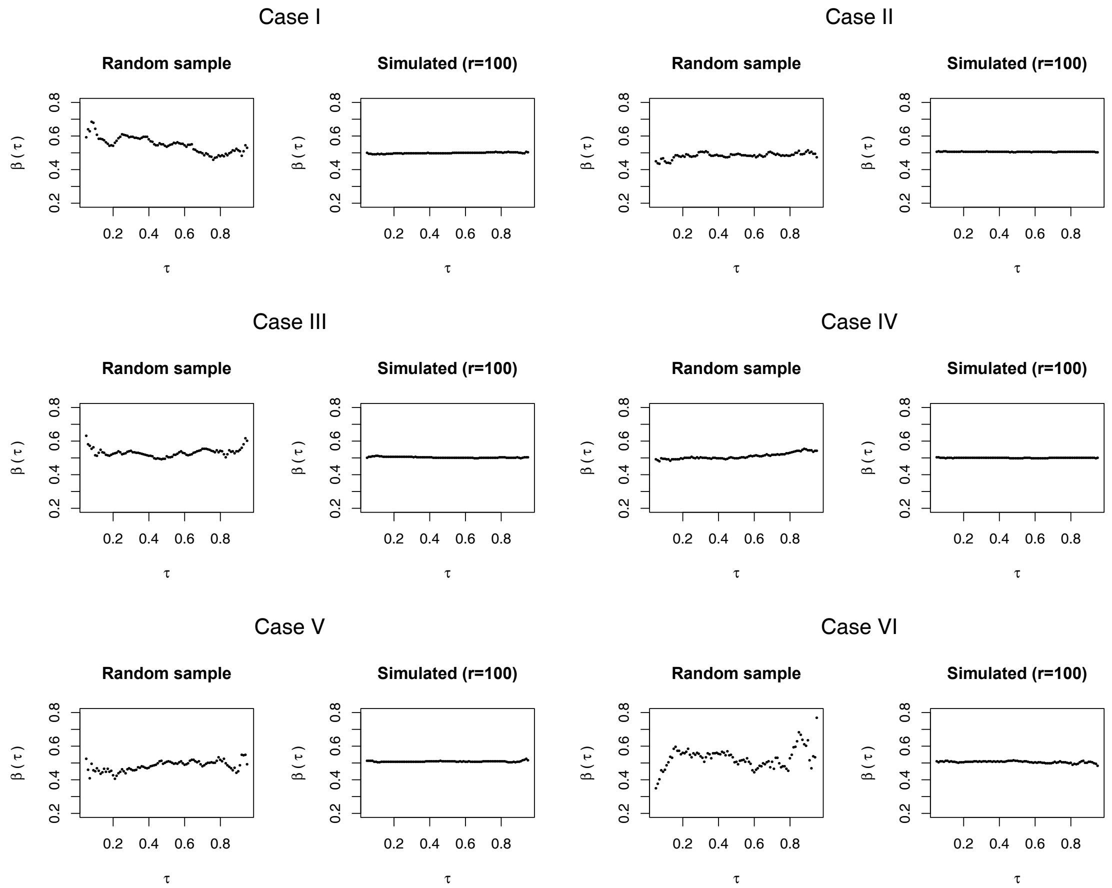
Notes: The estimation results from the quantile regressions of the UK inflation uncertainty on the euro inflation uncertainty for each horizon are presented. The estimated coefficients are plotted as a function of τ. The x-axis is $\tau = 0.05, 0.06, \cdots, 0.94, 0.95$. Y-axis is fixed across the figures for comparison.

Figure C2 The estimated slope coefficients of linear quantile regressions (II)



Notes: The estimation results from the quantile regressions of the euro inflation uncertainty on the UK inflation uncertainty for each horizon are presented. The estimated coefficients are plotted as a function of τ. The x-axis is $\tau = 0.05, 0.06, \cdots, 0.94, 0.95$. Y-axis is fixed across the figures for comparison.

Figure C3 The estimated slope coefficients of linear quantile regression (simulated)



Notes: The estimated coefficients, $\widehat{\beta(\tau)}$, using simulated data are plotted as a function of τ. A model of random variables X and Y: $Y = 0.5X + \varepsilon$. Case I: $\varepsilon \sim iidN(0,1)$, $X \sim N(2,1)$. Case II: $\varepsilon \sim iidN(0,1)$, $X \sim t(5)$. Case III: $\varepsilon \sim iid\, t(5)$, $X \sim t(5)$. Case IV: $\varepsilon \sim iidN(0,1)$, $X \sim N(2,1) + \chi^2(4)$. Case V: $\varepsilon \sim iid\, t(5)$, $X \sim N(2,1)$. Case VI: $\varepsilon \sim iidN(2,1) + \chi^2(4)$, $X \sim N(2,1)$. The sample size is $n = 1001$ for drawing X. The error terms are drawn for $r = 100$ times to compute Y.

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Empirical Quest for Development Effectiveness

발제: **정 혁 · 이 진 이**(서울대 국제대학원)

토론: **강 창 희**(중앙대 경제학부)

EMPIRICAL QUEST FOR DEVELOPMENT EFFECTIVENESS

정혁 ▪ 이진이
서울대학교 국제대학원

2022년 한국개발정책학회 추계학술포럼

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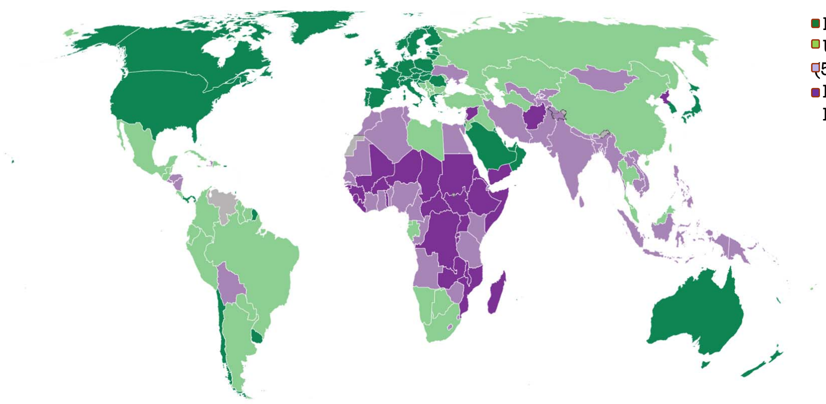
MOTIVATION

WB CLASSIFICATION BY INCOME GROUP [GNI PER CAPITA (2021)]



- High Income [$13,206 or higher] (81)
- Upper Middle Income [$4,256 – 13,205] (54)
- Lower Middle Income [$1,086 – 4,255] (54)
- Low Income [$1,085 or less] (28)

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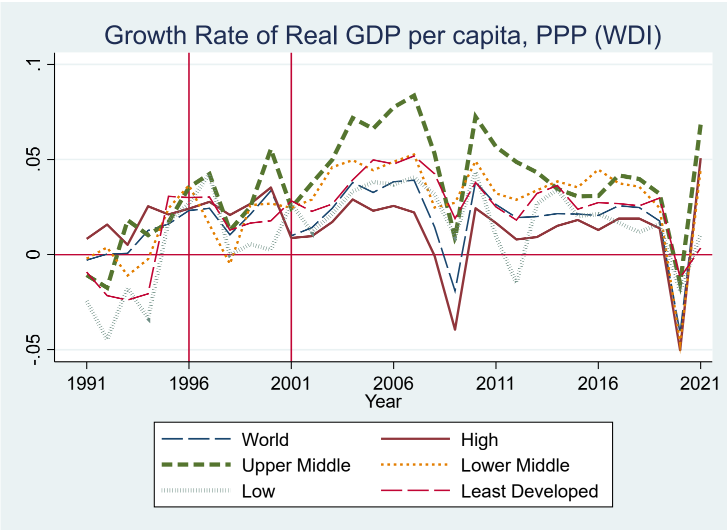
REVERSAL OF FORTUNE



Income Group	Annual average growth
WLD	1.8%
HIC	1.5%
UMC	3.7%
LMC	2.6%
LIC	1.3%
LDC	2.1%

Critical turning points for global Growth dynamics

1. 1995-1996: First time when g_UMC, g_LMC, g_LIC > g_HIC
2. g_UMC, g_LMC >> g_HIC after 2000-2001 and onward

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QUESTIONS

1. Sources of the developing countries' growth for the 1971-2019 period
2. Development effectiveness from ODA?
3. Structural change before and after 2001? Was the development effectiveness improved for real income growth after the MDGs initiative?
4. How about the SDG era?
5. Development effectiveness from ODA or from globalization?

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METHOD

GROWTH MODEL AND GROWTH REGRESSION

- Utilize the growth regression analysis (based on the neoclassical growth model) to identify the role of ODA for development effectiveness
- Any kind of neoclassical growth model implies the following log-linear approximation of income (measured by the real GDP per capita)
  - $\ln\tilde{y}(t) = e^{-\lambda t} ln\tilde{y}(0) + \left(1 - e^{-\lambda t}\right) ln\tilde{y}^{ss}$ where $\tilde{y} = \frac{Y}{AhL}$ and $\tilde{y}^{ss}$: steady-state level
  - $g_y(t) = [x + \eta] + \beta[ln\tilde{y}^{ss} - ln\tilde{y}(0)]$ where $\beta = \frac{(1-e^{\lambda t})}{t}$
  - $\tilde{y}^{ss}$ depends on specification of the underlying model, e.g., canonical human-capital-augmented neoclassical growth model implies

$$\tilde{y}^{ss} = \left(\frac{\gamma}{\delta + x + n + \eta}\right)^{\frac{\alpha}{1-\alpha}}$$

where $g_A = x, g_L = n, g_h = \eta, \gamma = \frac{I}{Y}$, α: capital share, δ: capital depreciation rate

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INTERPRETING GROWTH REGRESSION

- Note that growth regression equation has basically two parts
  1. Steady-state growth: $[x + \eta] \Rightarrow$ source of long-run growth, i.e. , sustainable development
  2. Transitional growth: $\beta[ln\tilde{y}^{ss} - ln\tilde{y}(0)] \Rightarrow$ growth due to the distance between initial and steady-state levels of a state variable, i.e., growth from input expansion without productivity growth
  3. Via which channels do we observe the (lack of) development effectiveness?

DECOMPOSED GROWTH REGRESSION

- Empirical strategy to identify the channels of promoting development effectiveness
  1. Apply growth regression analysis to income growth as well as to the its components such that TFP growth, composite input growth, employment rate growth

<table>
<tr><td colspan="5">PPP Adjusted Real GDP per capita</td></tr>
<tr><td colspan="4">Real GDP per capita in national account</td><td rowspan="2">PPP adjustment term
A = RGDPE/RGDPNA</td></tr>
<tr><td>Real GDP per capita</td><td>TFP</td><td>Composite Input</td><td>Employment Rate</td></tr>
</table>

  2. Resolve the endogeneity issues of the ODA by using the donor-recipient bilateral relationship variables as IV's
  3. Decompose the sample period into different eras when the global development cooperation initiatives take different approach: pre-MDG vs. MDG vs. SDG
  4. Use various ODA measures: total, grant, loan, sectoral components

ESTIMATION RESULTS

OLS ESTIMATION OF INCOME GROWTH BY PERIOD

Income growth	All (2971-2019)	Pre-MDG (1971-2001)	MDG (2001-2015)	SDG (2015-2019)
ODA/GNI	**0.092 *****	**0.070***	**0.043**	**-0.129**
Initial Income	-0.066 ***	-0.076 ***	-0.147 ***	-0.013
Openness	0.018 ***	0.004	0.082 ***	-0.006
ToT Change	0.145 ***	0.119 ***	0.156 ***	0.151 *
Investment	-0.005	0.045 **	0.119 ***	0.015
Govn't Share	0.013	0.024	0.066	-0.052
Inflation	-0.137 ***	-0.055 ***	-0.153 ***	-0.121
Life Expectancy	0.048 ***	0.107 ***	-0.144 ***	0.038
Years of Schooling	0.005 ***	0.016 ***	-0.028 ***	0.004
Fertility	-0.0225 ***	-0.061 ***	-0.047 **	-0.019
Revolutions	0.002	0.0001	0.005	0.002
Ethnic Fraction	-0.091 ***	-0.002	-0.281 **	0.021
Institution	0.007 ***	-0.003 *	0.021 ***	0.003
Democracy	0.003 ***	0.002	0.004 *	-0.004
Geography	-0.830 ***	-0.576	0.227	-0.011
N	3177	1637	1127	70
R^2	0.451	0.493	0.652	0.294

Empirical Quest for Development Effectiveness, Hyeok Jeong and Jeanni Lee

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ODA SELECTION ESTIMATION BY PERIOD

ODA/GNI	All	Pre-MDG	MDG	SDG
Official Common Language	0.002 ***	0.002 ***	0.002 ***	0.002 ***
Colonial Relationship	0.004 ***	0.006 ***	0.002 ***	0.001 ***
UN Friendship	0.001 ***	0.001 ***	0.001 ***	0.00166 ***
Relative Population Size	-0.001 ***	-0.007 ***	0.002 ***	-0.00176
Import Share from Recipient	0.001	-0.008	-0.008 **	-0.00797
Export Share to Recipient	-0.008**	-0.016 *	-0.001	-0.00001
Initial Income	-0.001***	-0.001 ***	-0.001 ***	-0.00161
Openness	0.0003 *	0.001 ***	-0.001 *	0.00079
ToT Change	0.001 ***	0.002 ***	0.002 ***	0.00008
Investment	-0.0002	0.003 ***	-0.001	0.005 **
Government Share	0.005 ***	0.002 ***	0.003 ***	0.00041
Inflation	-0.0004	-0.002 ***	0.000	0.00006
Life Expectancy	-0.005 ***	-0.004 ***	-0.004 ***	-0.019*
Years of Schooling	0.0001 **	-0.0005 ***	0.0002 **	0.00012
Fertility	-0.0004 *	-0.003 ***	0.001	0.00132
Revolutions	0.00005	0.0003 **	0.000	0.00049
Ethnic Fraction	0.002 **	0.002	0.002	-0.03208
Institution	-0.00009 **	0.00004	0.00006	0.00013
Democracy	0.0001 ***	0.0002 ***	0.000	-0.00012
Geography	-0.010	0.001	0.002	-0.00139
N	61521	28464	33057	6821
R^2	0.188	0.213	0.192	0.231

Empirical Quest for Development Effectiveness, Hyeok Jeong and Jeanni Lee

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IV ESTIMATION OF INCOME GROWTH

	All		Pre-MDG		MDG		SDG	
Income growth	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**	**OLS**	**IV**
Aid/GNI	**0.092 *****	**0.037**	**0.070***	**0.047 ***	**0.043**	**-0.348 ****	**-0.129**	**0.011**
Initial Income	-0.066 ***	-0.067 ***	-0.076 ***	-0.080 ***	-0.147 ***	-0.159 ***	-0.013	-0.008
Openness	0.018 ***	0.019 ***	0.004	0.006	0.082 ***	0.074 ***	-0.006	-0.008
ToT Change	0.145 ***	0.149 ***	0.119 ***	0.124 ***	0.156 ***	0.164 ***	0.151 *	0.159*
Investment	-0.005	-0.005	0.045 **	0.051 **	0.119 ***	0.117 ***	0.015	0.012
Government Share	0.013	0.013	0.024	0.017	0.066	0.106 **	-0.052	-0.067
Inflation	-0.137 ***	-0.139 ***	-0.055 ***	-0.057 ***	-0.153 ***	-0.155 ***	-0.121	-0.125
Life Expectancy	0.048 ***	0.045 ***	0.107 ***	0.106 ***	-0.144 ***	-0.178 ***	0.038	0.037
Years of Schooling	0.005 ***	0.005 **	0.016 ***	0.016 ***	-0.028 ***	-0.029 ***	0.004	0.003
Fertility	-0.0225 ***	-0.023 ***	-0.061 ***	-0.061 ***	-0.047 **	-0.044 *	-0.019	-0.02
Revolutions	0.002	0.002	0.0001	-0.000	0.005	0.006	0.002	0.003
Ethnic Fraction	-0.091 ***	-0.089 **	-0.002	-0.002	-0.281 **	-0.318 **	0.021	0.04
Institution	0.007 ***	0.007 ***	-0.003 *	-0.003	0.021 ***	0.0209 ***	0.003	0.003
Democracy	0.003 ***	0.003 ***	0.002	0.002 **	0.004 *	0.005 **	-0.004	-0.0040
Geography	-0.830 ***	-0.858 ***	-0.576	-0.519	0.227	0.283	-0.011	-0.011
N	3177	3157	1637	1621	1127	1127	70	70
R^2	0.451	0.451	0.493	0.493	0.652	0.654	0.294	0.285

Empirical Quest for Development Effectiveness, Hyeok Jeong and Jeanni Lee

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DECOMPOSITION OF GROWTH SOURCES (ALL PERIOD)

	g_TFP		g_X		g_emp		g_A	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
ODA/GNI	0.15847	-0.05300	-0.00545	0.14858	0.01240	-0.04785	-0.00021	-0.05306
	(0.000)***	(0.079)*	(0.626)	(0.000)***	(0.116)	(0.000)***	(0.994)	(0.159)
Initial Income	-0.04894	-0.05316	-0.00085	0.00102	-0.00399	-0.00458	0.01516	0.01480
	(0.000)***	(0.000)***	(0.508)	(0.414)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Openness	0.00722	0.00814	0.00339	0.00435	-0.00329	-0.00340	0.01458	0.01429
	(0.032)**	(0.017)**	(0.047)**	(0.009)***	(0.014)**	(0.011)**	(0.001)***	(0.001)***
ToT Change	-0.02355	-0.01921	0.03620	0.03346	0.01522	0.01666	0.10726	0.10850
	(0.003)***	(0.016)**	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Investment	0.00725	0.00778	0.02463	0.03116	-0.00517	-0.00679	-0.07479	-0.07668
	(0.401)	(0.377)	(0.000)***	(0.000)***	(0.126)	(0.045)**	(0.000)***	(0.000)***
Government Share	0.06480	0.07278	-0.02136	-0.03078	0.00190	0.00565	-0.03415	-0.03052
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.571)	(0.098)*	(0.002)***	(0.007)***
Inflation	-0.03216	-0.03552	0.01277	0.01042	-0.01527	-0.01457	-0.09446	-0.09363
	(0.000)***	(0.000)***	(0.001)***	(0.005)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Life Expectancy	0.03836	0.02695	0.00640	0.01058	-0.01916	-0.02081	0.00437	0.00329
	(0.001)***	(0.026)**	(0.295)	(0.076)*	(0.000)***	(0.000)***	(0.759)	(0.817)
Years of Schooling	0.00474	0.00437	-0.00875	-0.00835	-0.00142	-0.00158	-0.00090	-0.00104
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.003)***	(0.001)***	(0.565)	(0.508)
Fertility	-0.01327	-0.01390	-0.01000	-0.01175	-0.01088	-0.00959	0.00817	0.00968
	(0.006)***	(0.005)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.172)	(0.111)
Revolutions	0.00343	0.00444	-0.00084	-0.00147	-0.00040	-0.00021	0.00311	0.00326
	(0.036)**	(0.007)***	(0.312)	(0.069)*	(0.531)	(0.738)	(0.143)	(0.125)
Ethnic Fraction	0.01377	0.01802	0.01382	0.01654	0.00944	0.00828	-0.10955	-0.11118
	(0.533)	(0.419)	(0.216)	(0.130)	(0.285)	(0.347)	(0.000)***	(0.000)***
Institution	0.00372	0.00324	0.00027	0.00088	0.00013	0.00004	0.00409	0.00399
	(0.000)***	(0.000)***	(0.480)	(0.022)**	(0.675)	(0.886)	(0.000)***	(0.000)***
Democracy	0.00045	0.00091	0.00031	0.00006	0.00079	0.00094	-0.00061	-0.00050
	(0.387)	(0.086)*	(0.243)	(0.803)	(0.000)***	(0.000)***	(0.350)	(0.441)
Geography	0.16328	0.15929	-0.11441	-0.18579	-0.05306	-0.02075	-0.58404	-0.54885
	(0.250)	(0.269)	(0.112)	(0.009)***	(0.360)	(0.722)	(0.002)***	(0.005)***
N	2434	2434	2434	2434	3152	3152	3177	3177
R^2	0.462	0.450	0.562	0.581	0.295	0.299	0.270	0.270

Empirical Quest for Development Effectiveness, Hyeok Jeong and Jeanni Lee

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DECOMPOSITION OF GROWTH SOURCES (PRE-MDG PERIOD)

	g_TFP		g_X		g_emp		g_A	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
ODA/GNI	0.13129	-0.00550	-0.00299	0.04574	-0.00924	-0.02319	0.04086	-0.03157
	(0.000)***	(0.732)	(0.829)	(0.000)***	(0.372)	(0.000)***	(0.175)	(0.062)*
Initial Income	-0.08110	-0.08891	0.01065	0.00859	-0.00711	-0.00568	0.02943	0.02825
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***
Openness	0.00548	0.00862	0.00514	0.00608	-0.00201	-0.00275	-0.00629	-0.00600
	(0.242)	(0.066)*	(0.023)**	(0.006)***	(0.265)	(0.124)	(0.235)	(0.253)
ToT Change	-0.03396	-0.02907	0.04593	0.04671	0.01804	0.01834	0.06952	0.07222
	(0.001)***	(0.004)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Investment	0.01778	0.02880	0.01552	0.01427	-0.01868	-0.01778	-0.08688	-0.08270
	(0.209)	(0.041)**	(0.023)**	(0.031)**	(0.000)***	(0.001)***	(0.000)***	(0.000)***
Government Share	0.11706	0.10896	-0.00682	-0.00960	-0.00426	-0.00288	-0.03984	-0.04006
	(0.000)***	(0.000)***	(0.279)	(0.119)	(0.370)	(0.542)	(0.004)***	(0.004)***
Inflation	-0.04748	-0.05169	0.02691	0.02600	-0.01855	-0.01794	-0.02003	-0.01978
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.085)*	(0.089)*
Life Expectancy	0.05869	0.05590	0.00564	0.00346	-0.03036	-0.02993	0.04588	0.04481
	(0.007)***	(0.011)**	(0.590)	(0.737)	(0.000)***	(0.000)***	(0.025)**	(0.029)**
Years of Schooling	0.02184	0.02097	-0.01698	-0.01545	0.00068	-0.00012	0.00735	0.00593
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.458)	(0.895)	(0.006)***	(0.031)**
Fertility	-0.03442	-0.03755	-0.02071	-0.01972	-0.01662	-0.01679	0.00161	0.00095
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.861)	(0.918)
Revolutions	0.00271	0.00309	-0.00378	-0.00449	-0.00013	0.00006	0.00117	0.00161
	(0.226)	(0.174)	(0.000)***	(0.000)***	(0.881)	(0.942)	(0.635)	(0.516)
Ethnic Fraction	-0.02317	-0.01830	0.03728	0.03241	0.00456	0.00655	-0.18476	-0.18046
	(0.677)	(0.745)	(0.163)	(0.218)	(0.834)	(0.762)	(0.004)***	(0.005)***
Institution	-0.00116	-0.00102	-0.00052	-0.00047	-0.00054	-0.00051	-0.00185	-0.00166
	(0.413)	(0.473)	(0.441)	(0.481)	(0.296)	(0.317)	(0.224)	(0.275)
Democracy	-0.00007	0.00027	-0.00047	-0.00028	0.00069	0.00053	-0.00167	-0.00164
	(0.929)	(0.717)	(0.195)	(0.424)	(0.011)**	(0.046)**	(0.036)**	(0.038)**
Geography	-0.16583	-0.06630	-0.08845	-0.04127	-0.00391	-0.02458	-0.63063	-0.61720
	(0.532)	(0.804)	(0.488)	(0.742)	(0.968)	(0.800)	(0.029)**	(0.032)**
N	1252	1252	1252	1252	1615	1615	1637	1637
R^2	0.554	0.546	0.717	0.726	0.404	0.411	0.318	0.319

Empirical Quest for Development Effectiveness, Hyeok Jeong and Jeanni Lee

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DECOMPOSITION OF GROWTH SOURCES (MDG PERIOD)

	g_TFP		g_X		g_emp		g_A	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
ODA/GNI	**0.148**	**-0.148**	**0.017**	**0.103**	**0.025**	**0.037**	**0.129**	**-0.187**
	(0.001)***	**(0.000)*****	**(0.458)**	**(0.000)*****	**(0.140)**	**(0.069)***	**(0.041)****	**(0.015)****
Initial Income	-0.136	-0.150	-0.011	-0.005	-0.009	-0.008	0.058	0.043
	(0.000)***	(0.000)***	(0.019)**	(0.247)	(0.005)***	(0.023)**	(0.000)***	(0.001)***
Openness	0.039	0.040	0.002	0.0002	-0.005	-0.006	0.104	0.104
	(0.000)***	(0.000)***	(0.629)	(0.959)	(0.135)	(0.112)	(0.000)***	(0.000)***
ToT Change	0.045	0.051	0.031	0.027	-0.004	-0.004	0.098	0.108
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.505)	(0.463)	(0.000)***	(0.000)***
Investment	0.026	0.030	0.008	0.009	0.001	0.0009	0.052	0.054
	(0.158)	(0.095)*	(0.440)	(0.386)	(0.883)	(0.912)	(0.069)*	(0.058)*
Government Share	0.020	0.052	-0.045	-0.049	-0.007	-0.006	0.165	0.207
	(0.451)	(0.048)**	(0.002)***	(0.001)***	(0.553)	(0.57)	(0.000)***	(0.000)***
Inflation	-0.032	-0.036	-0.006	-0.007	-0.009	-0.009	-0.096	-0.096
	(0.000)***	(0.000)***	(0.229)	(0.185)	(0.056)*	(0.047)**	(0.000)***	(0.000)***
Life Expectancy	-0.131	-0.140	0.041	0.029	0.077	0.069	-0.011	0.0008
	(0.000)***	(0.000)***	(0.008)***	(0.055)*	(0.000)***	(0.000)***	(0.824)	(0.987)
Years of Schooling	-0.011	-0.011	-0.004	-0.003	0.001	0.002	-0.024	-0.025
	(0.000)***	(0.000)***	(0.012)**	(0.025)**	(0.254)	(0.171)	(0.000)***	(0.000)***
Fertility	0.065	0.072	-0.004	-0.005	-0.058	-0.059	-0.071	-0.064
	(0.000)***	(0.000)***	(0.581)	(0.469)	(0.000)***	(0.000)***	(0.001)***	(0.003)***
Revolutions	-0.006	-0.005	-0.002	-0.002	-0.001	-0.0008	0.021	0.022
	(0.013)**	(0.066)*	(0.193)	(0.139)	(0.520)	(0.506)	(0.000)***	(0.000)***
Ethnic Fraction	0.165	0.130	-0.019	0.014	-0.042	-0.033	-0.147	-0.180
	(0.008)***	(0.040)**	(0.571)	(0.687)	(0.156)	(0.262)	(0.184)	(0.106)
Institution	0.012	0.013	0.002	0.002	-0.002	-0.002	0.023	0.024
	(0.000)***	(0.000)***	(0.167)	(0.215)	(0.141)	(0.139)	(0.000)***	(0.000)***
Democracy	0.001	0.001	0.0004	0.0005	0.001	0.001	0.0001	0.001
	(0.607)	(0.656)	(0.529)	(0.497)	(0.204)	(0.142)	(0.951)	(0.585)
Geography	0.145	0.193	0.126	0.119	-0.112	-0.108	-0.139	-0.134
	(0.452)	(0.317)	(0.234)	(0.256)	(0.257)	(0.275)	(0.706)	(0.716)
N	860	860	860	860	1127	1127	1127	1127
R^2	0.656	0.656	0.667	0.676	0.515	0.516	0.525	0.526

Empirical Quest for Development Effectiveness, Hyeok Jeong and Jeanni Lee

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DECOMPOSITION OF GROWTH SOURCES (SDG PERIOD)

	g_TFP		g_X		g_emp		g_A	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
ODA/GNI	0.158	-0.050	-0.096	0.013	0.0002	-0.032	-0.020	-0.008
	(0.325)	(0.277)	(0.432)	(0.711)	(0.997)	(0.138)	(0.839)	(0.850)
Initial Income	-0.012	-0.017	0.002	0.004	-0.004	-0.005	-0.004	-0.003
	(0.088)*	(0.016)**	(0.708)	(0.426)	(0.314)	(0.115)	(0.554)	(0.548)
Openness	-0.003	-0.011	-0.0196	-0.018	-0.001	-0.006	0.028	0.027
	(0.840)	(0.511)	(0.090)*	(0.176)	(0.839)	(0.443)	(0.035)**	(0.060)*
ToT Change	0.003	-0.024	0.094	0.0997	-0.047	-0.059	0.038	0.035
	(0.961)	(0.700)	(0.031)**	(0.042)**	(0.087)*	(0.036)**	(0.454)	(0.510)
Investment	-0.055	-0.037	0.064	0.061	0.015	0.026	0.024	0.027
	(0.155)	(0.393)	(0.034)**	(0.073)*	(0.416)	(0.178)	(0.474)	(0.462)
Government Share	-0.036	-0.039	-0.096	-0.096	-0.019	-0.027	0.116	0.112
	(0.553)	(0.522)	(0.046)**	(0.047)**	(0.460)	(0.282)	(0.019)**	(0.023)**
Inflation	-0.0612	-0.056	-0.066	-0.064	0.061	0.069	0.044	0.046
	(0.528)	(0.569)	(0.377)	(0.400)	(0.130)	(0.083)*	(0.552)	(0.535)
Life Expectancy	0.057	0.029	-0.0097	-0.004	-0.019	-0.039	0.022	0.017
	(0.302)	(0.645)	(0.816)	(0.940)	(0.503)	(0.209)	(0.675)	(0.778)
Years of Schooling	0.0003	0.0006	0.002	0.002	0.0007	0.001	0.003	0.003
	(0.866)	(0.731)	(0.210)	(0.252)	(0.415)	(0.339)	(0.091)*	(0.091)*
Fertility	-0.02	-0.021	0.005	0.004	-0.003	-0.004	0.012	0.012
	(0.134)	(0.126)	(0.630)	(0.669)	(0.619)	(0.483)	(0.288)	(0.308)
Revolutions	-0.002	0.003	0.032	0.032	0.010	0.012	0.024	0.025
	(0.951)	(0.926)	(0.179)	(0.192)	(0.542)	(0.439)	(0.424)	(0.410)
Ethnic Fraction	0.006	-0.038	-0.013	-0.001	0.003	-0.023	0.028	0.021
	(0.674)	(0.368)	(0.268)	(0.982)	(0.693)	(0.216)	(0.038)**	(0.553)
Institution	-0.0002	0.001	0.004	0.003	-0.002	-0.001	-0.005	-0.004
	(0.932)	(0.694)	(0.139)	(0.224)	(0.235)	(0.422)	(0.118)	(0.145)
Democracy	-0.002	-0.002	-0.0001	0.00004	0.002	0.002	-0.003	-0.003
	(0.311)	(0.189)	(0.918)	(0.975)	(0.015)**	(0.057)*	(0.099)*	(0.098)*
Geography	0.017	0.011	-0.017	-0.015	0.001	-0.0002	0.017	0.017
	(0.419)	(0.578)	(0.288)	(0.355)	(0.907)	(0.986)	(0.370)	(0.385)
N	52	52	52	52	70	70	70	70
R^2	0.367	0.373	0.465	0.457	0.239	0.269	0.397	0.397

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COMPARISON BY PERIOD: INCOME GROWTH (IV)

g_y	All	Pre-MDG	MDG	SDG
Aid/GNI	0.03694 (0.469)	0.04688 (0.072)*	-0.34796 (0.041)**	0.01082 (0.836)
Initial Income	-0.06722 (0.000)***	-0.07977 (0.000)***	-0.15944 (0.000)***	-0.00799 (0.370)
Openness	0.01847 (0.000)***	0.00611 (0.336)	0.07482 (0.000)***	-0.00750 (0.706)
ToT Change	0.14807 (0.000)***	0.12358 (0.000)***	0.16411 (0.000)***	0.15941 (0.054)*
Investment	-0.00456 (0.737)	0.05121 (0.013)**	0.11714 (0.000)***	0.01239 (0.818)
Government Share	0.01323 (0.341)	0.01749 (0.319)	0.10557 (0.034)**	-0.06666 (0.350)
Inflation	-0.13854 (0.000)***	-0.05716 (0.000)***	-0.15543 (0.000)***	-0.12459 (0.274)
Life Expectancy	0.04534 (0.009)***	0.10611 (0.000)***	-0.17762 (0.001)***	0.03747 (0.662)
Years of Schooling	0.00489 (0.012)**	0.01627 (0.000)***	-0.02943 (0.000)***	0.00330 (0.193)
Fertility	-0.02346 (0.001)***	-0.06122 (0.000)***	-0.04385 (0.062)*	-0.02026 (0.255)
Revolutions	0.00171 (0.505)	-0.00010 (0.975)	0.00621 -0.213	0.00306 (0.947)
Ethnic Fraction	-0.08899 (0.011)**	-0.00202 (0.980)	-0.31767 (0.011)**	0.03999 (0.692)
Institution	0.00680 (0.000)***	-0.00306 (0.110)	0.02093 (0.000)***	0.00258 (0.589)
Democracy	0.00282 (0.000)***	0.00201 (0.046)**	0.0049 (0.033)**	-0.00389 (0.124)
Geography	-0.85819 (0.000)***	-0.51902 (0.155)	0.27256 -0.507	-0.01124 (0.698)

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COMPARISON BY PERIOD: TFP GROWTH (IV)

g_TFP	All	Pre-MDG	MDG	SDG
Aid/GNI	-0.05300 (0.079)*	-0.00550 (0.732)	-0.14762 (0.000)***	-0.04967 (0.277)
Initial Income	-0.05316 (0.000)***	-0.08891 (0.000)***	-0.14971 (0.000)***	-0.01675 (0.016)**
Openness	0.00814 (0.017)**	0.00862 (0.066)*	0.03984 (0.000)***	-0.01105 (0.511)
ToT Change	-0.01921 (0.016)**	-0.02907 (0.004)***	0.05133 (0.000)***	-0.02376 (0.700)
Investment	0.00778 (0.377)	0.02880 (0.041)**	0.03044 (0.095)*	-0.03714 (0.393)
Government Share	0.07278 (0.000)***	0.10896 (0.000)***	0.05240 (0.048)**	-0.03918 (0.522)
Inflation	-0.03552 (0.000)***	-0.05169 (0.000)***	-0.03603 (0.000)***	-0.05602 (0.569)
Life Expectancy	0.02695 (0.026)**	0.05590 (0.011)**	-0.13980 (0.000)***	0.02861 (0.645)
Years of Schooling	0.00437 (0.000)***	0.02097 (0.000)***	-0.01148 (0.000)***	0.00060 (0.731)
Fertility	-0.01390 (0.005)***	-0.03755 (0.000)***	0.07182 (0.000)***	-0.02067 (0.126)
Revolutions	0.00444 (0.007)***	0.00309 (0.174)	-0.00476 (0.066)*	0.00295 (0.926)
Ethnic Fraction	0.01802 (0.419)	-0.01830 (0.745)	0.12949 (0.040)**	-0.03805 (0.368)
Institution	0.00324 (0.000)***	-0.00102 (0.473)	0.01330 (0.000)***	0.00121 (0.694)
Democracy	0.00091 (0.086)*	0.00027 (0.717)	0.00057 (0.656)	-0.00233 (0.189)
Geography	0.15929 (0.269)	-0.06630 (0.804)	0.19312 (0.317)	0.01141 (0.578)

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COMPARISON BY PERIOD: INPUT GROWTH (IV)

g_X	All	Pre-MDG	MDG	SDG
Aid/GNI	0.14858	0.04574	0.10291	0.01297
	(0.000)***	(0.000)***	(0.000)***	(0.711)
Initial Income	0.00102	0.00859	-0.00549	0.00410
	(0.414)	(0.000)***	(0.247)	(0.426)
Openness	0.00435	0.00608	0.00023	-0.01770
	(0.009)***	(0.006)***	(0.959)	(0.176)
ToT Change	0.03346	0.04671	0.02745	0.09967
	(0.000)***	(0.000)***	(0.000)***	(0.042)**
Investment	0.03116	0.01427	0.00855	0.06106
	(0.000)***	(0.031)**	(0.386)	(0.073)*
Government Share	-0.03078	-0.00960	-0.04943	-0.09602
	(0.000)***	(0.119)	(0.001)***	(0.047)**
Inflation	0.01042	0.02600	-0.00662	-0.06401
	(0.005)***	(0.000)***	(0.185)	(0.400)
Life Expectancy	0.01058	0.00346	0.02880	-0.00361
	(0.076)*	(0.737)	(0.055)*	(0.940)
Years of Schooling	-0.00835	-0.01545	-0.00322	0.00155
	(0.000)***	(0.000)***	(0.025)**	(0.252)
Fertility	-0.01175	-0.01972	-0.00504	0.00438
	(0.000)***	(0.000)***	(0.469)	(0.669)
Revolutions	-0.00147	-0.00449	-0.00208	0.03213
	(0.069)*	(0.000)***	(0.139)	(0.192)
Ethnic Fraction	0.01654	0.03241	0.01373	-0.00074
	(0.130)	(0.218)	(0.687)	(0.982)
Institution	0.00088	-0.00047	0.00160	0.00291
	(0.022)**	(0.481)	(0.215)	(0.224)
Democracy	0.00006	-0.00028	0.00047	0.00004
	(0.803)	(0.424)	(0.497)	(0.975)
Geography	-0.18579	-0.04127	0.11904	-0.01467
	(0.009)***	(0.742)	(0.256)	(0.355)

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COMPARISON BY PERIOD: EMPLOYMENT RATE GROWTH (IV)

g_employment rate	All	Pre-MDG	MDG	SDG
Aid/GNI	-0.04785	-0.02319	0.03729	-0.03157
	(0.000)***	(0.000)***	(0.069)*	(0.138)
Initial Income	-0.00458	-0.00568	-0.00807	-0.00476
	(0.000)***	(0.001)***	(0.023)**	(0.115)
Openness	-0.00340	-0.00275	-0.00566	-0.00569
	(0.011)**	(0.124)	-0.112	(0.443)
ToT Change	0.01666	0.01834	-0.0041	-0.05938
	(0.000)***	(0.000)***	-0.463	(0.036)**
Investment	-0.00679	-0.01778	0.00085	0.02641
	(0.045)**	(0.001)***	-0.912	(0.178)
Government Share	0.00565	-0.00288	-0.00645	-0.02739
	(0.098)*	(0.542)	-0.57	(0.282)
Inflation	-0.01457	-0.01794	-0.00915	0.06912
	(0.000)***	(0.000)***	(0.047)**	(0.083)*
Life Expectancy	-0.02081	-0.02993	0.06945	-0.03920
	(0.000)***	(0.000)***	(0.000)***	(0.209)
Years of Schooling	-0.00158	-0.00012	0.00176	0.00084
	(0.001)***	(0.895)	-0.171	(0.339)
Fertility	-0.00959	-0.01679	-0.05856	-0.00434
	(0.000)***	(0.000)***	(0.000)***	(0.483)
Revolutions	-0.00021	0.00006	-0.00079	0.01241
	(0.738)	(0.942)	-0.506	(0.439)
Ethnic Fraction	0.00828	0.00655	-0.03348	-0.02324
	(0.347)	(0.762)	-0.262	(0.216)
Institution	0.00004	-0.00051	-0.00167	-0.00125
	(0.886)	(0.317)	-0.139	(0.422)
Democracy	0.00094	0.00053	0.00081	0.00171
	(0.000)***	(0.046)**	-0.142	(0.057)*
Geography	-0.02075	-0.02458	-0.10759	-0.00018
	(0.722)	(0.800)	-0.275	(0.986)

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COMPARISON BY PERIOD: PPP ADJUSTMENT GROWTH (IV)

g_PPP_Adjustment	All	Pre-MDG	MDG	SDG
Aid/GNI	-0.05306 (0.159)	-0.03157 (0.062)*	-0.18668 (0.015)**	-0.00756 (0.850)
Initial Income	0.01480 (0.000)***	0.02825 (0.000)***	0.04262 (0.001)***	-0.00341 (0.548)
Openness	0.01429 (0.001)***	-0.00600 (0.253)	0.10406 (0.000)***	0.02683 (0.060)*
ToT Change	0.10850 (0.000)***	0.07222 (0.000)***	0.10817 (0.000)***	0.03469 (0.510)
Investment	-0.07668 (0.000)***	-0.08270 (0.000)***	0.05434 (0.058)*	0.02723 (0.462)
Government Share	-0.03052 (0.007)***	-0.04006 (0.004)***	0.20730 (0.000)***	0.11160 (0.023)**
Inflation	-0.09363 (0.000)***	-0.01978 (0.089)*	-0.09574 (0.000)***	0.04641 (0.535)
Life Expectancy	0.00329 (0.817)	0.04481 (0.029)**	0.00081 (0.987)	0.01658 (0.778)
Years of Schooling	-0.00104 (0.508)	0.00593 (0.031)**	-0.02537 (0.000)***	0.00283 (0.091)*
Fertility	0.00968 (0.111)	0.00095 (0.918)	-0.06441 (0.003)***	0.01199 (0.308)
Revolutions	0.00326 (0.125)	0.00161 (0.516)	0.02150 (0.000)***	0.02508 (0.410)
Ethnic Fraction	-0.11118 (0.000)***	-0.18046 (0.005)***	-0.18033 (0.106)	0.02103 (0.553)
Institution	0.00399 (0.000)***	-0.00166 (0.275)	0.02350 (0.000)***	-0.00434 (0.145)
Democracy	-0.00050 (0.441)	-0.00164 (0.038)**	0.00112 (0.585)	-0.00281 (0.098)*
Geography	-0.54885 (0.005)***	-0.61720 (0.032)**	-0.13409 (0.716)	0.01666 (0.385)

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CONCLUSION

SUMMARY OF ODA DEVELOPMENT EFFECTIVENESS

	Income growth	TFP growth	Input growth	Job creation	PPP adjustment
All (1971-2019)	0.037	**-0.053***	**0.149****	**-0.048****	-0.053
Pre-MDG (1971-2001)	**0.047 ***	-0.006	**0.046****	**-0.023****	**-0.032 ***
MDG (2001-2015)	**-0.348***	**-0.148****	**0.103****	**0.038 ***	**-0.187 ****
SDG (2015-2019)	0.011	-0.050	0.013	-0.032	0.008

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IMPLICATIONS TO IMPROVE DEVELOPMENT EFFECTIVENESS

1. Incorporating donors' ODA selection, ODA contributed positively to input expansion, but negatively to job creation and TFP growth, and their net effect on income growth was null.
2. No reason to abandon the positive contribution of ODA to input growth, but it is important to notice that this growth effect is transitional and will disappear soon. This is exactly why most of the poor economies are caught by the middle-income trap and show no sustained growth.
3. Despite the loud voice for job creation for effective development, ODA's contribution to job creation was negative. All job-creation related ODA programs need to be reviewed.
4. ODA contributed negatively to TFP growth, the source of long-run growth, hence the sustainable development. This implies that ODA will deteriorate the long-term growth of developing countries, although it has a positive role for input expansion which is transitional.
5. Overall contribution of the PPP adjustment was insignificant.

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IMPLICATIONS TO IMPROVE DEVELOPMENT EFFECTIVENESS

6. Major sources of growth of the developing countries were not ODA. They are openness, terms of trade, schooling, life expectancy, institutional quality, macroeconomic stability, and democracy. Their effects on growth remain robust after controlling their effects via ODA. Need to broaden the scope of the development cooperation into non-ODA dimensions, being harmonized with the sustainable economic cooperation.
7. Fundamental re-design of the ODA and non-ODA measures of development cooperation in terms of effective development is needed.
   - ODA's positive role on input growth still can be important for the low or lower-middle income countries.
   - However, for the upper-middle income countries, current ODA programs which negatively contribute to TFP growth and job creation need to be modified into non-ODA development cooperation, aiming to be transformed into economic cooperation for the sake of the mutual prosperity between donor and recipient countries.
8. No effective development by any measures seemed to happen via ODA during the SDG era, despite such loud voices. Too short time span to observe the effects?

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[THE END]

세션2 환경과 국제개발

- Early-life Exposure to Cold Weather Shocks and Growth Stunting: Evidence from Tanzania
  발제: 한유진(연세대 경제학과) | 토론: 윤정환(KIEP)

- Good Governance and Household Resilience to Natural Disasters: Evidence from Vietnam
  발제: 윤세미(서울대 국제대학원) | 토론: 정재현(이화여대 국제대학원)

- Welfare Gains from Trade across Space with Transboundary Air Pollutants
  발제: 임희현(KDI) | 토론: 정지원(KIEP)

제2세션 | 환경과 국제개발

Early-life Exposure to Cold Weather Shocks and Growth Stunting: Evidence from Tanzania

발제: 한 유 진(연세대 경제학과)

토론: 윤 정 환(KIEP)

Early-life exposure to cold weather shocks and growth stunting: Evidence from Tanzania

Josephat J Hongoli Youjin Hahn

Yonsei University

2022

Introduction

- Globally, child malnutrition (stunting, wasting, and underweight) has declined significantly over the recent decades.
- However, child stunting in SSA has remained high (World Bank Group, 2017).
- Stunting rate in Tanzania (2018), 31.8% (2.9 million) > 22.9% (global average)
- Child malnutrition accounts for over 45% of child mortality and morbidities in SSA
- In 2016: 1 Mil. children (globally) died due to malnutrition [1]

[1] World Health Organization and others (2018)

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Stunted growth at an early age

- Increased risk of adulthood obesity and chronic diseases
- Impairs child's cognitive development and educational attainment
- Associated with poor future labour market outcomes
- Overall: Have lasting adverse consequences; personal and economic development
- Child stunting in SSA has not significantly declined, despite efforts on curbing malnutrition through intervention in health care access, nutritional and micronutrients supplements program
- Recent studies: Effects of environmental and geography on child health outcomes: Mortality and Morbidity, Height-for-age and child nutritional status

What we do

- Examine the effects of cold weather shocks on child stunting in Tanzania

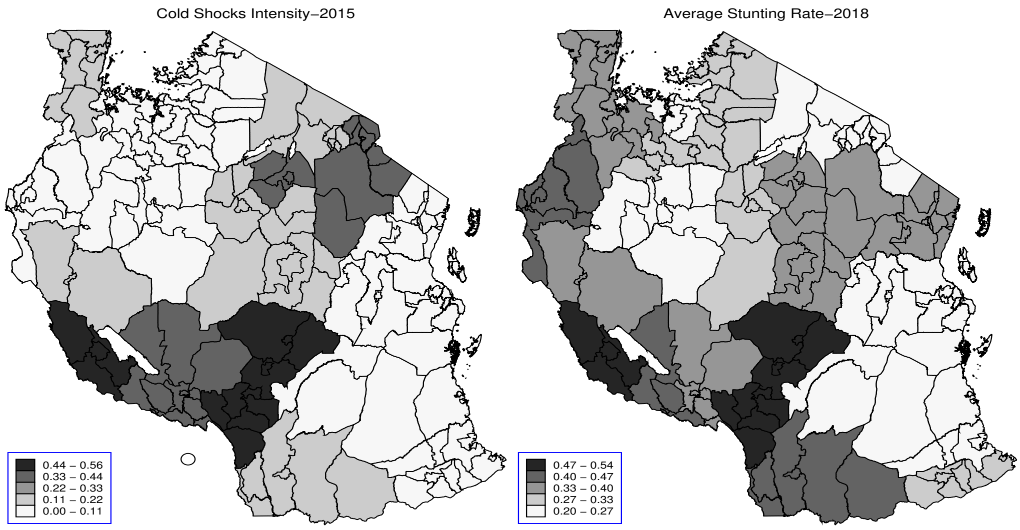
Our Contribution:

- Use high resolution and daily weather variations
- Estimate both pre-and post-natal effects of exposure to colds
- Add to limited studies on the effects of weather shocks on child health in a developing country setting

Why we focus on Tanzania?

- TZ among the top ten SSA countries with the highest stunting rate
- High geographical variations: Stunting and weather conditions

Introduction



Summary of Findings

- Strong association between cold weather and child stunting probability
- Strong effects of prenatal exposure on child wasting
- No substantial effect of prenatal exposure on under-weight
- Heterogeneity effects across age, location (rural) and wealth
- Possibility of later catch-up growth effects

Previous studies

- Berko (2014); Deschênes and Greenstone (2011); Wang et al. (2016): Excess mortality and morbidity in the U.S.
- Analitis et al. (2008) in 15 European cities: $\downarrow$ in min temp $\rightarrow \uparrow$ natural, cardiovascular, respiratory, cerebrovascular deaths
- Burgess et al. (2013) in India: Excess mortality
- Ogasawara and Yumitori (2019) in Japan significant effects on child height
- Sanchez (2018) in Peru and Rashid et al. (2017) in Bangladesh - lower height-for-age
- Tusting et al. (2020): Hotter part of SSA less likely to be stunted

Conceptual Framework

Child health production function (Maccini and Yang (2009), Rabassa et al. (2014), and Grossman (1972)):

$$H_{it} = h(H_{i0}, N_{it}, X_i, A_t, D_t) \tag{1}$$

H: Initial health endowment, N: Investment in health production
X: Demo chars, A: Access to health facilities, D: Diseases environment
Potential Mechanisms:

- Food-energy trade-off: $\downarrow$ Nutritional-food uptake and $\downarrow$ Investment in health production inputs
- Investment in anti-cold facilities: Warm clothing, home heating
- Prenatal stress: $\downarrow$ Child birth outcomes
- Disease environments: Immunity $\downarrow$, resp diseases (pneumonia and influenza), hypothermia, etc
- Shocks on agricultural productivity: severe and prolonged cold weather

Data Sources

The Tanzania National Panel Survey Data (TNPS):

- Nationally representative household survey collected by Tanzania National Burea of Statistics (NPS) and World Bank (WB)
- 2008/09, 2010/11, 2012/13, 2014/2015
- Anthropometric information for under-5 children
- TNPS is geo-referenced at the cluster level (advantage over DHS)

The Weather Data

- Daily weather data from *Terrestrial Hydrology Research Group at Princeton University*
- Daily minimum temperature from 2003 to 2015
- 0.25*0.25-degree resolution (28 km x 28 km)
- Merge data to the main dataset based on geo-location

Variables

The Outcome Variables: WHO Standards

- Stunting (haz is below 2 SD below median)
- Severe Stunting (haz is below 3 SD below median)
- Wasting & underweight-Short-term nutritional status

Shock Variables: Exposure to Weather Shocks Intensity

- Binning Approach (Degree days)
- Cold Weather Shocks-Min temp fall below 1 SD from the long-run avg
- Bin k=1 if 0-15, k=2 if 15-21, and k=3 if 21>
- Compute the number of days in each bin (as % lifetime days)
- Lifetime exposure (after birth) and in-utero exposure (before birth)
- Widely applied on health, agricultural, conflict, and economic growth

Descriptive Statistics

Table 1: Descriptive Statistics

	2008/9		2010/11		2012/13		2014/15	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Outcome Variables								
Stunting	0.42	0.49	0.35	0.48	0.36	0.48	0.33	0.47
Severe Stunting	0.18	0.38	0.13	0.34	0.14	0.35	0.14	0.35
Panel B: Child Information								
Sex (1=Female)	0.52	0.50	0.50	0.50	0.50	0.50	0.50	0.50
Age (in Months)	31.52	16.78	27.99	17.24	28.66	17.19	28.34	17.00
Rural	0.74	0.44	0.78	0.42	0.75	0.43	0.69	0.46
Panel C: Household Information								
Head: Age	42.11	13.56	42.70	13.88	42.70	14.40	40.96	12.84
Head: Male	0.83	0.38	0.82	0.38	0.83	0.38	0.79	0.41
Head: No Education	0.19	0.39	0.22	0.41	0.23	0.42	0.23	0.42
Head: Secondary and Above	0.12	0.33	0.12	0.32	0.14	0.34	0.17	0.37
Head: Work in Agriculture	0.70	0.46	0.67	0.47	0.66	0.47	0.60	0.49
Head: Employee	0.12	0.33	0.13	0.34	0.15	0.36	0.19	0.39
Head: Self Employee	0.14	0.34	0.14	0.35	0.15	0.35	0.18	0.39
Household Size	6.90	3.86	7.52	5.07	7.51	5.02	6.81	3.85
Wealth Index	-0.00	2.11	0.60	2.93	-0.28	2.18	-0.17	2.16
Piped Water	0.15	0.35	0.10	0.30	0.10	0.29	0.37	0.48
Drinking Water: Safe	0.31	0.46	0.05	0.21	0.08	0.26	0.11	0.32
Food Assistance	0.03	0.16	0.05	0.22	0.10	0.30	0.04	0.21
Panel D: Weather Information								
Minimum Temperature (°C)	18.87	2.68	18.93	2.58	18.84	2.45	18.95	2.46
Shock[1]	12.48	21.15	10.28	18.74	11.40	18.50	10.29	17.58
Shock[2]	62.33	27.70	64.25	27.80	66.98	25.49	67.64	27.24
Precipitation mm (SD)	0.09	1.21	0.06	1.03	-0.11	0.87	0.00	0.92
Drought Severity Index	-1.41	2.30	-1.21	2.32	-2.04	1.95	-2.17	1.70

Shock[1] is the cumulative number of days with a temperature below one standard deviation from the long-run average.
Shock[2] is the cumulative number of days with a standard deviation below and above the long-run average

Empirical Strategy

The effects of lifetime exposure to shocks on growth stunting

$$Y_{ijr_\tau t} = \alpha + \lambda_{rm} + \lambda_{rt} + \mu_b + \sum_{k=1}^{2} \gamma_k Shock^k_{ijr_\tau t} + X'_{ijr_\tau t}\xi + C'_{ijr_\tau t}\rho + \epsilon_{ijr_\tau t} \quad (2)$$

$Y_{ijr_\tau t}$ Outcome of child i in household j, regions r, born in τ and year t
$Shock-$ The intensity of exposure to shocks (as % of lifetime days)
$k-$ Temperature bins, k=1 if 0-15,k=2 if 15-21, k=3 if > 21
$\tau-$ Month of birth and t survey year
$X-$ Vector of demographic covariates (child & household covariates)
$C-$ Vector of climatic covariates (precipitation & drought)
$\lambda_r m-$ Regional-month of birth fixed effects
$\lambda_{rt}-$ Region-survey year fixed effects
μ_b- Cohort of birth fixed Effects
$\varepsilon-$ mean zero error term

Empirical Strategy

The effects of prenatal (in utero) exposure to shocks

$$Y_{ijr_\tau t} = \alpha+\lambda_{rm}+\lambda_{rt}+\mu_b+\sum_{k=1}^{2}\gamma_k Pshock^k_{ijr_\tau t,n}+X'_{ijr_\tau t}\xi+C'_{ir_\tau t}\rho+\epsilon_{ijr_\tau t} \quad (3)$$

Y – Outcome variables (waz and wasting)
$n\tau$- Denote the n^{th} month prior to the month of birth (τ)
Identification Assumption:

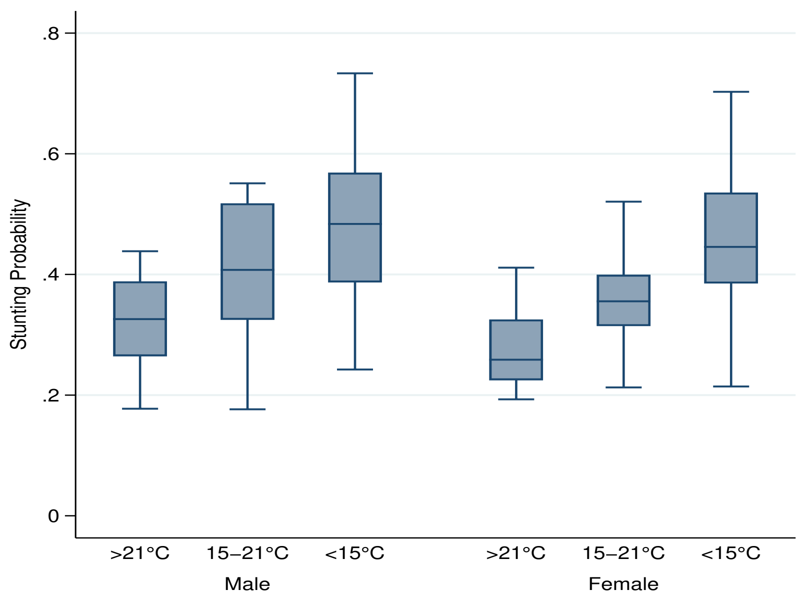
- Weather shocks assumed to be orthogonal to other factors
- Exogenous (no confounding factors)

Threats to above empirical strategy:

- Selection due to endogenous migration
- Selection due to mortality/child survival
- We test both threats. No selection bias Appendix

Stunting by minimum temperature

Figure 1: Growth stunting by average minimum temperature



Note: The horizontal axis shows the range in minimum temperature in degrees Celsius.

Baseline Results

Table 2: Effects of early life exposure to cold shocks on stunting: Baseline results

	Stunting			Severe Stunting		
	(1)	(2)	(3)	(4)	(5)	(6)
$Shock^1$	0.0013***	0.0017***	0.0017***	0.0007***	0.0011***	0.0012***
	(0.0003)	(0.0005)	(0.0005)	(0.0002)	(0.0004)	(0.0004)
$Shock^2$	-0.0002	0.0010**	0.0010**	-0.0001	0.0006*	0.0008**
	(0.0002)	(0.0005)	(0.0005)	(0.0001)	(0.0004)	(0.0004)
Controls	√	√	√	√	√	√
Birth cohort fixed effects	√	√	√	√	√	√
Survey-year fixed effects		√	√		√	√
Region-month fixed effects		√	√		√	√
Region-year fixed effects			√			√
Climatic controls			√			√
Mean of dep. variable	0.363	0.363	0.363	0.145	0.145	0.145
Adjusted R^2	0.037	0.049	0.055	0.017	0.031	0.035
Observations	10561	10561	10561	10561	10561	10561

Note: $Shock^1$ is the cumulative number of days with minimum temperature below one standard deviation from the long-run average. $Shock^2$ is the cumulative number of days with minimum temperature one standard deviation below and above the long-run average. The robust standard errors clustered at the cluster level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 per cent levels, respectively

Heterogeneity Effects

- We estimate the following model:

$$Y_{ijr_\tau t} = \alpha + \lambda_{rm} + \lambda_{rt} + \mu_b + \sum_{k=1}^{2} \gamma_k Shock^k_{ijr_\tau t} + \tag{4}$$

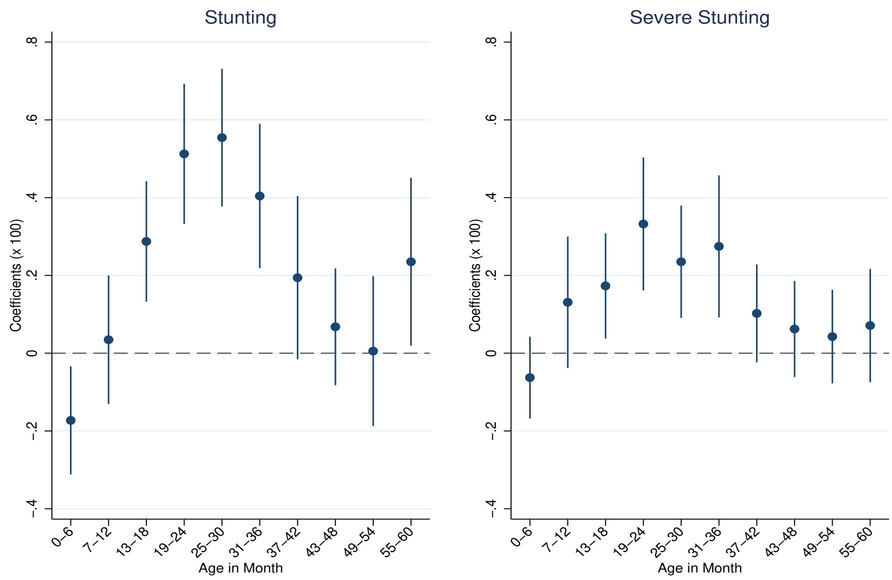
$$\sum_{k=1}^{2} \pi_k (Shock^k_{ijr_\tau t} * \theta) + X^{'}_{ijrt}\xi + C^{'}_{jrt}\rho + \epsilon_{ijrt}$$

$Y-$ Outcome variables (haz and stunting)
$\theta-$ Dummies for age groups, gender and wealth status
All other variables as defined before.

Heterogeneity Effects

- Heterogeneity effects across age group [x 0-15 °C]
- We find an inverted U-shaped (Catch-up group) effect

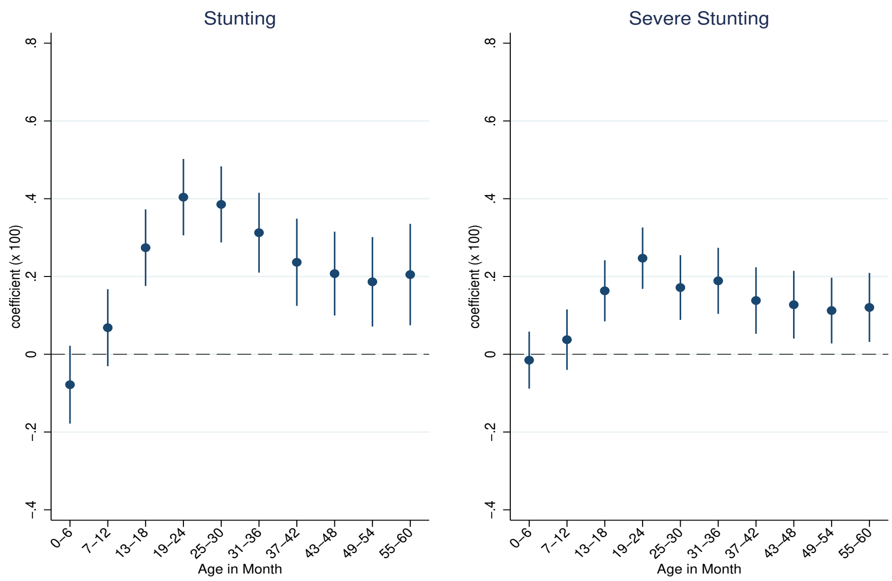
Figure 2: Effects of early life exposure to cold shocks on stunting across age group



Heterogeneity Effects

- Heterogeneity effects across age group [x 15-21 °C]
- We find an inverted U-shaped (Catch-up group) effect

Figure 3: Effects of early life exposure to cold shocks on stunting across age group



Heterogeneity Effects

- Heterogeneity effects by rural/urban, gender and wealth status

Table 3: Heterogeneity effects of cold weather shocks on growth stunting

	Stunting			Severe Stunting		
	(1)	(2)	(3)	(4)	(5)	(6)
Rural x Shock[1]	0.0018**			0.0012**		
	(0.0007)			(0.0005)		
Rural x Shock[2]	0.0008			0.0001		
	(0.0005)			(0.0003)		
Female x Shock[1]		0.0010*			-0.0003	
		(0.0006)			(0.0004)	
Female x Shock[2]		0.0002			-0.0005***	
		(0.0001)			(0.0001)	
Poor x Shock[1]			0.0007			0.0008*
			(0.0005)			(0.0004)
Poor x Shock[2]			0.0005**			0.0001
			(0.0002)			(0.0001)
Shock[1]	0.0002	0.0015**	0.0013**	0.0002	0.0014***	0.0008*
	(0.0008)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Shock[2]	0.0005	0.0014***	0.0007	0.0007	0.0010***	0.0007*
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Controls	√	√	√	√	√	√
Birth cohort fixed effects	√	√	√	√	√	√
Survey-year fixed effects	√	√	√	√	√	√
Region-month fixed effects	√	√	√	√	√	√
Region-year fixed effects	√	√	√	√	√	√
Climatic controls	√	√	√	√	√	√
Mean of dep. variable	0.363	0.363	0.363	0.145	0.145	0.145
Adjusted R^2	0.055	0.056	0.055	0.036	0.038	0.036
Observations	10561	10561	10561	10561	10561	10561

Results: Effects on Other Health Outcomes

Table 4: Effect of early life exposure to cold shocks on other health outcomes

	(1) Height for Age	(2) Weight for Age	(3) Underweight	(4) Wasting
Shock[1]	-0.0060*	-0.0004	0.0006	0.0000
	(0.0033)	(0.0038)	(0.0004)	(0.0003)
Shock[2]	-0.0001	0.0004	0.0008**	0.0000
	(0.0033)	(0.0042)	(0.0004)	(0.0003)
Controls	√	√	√	√
Birth cohort fixed effects	√	√	√	√
Survey-year fixed effects	√	√	√	√
Region-month fixed effects	√	√	√	√
Region-year fixed effects	√	√	√	√
Climatic controls	√	√	√	√
Mean of dep. variable	-1.427	-0.692	0.142	0.055
Adjusted R^2	0.041	0.041	0.030	0.020
Observations	10561	10561	10561	10561

Note: The robust standard errors clustered at the cluster level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 per cent levels, respectively

Results: Effects of In-utero Exposure

Table 5: The effect of prenatal exposure to cold weather shocks

	First Trimester		Second Trimester		Third Trimester	
	(1) Stunting	(2) Severe Stunting	(3) Stunting	(4) Severe Stunting	(5) Stunting	(6) Severe Stunting
Shock[1]	0.0012	0.0012*	0.0027***	0.0024***	0.0011	0.0011
	(0.0010)	(0.0007)	(0.0010)	(0.0007)	(0.0010)	(0.0007)
Shock[2]	0.0002	0.0001	0.0011	0.0014***	-0.0002	0.0001
	(0.0008)	(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0005)
Controls	√	√	√	√	√	√
Birth cohort fixed effects	√	√	√	√	√	√
Survey-year fixed effects	√	√	√	√	√	√
Region-month fixed	√	√	√	√	√	√
Region-year fixed effects	√	√	√	√	√	√
Climatic controls	√	√	√	√	√	√
Mean of dep. variable	0.235	0.107	0.235	0.107	0.235	0.107
Adjusted R^2	0.058	0.037	0.061	0.039	0.059	0.036
Observations	2373	2373	2373	2373	2373	2373

Note: The estimation is restricted to children aged less than 12 months at the time of the survey.The robust standard errors clustered at the cluster level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 per cent levels, respectively

Source: Author Computation

Results: Effects of In-utero Exposure

Table 6: The effect of prenatal exposure to cold weather shocks

	First Trimester		Second Trimester		Third Trimester	
	(1) underweight	(2) wasting	(3) underweight	(4) wasting	(5) underweight	(6) wasting
Shock[1]	-0.0006	0.0014*	0.0004	0.0020***	-0.0005	0.0007
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Shock[2]	-0.0009	0.0003	-0.0001	0.0015**	-0.0010	0.0000
	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Controls	√	√	√	√	√	√
Birth cohort fixed effects	√	√	√	√	√	√
Survey-year fixed effects	√	√	√	√	√	√
Region-month fixed effects	√	√	√	√	√	√
Region-year fixed effects	√	√	√	√	√	√
Climatic controls	√	√	√	√	√	√
Mean of dep. variable	0.107	0.112	0.107	0.112	0.107	0.112
Adjusted R^2	0.059	0.004	0.058	0.005	0.059	0.002
Observations	2373	2373	2373	2373	2373	2373

Note: The estimation is restricted to children aged less than 12 months at the time of the survey.The robust standard errors clustered at the cluster level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 per cent levels, respectively

Source: Author Computation

Results: Robustness Check

Table 7: Impact of Cold Weather Shocks on Stunting: Robustness check

	Exclude					
	(1) None	(2) ZNZ	(3) ZNZ + DSM	(4) ZNZ + Coastal	(5) ZNZ + Coastal + Lake	(6) All Except Highland
$Shock^1$	0.0017***	0.0018***	0.0021***	0.0016**	0.0022***	0.0023
	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0023)
$Shock^2$	0.0010**	0.0012**	0.0015***	0.0011	0.0020**	0.0012
	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0009)	(0.0026)
Controls	√	√	√	√	√	√
Birth cohort fixed effects	√	√	√	√	√	√
Survey-year fixed effects	√	√	√	√	√	√
Region-month fixed effects	√	√	√	√	√	√
Region-year fixed effects	√	√	√	√	√	√
Climatic controls	√	√	√	√	√	√
Mean of dep. variable	0.363	0.368	0.382	0.381	0.388	0.458
Adjusted R^2	0.054	0.056	0.052	0.054	0.058	0.057
Observations	10561	9461	8354	7086	4530	983

Note: Z-Zanzibar, D-Dar es Salaam, C-Coastal Regions, L-Lake zone Regions, SH-Southern Highland Regions. The robust standard errors clustered at the cluster level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 per cent levels, respectively

Source: Author Computation

Results: Sensitivity check

Table 8: Impact of Cold Weather Shocks on Stunting: Sensitivity Check

	(1)	(2)	(3)	(4)
$Shock^{(1)}$	0.0009**			
	(0.0004)			
$Shock^{(2)}$		0.0008***		
		(0.0003)		
$Shock^{(3)}$			0.0013***	
			(0.0004)	
$Shock^{(4)}$				-0.0001
				(0.0004)
Controls	√	√	√	√
Birth cohort fixed effects	√	√	√	√
Survey-year fixed effects	√	√	√	√
Region-month fixed effects	√	√	√	√
Region-year fixed effects	√	√	√	√
Climatic controls	√	√	√	√
Mean of dep. variable	0.363	0.363	0.363	0.363
Adjusted R^2	0.054	0.054	0.054	0.054
Observations	10561	10561	10561	10561

Note: $Shocks^1$ is the shocks with 0-15°C range (below 1 SD), $Shocks^2$ is the shocks with 18°C cutoff (below average), $Shocks^3$ is the shocks with 0-21°C cutoff (below 1

Summary and Conclusion

- Examined the nonlinear effects of exposure to cold weather on the child stunting probability of under-five children in Tanzania
- Cumulative exposure to colds shocks adversely affects child health outcomes
- A 10% $\uparrow$ in cold shocks $\uparrow$ prob. stunt and sev. stunt by 1.7 & 1.2%p
- Strong effects of prenatal exposure on child wasting.
- A 10% $\uparrow$ cold shocks $\uparrow$ wasting prob by 1.3%p and 1.9%p during pregnancy and two final trimesters.
- No substantial effect of prenatal exposure on under-weight.
- Heterogeneity effects across age, location (rural), gender and wealth
- Later catch-up growth effects

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Thank you!

Email: youjin.hahn@yonsei.ac.kr

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Endogenous Migration

Table 9: Impact of Cold Weather Shocks on Stunting: Sample and Non-Migrant

	Under-five Sample		Non-migrant Sample	
	(1) Stunting	(2) Severe Stunting	(3) Stunting	(4) Severe Stunting
Shock[1]	0.0017***	0.0012**	0.0016***	0.0013***
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Shock[2]	0.0010**	0.0008*	0.0011**	0.0009**
	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Moved Household	-0.0338*	-0.0155		
	(0.0179)	(0.0105)		
Controls	√	√	√	√
Birth cohort fixed effects	√	√	√	√
Survey-year fixed effects	√	√	√	√
Region-month fixed effects	√	√	√	√
Region-year fixed effects	√	√	√	√
Climatic controls	√	√	√	√
Mean of dep. variable	0.363	0.145	0.374	0.150
Adjusted R^2	0.055	0.035	0.054	0.034
Observations	10561	10561	8967	8967

Note: The robust standard errors clustered at the cluster level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 per cent levels, respectively.

Endogenous Mortality

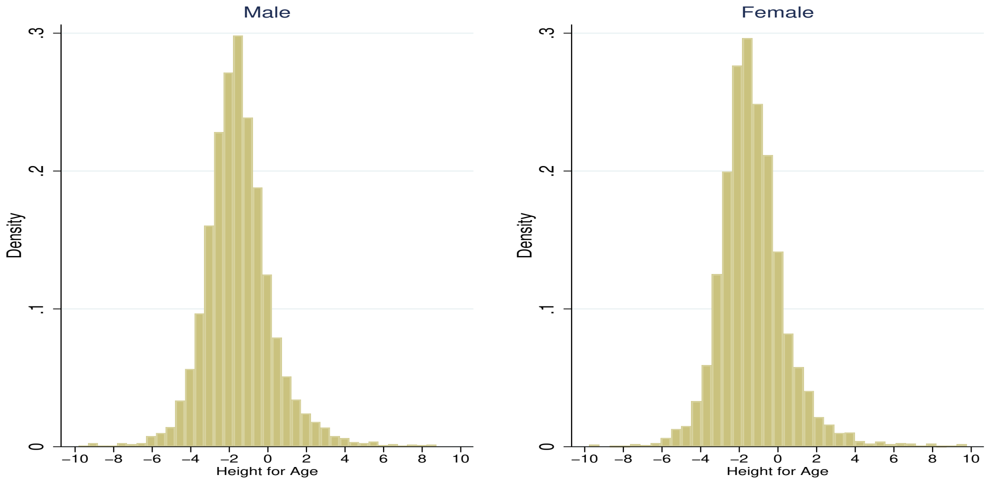
Table 10: Impact of Cold Weather Shocks on Child Mortality

	(1)	(2) Rural	(3) Urban
Shock[1]	-0.0002	0.0001	-0.0017
	(0.0006)	(0.0005)	(0.0016)
Shock[2]	-0.0006	-0.0002	-0.0025
	(0.0006)	(0.0005)	(0.0015)
Controls	√	√	√
Survey-year fixed effects	√	√	√
Region fixed effects	√	√	√
Region-year fixed effects	√	√	√
Mean of dep. variable	0.053	0.048	0.066
Adjusted R^2	0.050	0.061	0.097
Observations	4512	3186	1326

Note: The outcome variable is the dummy variable equal to 1 if the household lost a child aged 0-24 months during the past two years before the survey. The robust standard errors clustered at the clus

HEIGHT FOR AGE Z-SCORE

FIGURE 4: Distribution of height for Age z-score



Note: Notes: Author computation from Tanzania Panel Survey data

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Early-life Exposure to Cold Shocks and Child Growth: Evidence from Tanzania

Josephat J. Hongoli * Youjin Hahn †

2022

Abstract

The paper examines the effects of early life and in-utero exposure to cold weather shocks on the stunting incidence of under-five children in Tanzania. We find that a 10% increase in exposure to days with temperature below 15 degrees Celsius (1 SD below long-run norm) is associated with an increase in stunting and severe stunting probability by 1.8 and 1.2 percentage points, respectively. The results also show strong effects of in-utero exposure on child stunting and wasting, with higher effects during the second trimester. An inverted U-shaped effect of the cold weather shocks is observed across age groups suggesting a later catch-up growth. Our findings suggest that exposure to cold shocks during pregnancy and early life negatively affects early child growth and largely explains Tanzania's observed child stunting heterogeneity.

Keywords: Weather Shocks, Child Growth, Tanzania

JEL Codes: I18,I19, Q54, N37

*Yonsei University, School of Economics. Email: josephat2019@yonsei.ac.kr
†Yonsei University, School of Economics. Email: youjin.hahn@yonsei.ac.kr

1 Introduction

Despite a declining trend in child malnutrition in the recent decade, child stunting has remained a significant problem, particularly in developing countries (World Bank Group, 2017). In Tanzania, for instance, in 2018, about 31.8 percent (2.9 million) of under-five children were estimated to be stunted (URT, 2018), and this rate by far exceeds the global average of 22.9 percent (UNICEF-WHO-WB, 2018). In Sub-Saharan Africa (SSA), child stunting accounts for about 45 percent of child death and morbidities (World Bank Group, 2017). Studies also show that poor child growth at an early age poses a high risk for future child development (Allen and Gillespie, 2001; World Bank Group, 2017); adulthood obesity, chronic diseases, impaired cognitive development (Hoddinott et al., 2013; Islam et al., 2020; Ogasawara and Yumitori, 2019; UNICEF, 2013) and also related to low educational attainment and poor future labor market outcomes (Acharya et al., 2019; Maccini and Yang, 2009; UNICEF, 2013). Broadly, the consequences of poor childhood growth are irrevocable and have a substantial lifelong burden on personal and economic development (Hoddinott et al., 2013; Martins et al., 2011; Zhu et al., 2021).

Several underlying factors account for the high child stunting in developing countries, including poor nutrition, food insecurity, inadequate complementary feeding and breast-feeding, and infectious diseases (Allen and Gillespie, 2001; Rashid et al., 2017; Skoufias et al., 2019). Other factors include poor health and health care, maternal education, access to safe water, sanitation, and environmental conditions (see Islam et al., 2020 for a detailed review). Nevertheless, albeit improved and increased intervention in health care access, nutritional and micro-nutrient supplements program, and maternal education, child stunting has not significantly declined (World Bank Group, 2017). Thus, further empirical researches on the key driving factors are in demand to help better design a sustainable multi-sector intervention strategy (Allen and Gillespie, 2001; Skoufias et al., 2019). This warrants further empirical studies examining the forces and the possible alternative intervention to reduce child stunting in developing countries.

This paper examines the effects of early life and in-utero exposure to cold weather shocks on child growth in Tanzania. The study contributes to several empirical studies on the impact of exposure to natural and climatic shocks[1] on child health outcomes. Our contributions are in three different ways. First, to establish the causal effects of weather shocks, we use the high-resolution daily weather variations in contrast to those using by-month or by-year variations, which are prone to aggregation bias (Dell et al., 2014). Secondly, we examine the effects of exposure to extreme cold weather shocks in the context of developing countries, the area least able to mitigate the adverse effects of climatic shocks. Thirdly, while several studies examine the impact of extremely hot temperatures, we examine the impact of early after birth and in-utero exposure to cold shocks on child growth. To existing knowledge, this is the first paper to study the exposure effects of cold weather shocks on child health outcomes using high-resolution and daily weather variations in the context of developing countries—Tanzania in particular.

Several other recent studies in developed countries found adverse effects of exposure to extreme weather conditions on child health and human capital investment[2]. For instance, Deschênes and Greenstone (2011) and Gasparrini et al. (2015) found a higher association between exposure to extreme weather shocks with mortality and Wilde et al. (2017) found a closer link between early-life and in-utero exposure on long-run human capital outcomes in SSA. Other studies suggest that in-utero and early-life exposure to extreme low and high temperatures increase the individual risk for injury, death, mortality and worsening pre-existing chronic conditions, especially respiratory and cardiovascular diseases (Gasparrini et al., 2015; Benmarhnia et al., 2019).

Studies on weather-health links focus more on extremely high temperatures due to

[1]Effects of extreme weather shocks, natural earthquakes, war and conflict and storms see Abiona (2017); Lee (2014); Sardoschau (2019); Singhal (2019).

[2]See for example Fudge et al. (2015); Benmarhnia et al. (2019); Analitis et al. (2008); Berko (2014); Burgess et al. (2013); Deschênes and Greenstone (2011); Wang et al. (2016); Wilde et al. (2017).

growing concern over the impact of climatic change. However, studies by Berko (2014) and Gasparrini et al. (2015) suggest that low temperatures contribute substantially to weather-related deaths and mortality. The previous studies collectively confirm adverse effects of exposure to severe cold and hot waves on health outcomes in developed countries (Berko, 2014; Burgess et al., 2013; Deschênes and Greenstone, 2011). There are scarce related empirical studies on its effects on child growth, more importantly, in developing countries' contexts. In Peru, Sanchez (2018) found that early life exposure to cold months was associated with lower height-for-age. In Bangladesh, Rashid et al. (2017) found similar evidence. Meanwhile, on the opposite note a recent study in SSA found that children born in temperature spikes are less likely to be stunted (Tusting et al., 2020) and attain high educational attainment (Wilde et al., 2017). In sum, the earlier studies in developed and developing countries document a high impact of cold and heat shocks on child health and educational outcomes. However, notwithstanding the growing evidence on the effects of cold weather shocks on child excess mortality and morbidity, the effects of cold shocks on early childhood growth have been neglected in the context of developing countries. To bridge this gap, in the present study, we examine the effect of early life and in-utero exposure to extreme cold conditions on the stunting probability of under-five children in Tanzania.

The study focuses on child growth/stunting in Tanzania for two main reasons. First, Tanzania is among the top five SSA countries with the highest child stunting rate (Skoufias et al., 2019; UNICEF-WHO-WB, 2018; Zhu et al., 2021) and second, due to the existence of high geographical variation in stunting and weather conditions. The stunting rate in Tanzania varies markedly across regions and between rural and urban areas (URT, 2018; Zhu et al., 2021). The recent nutrition survey (URT, 2018) shows that regions in the southern highland had the highest child stunting incidence of over 47 percent while other areas had less than 21 percent (See figure 1 in appendix). Contrary to the nutritional and dietary-diversity based evidence, regions with food sufficiency[3] and less food poverty recorded high stunting rates (URT, 2018). The observed high rate in food surplus and less poor areas suggest that nutritional factors such as food security and dietary diversity cannot exhaustively explain much of the observed geographical variation in the stunting incidence. Studies in Tanzania have focused on nutritional foods deficiency, lack of dietary diversity, inadequate breastfeeding and maternal education (Makoka and Masibo, 2015; Zhu et al., 2021) but less is known on why there exist high heterogeneity across regions and a high rate in food-surplus and relatively less poor regions.

We utilize the four survey waves from the nationally representative Tanzania National Panel Survey (TNPS) and the Global Meteorological Forcing Dataset from the Terrestrial Hydrology Research Group. With many other household and individual level information, the TNPS collects anthropometric information for under-five children. We use this information to compute the child growth (stunting) indicators based on the approach by Leroy (2011). We use child stunting and severe stunting indicators as child growth outcome variables. The TNPS is geo-referenced at the cluster level enabling us to merge with a high-resolution meteorological dataset from Global Meteorological Forcing Dataset, which is the main advantage over other sources. From weather data, we use the daily minimum temperature recorded from 2003 to 2015. We define cold weather shocks if the temperature falls below one standard deviation from the long-run minimum average.

We find the strong negative effects of early life and in-utero exposure to cold shocks on child growth. For example, our results show that an increase in early-life exposure to days with minimum temperature below 15 degrees Celsius (1 SD below long-run average) by 10% is associated with an increase in stunting and severe stunting probability by 1.8 and 1.2 percentage points, respectively. In addition, we find strong effects of in-utero exposure during pregnancy on child stunting and wasting. We observe high and

[3]See for example the study by Cochrane and D'Souza (2015) which shows that regions in the southern highland regions are food surplus, have lowest food basket cost compared to other regions

statistically significant effects during the second trimester and weak effects of in-utero exposure during the first and third trimester. The higher effects on stunting growth and wasting during the second trimester suggest that high effects of exposure become severe during mid fetus development. It is important to mention that our estimates are not threat-free. We further test whether these findings are driven by self-selection due to endogenous migration and fetal loss/mortality. We find no detectable association between cold shocks with endogenous migration and child mortality, suggesting that the self-selection is unlikely and thus does not drive our main results.

Finally, we find that the effects of early-life exposure to cold shocks are heterogeneous across age, gender, rural location, and wealth. More importantly, we find that the effects are high and significant for 19 to 36-month-old children with later catch-up growth effects. We also find that effects are much higher for poor and rural households than wealthier and urban families. Across gender, we find that girls are more vulnerable to cold weather shocks, suggesting possible gender-based discrimination in allocating resources within households. Our empirical results are consistent with the earlier hypothesis that exposure to cold weather conditions is a strong predictor of early-stage poor child growth and in line with other studies (Ogasawara and Yumitori, 2019). Taken together, our findings suggest that early-life and in-utero exposure to cold shocks negatively affect early child growth and largely explain the observed child stunting heterogeneity in Tanzania.

The rest of the paper proceeds as follows. Section 2 layouts the conceptual framework that describes the mechanisms through which cold weather shocks might be expected to lead to child stunting. Section 3 discusses the data and section 4 describes the empirical strategy. Section 5 presents the empirical results, and section 6 concludes.

2 Conceptual Framework

The study follows the standard health production framework adopted from Maccini and Yang (2009) and Rabassa et al. (2014) modified from Grossman (1972). The model assumes that a child's health stock at a time (t) is determined by her initial inherited health endowment, which depreciates with age but increases with investment in health inputs. Thus, child health outcomes (H_{it}) is defined as a function of her initial health endowment (H_{iO}), investment in health production inputs (N_{it}), time-invariant demographic characteristics (X_i), access to health facilities (A_t) and the disease environment (D_t). The vector of health production inputs includes nutrient intake, household income, education, and time devoted to health-related procedures (Rabassa et al., 2014). The environmental conditions include the ambient temperature and sanitation systems. The general health production function can be specified as follows:

$$H_{it} = h(H_{i0}, N_{it}, X, A_t, D_t) \tag{1}$$

The initial health endowment (H_{i0}) is in turn partly determined by shocks experienced in the fetal stage (S_{-1}), disease environmental conditions (D_0) and other unobservable hocks (ε_0) experienced during the early life (Maccini and Yang, 2009). According to the fetal origin hypothesis, health shock experienced during the fetal period and early childhood may program to irreversible adulthood effects such as coronary heart disease and retarded growth (Barker, 1990). Thus, the initial health endowment might be determined with the following functional form:

$$H_{i0} = g(S_{i,-1}, D_0, \varepsilon_0) \tag{2}$$

Due to shocks during the fetal stage, the inter-generational transfer mechanism is transmitted via maternal psychological stress and other mother health conditions during pregnancy. Indeed, several studies found high and significant effects of in-utero exposure to shocks such as war/conflicts, natural shocks, famine, and ambient temperature on offspring health outcomes (see for example Lee (2014); Rashid et al. (2017); Sardoschau (2019)).

We primarily focus on the potential mechanisms through which in-utero and early childhood exposure to weather shocks might influence child growth. The cold weather shocks operate through three possible mechanisms: investment in adaption strategy, influence on disease environment, and maternal stress. Firstly, families trade between food and energy during cold weather (Beatty et al., 2014; Ogasawara and Yumitori, 2019) as an investment in adaptation strategy. Cold weather shocks are thus equivalent to income shocks for low-income families. The income shocks translate to lower investment on nutritional-food uptake and investment in health production inputs. Studies from the US by Bhattacharya et al. (2003) and Deschênes and Greenstone (2011) and UK by Beatty et al. (2014) indeed found high energy expenditures attributable to cold weather shocks among low-income families.

In developing countries, resource-poor families may not fully respond to cold weather shocks due to poor access to affordable and reliable energy and anti-cold facilities and equipment. Investment in cold weather adoption through anti-cold facilities can be viewed as an investment in health production inputs. Thus, living in fuel/energy poverty[4] and cold housing, directly and indirectly, impacts child health outcomes, with infants and the elderly being most vulnerable. Also, resource constraints determine the family's ability to adapt to various weather shocks through other self-protection strategies. Resource-poor families, especially those from rural may not afford the anti-cold facilities such as warm clothing to protect their children against cold weather conditions. This is due to

[4] According to González-Eguino (2015), energy poverty refers to the state where a household cannot fulfill all of their domestic energy needs (lighting, cooking, heating, cooling, information-communication) as a result of lack of access to energy services, an inability to afford them, or their poor quality or unreliability to, at minimum, safeguard their health and provide for opportunities to enhance their well-being.

underdeveloped home heating systems (climate-control technology) and proper housing conditions.

Secondly, cumulative exposure to colds increases the risk of circulatory diseases, mental health, and infectious diseases (Dear and McMichael, 2011; Ogasawara and Yumitori, 2019) which may affect overall child growth. The change of body temperature of mother during pregnancy also influences the metabolism of different nutrients and thus might affect the fetal growth (Rashid et al., 2017). Also, cold environments increase the risk of frostbite, hypothermia, and heat edema risk (Benmarhnia et al., 2019; Fudge et al., 2015). According to Dear and McMichael (2011) infants and young are susceptible to respiratory problems such as pneumonia and influenza because their bodies have less fat that insulates them against the cold. Consequently, cumulative exposure to cold-related diseases leads to long-term and lasting effects on child growth due to its impact on the disease environment.

Thirdly, maternal prenatal stress is another potential channel discussed in the literature. A well-nourished mother is necessary for proper fetus development and later birth outcomes. In-utero exposure to stress due to changes in environmental conditions may thus affect child later outcomes (Barker, 1990). Literature shows that the shocks during pregnancy have strong, negative, and persistent effects on various offspring health outcomes, Such as shorter gestation and low anthropometric outcomes (Lee, 2014; Rashid et al., 2017; Maccini and Yang, 2009). Several empirical studies show that fetal exposure to adverse environmental conditions, including the extreme cold or heat waves during pregnancy, has a significant impact on the likelihood for preterm birth, poor birth weight, and the probability of later life stunting growth (Lee, 2014; Rashid et al., 2017; Waldie et al., 2000).

The other potential channels discussed in empirical literature include the shocks on agricultural productivity (Nsabimana and Mensah, 2020; Ogasawara and Yumitori, 2019). The extreme cold or heat weather conditions are detrimental to agricultural productivity, affecting nutritional foods and family resources. This might be a potential challenge with heatwaves and insufficient rainfall than cold weather shocks (Rabassa et al., 2014). Testing the potential mechanism for cold weather-child growth is beyond the scope of this paper, and this is partly due to the nature of our data. Thus, our estimate reflects the composite effect of exposure to cold shocks on child growth outcomes. Given the potential mechanisms and drawing from previous studies, we hypothesize that cumulative exposure to cold weather shocks adversely affects child health and, more importantly, child growth outcomes.

3 Data

We use two data sources, the Tanzania National Panel Survey (TNPS) and the weather data from the Terrestrial Hydrology Research Group at Princeton University.

3.1 The TNPS Data

We use data from the TNPS collected by the National Bureau of Statistics (NBS) supported by the World Bank as part of living standards, and measurement surveys integrated agriculture surveys (LSMS-ISA). The TNPS is the nationally representative household survey that collects household and individual information for rural and urban areas. The survey uses the two-stage stratified sampling design. In addition to other information, the survey collects anthropometric information (height and weight) for under-five children. We use this information to compute two long-term growth indicators, child stunting and severe stunting incidence taking into account the age and gender of the child. We utilize data on children between 0 and 59-month from birth (under-five children) born between 2003 and 2015. We use data from all four waves collected in 2008/09, 2010/11, 2012/13, and 2014/15. Compared to other sources such as Tanzania Demographic Health Survey (DHS), the TNPS is geo-referenced at the cluster level, allowing us to merge with high-resolution daily weather information.

3.2 Weather Data

For weather data, we use the Global Meteorological Forcing Dataset from the Terrestrial Hydrology Research Group available at Princeton University. The dataset provides a globally high-resolution (at 0.25*0.25-degree resolution) gridded daily surface temperature and precipitation data from 1948 (Sheffield et al., 2006). The dataset is constructed from several global observation-based datasets with the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (Sheffield et al., 2006). From the dataset, we extract the daily minimum temperature from 2003 to 2015 (range of year of birth for our sample children). We merge the extracted dataset from Global Meteorological Forcing Dataset to our TNPS dataset based on the geolocation of the surveyed household (Picard, 2019).

4 Empirical Strategies

4.1 Early exposure to weather shocks and child growth

Estimating the effects of early-life exposure to cold shocks on child growth is not straightforward. First, the temperature tends to be correlated with seasons and the seasons tend to be correlated with health, educational, and labor market outcomes (Dell et al., 2014; Wilde et al., 2017). Second, geographic characteristics are also correlated with climatic outcomes (Wilde et al., 2017). We observe a similar pattern in Tanzania. For example, the regions in the lower altitude, mainly along the coast and Zanzibar island, tend to have high average temperatures compared to inland and mountainous regions. Following the highest correlation between temperature with seasons and geographic characteristics, we include region-by-month, region-by-year, and year-fixed effects to capture the seasonal variations and other geographical differences. The Equation is as follows:

$$Y_{ijrt} = \alpha + \lambda_{rm} + \lambda_{rt} + \mu_b + \sum_{k=1}^{2} \gamma_k \mathrm{Shock}^k_{ijrt,\tau t} + X'_{ijrt}\xi + C'_{ijrt}\rho + \varepsilon_{ijdt} \tag{3}$$

Where Y_{ijrt} stands for health outcomes of child i from household-j, region-r, born in τ and survey year-t. λ_{rm} and λ_{rt} stands for the region-by-month and region-by-year fixed effects, and μ_b stands for the cohort of birth fixed effects. The region-by-month (λ_{rm}) fixed effects control for the unobservable region-level seasonal variation in the month of birth. Region-by-year (λ_{rt}) fixed effects control for unobserved, regional level time-variant factors that may affect child health outcomes. The birth cohort (μ_b) fixed effects capture the unobservable cohort-specific, time in-variants characteristics. ε is the idiosyncratic error term.

We use stunting and severe stunting as a measure of child growth outcomes. Consistent with the WHO standard, a child is defined as stunted and severely stunted if the child i's height-for-age z-score is two and three standard deviations below the age-sex median of the well-nourished reference population (WHO-reference population). Unlike weight which measures short-term health, stunting shows the cumulative long-term growth of children (Agüero, 2014; World Bank Group, 2017).

Shock represents the intensity of exposure to cold weather shocks from birth (τ) to survey date (t). k is the temperature range (bin), the 1 SD below range (0-15°C), and within 1 SD below and above the long-run average minimum temperature (15-21°C). We compute the cumulative number of days from the month of birth to the month of the survey with the minimum temperature below 1 SD from the long-run average (0-15°C) and within 1 SD below and above the long-run average minimum temperature (15-21°C). Due to the absence of the exact date of birth, we calculate the cumulative number of days from the first day of the month of birth. We re-scale the number of days within bin-k as proportional (percent) to the total number of days from birth to survey month (lifetime). The degree range with the temperature above 21°C is the reference category for all our estimations. A similar approach is widely applied in empirical studies modeling the contemporary effects of weather shocks on various economic outcomes such as health, agricultural output, conflict, and economic growth (see Dell et al., 2014 for review)[5]. Compared to other approaches such as aggregation over time and space, this approach is arguably designed to capture exposure to cold weather shocks considering the spatial (space) and seasonal variations (time). According to Auffhammer et al. (2013) and Dell et al. (2014), data smoothing across space and time may produce misleading estimates due to aggregation bias. For robustness checks, we conduct some sensitivity with varying thresholds.

The X is the vector of other predetermined covariates, including a child and head demographics; gender, age, age, gender, education, and occupation. The household-level control variables include household size, wealth index, access to piped, and drinking water. We further control whether the household received food assistance from the government, non-governmental organizations (NGO), or relatives to measure household food deficiency. C is the vector of other climatic covariates, such as the average level of precipitation and drought severity. We control these variables following the recent empirical studies that show the closer link between weather shocks, agricultural activity, and health outcomes (Dell et al., 2014; Nsabimana and Mensah, 2020).

The γ_1 and γ_2 are the coefficients of interest throughout this paper, with γ_1 capturing the effect of extreme cold weather shocks. In this model, we are interested in the impact of early lifetime (postnatal) exposure to cold shocks on the child's short-term growth (stunting growth) outcomes.

[5]The weather shocks based on standardized scores cutoffs are widely employed in studies on similar subjects (Andalón et al., 2016; Rabassa et al., 2014; Sanchez, 2018). For instance, Andalón et al. (2016) defined cold weather shocks as the temperature below 0.7 SD from monthly mean temperature, Nsabimana and Mensah (2020) used a 1 SD cutoff threshold below and above the long-run mean of SPEI index to measure dry weather shocks and Rabassa et al. (2014) uses deviation from the long-run average as a measure of rainfall shocks in rural Nigeria. Deschênes and Greenstone (2011) using a similar strategy studied the effects on mortality and energy consumption in the US.

4.2 In-utero exposure to weather shocks and child growth

Following several other pieces of literature (Kumar et al., 2014; Rashid et al., 2017; Waldie et al., 2000; Wilde et al., 2017) on the significant effects of in-utero exposure to weather shocks on child health outcomes, we also estimate the following fixed effects specification.

$$Y_{ijrt} = \alpha + \lambda_{rm} + \lambda_{rt} + \mu_b + \sum_{k=1}^{2} \gamma_k \text{Shock}^k_{ijrt,\tau-n} + X'_{ijrt}\xi + C'_{irt}\rho + \varepsilon_{ijrt} \qquad (4)$$

In contrast to the baseline specification (Equation 3), shock is the intensity of exposure to cold weather shocks during n^{th} trimester. The in-utero exposure is measured during the first, second and third trimesters. The ideal measure of outcomes variable to estimate the effects of in-utero exposure to cold weather shocks is the health outcomes at birth. Due to the absence of such information, we restrict the estimation to children aged less than 12 months at the survey time. Thus γ measures the aggregate effects of in-utero exposure to cold weather shocks on the child growth outcomes. We use child stunting, underweight, and wasting as indicators of child health outcomes at birth.

Consistent with other studies (Deschênes and Greenstone, 2011; Nsabimana and Mensah, 2020; Ogasawara and Yumitori, 2019), the identification strategy relies on the unpredictability and plausibly randomness of the weather shocks. There are three main threats to the identification strategy, selective migration and selective mortality/fetal loss due cold shocks (Agüero, 2014; Deschênes and Greenstone, 2011) and parental compensatory investment (Wilde et al., 2017). We test whether our estimates are influenced by selective migration and child mortality. We found that self-selection is unlikely, and thus our estimates are not driven by self-selection. We discuss and present the endogeneity test in the appendix.

5 Results

5.1 The Effects of Early Exposure on Child Growth

Table 1 shows the descriptive statistics for the key variables; outcome, child, household, and weather variables for all four survey waves. The descriptive statistics show that 42, 35, 36, and 33 percent of our sample children were stunted in the first, second, third, and fourth survey wave, respectively. The average minimum temperature is 18°C, and the average degree day of exposure is 0.11 for 0-15°C and 0.64 for 15-21°C temperature range.

[Table 1]

Before presenting the main results based on the specification in Equation 3, in Figure 2, we graphically show a simple correlation between stunting growth and the average minimum temperature range. The plot shows that the average stunting rates are inversely proportional to the average minimum temperature range for males and females. On average, the male from areas that experience low temperature (0-15°C) had a stunting rate of 47 percent, and those from high average minimum temperature (above 21°C) had a 35 percent incidence rate, a 12 percent difference. The stunting difference for female children gives similar results. On average, the stunting probability for those from low temperate areas is 45 percent and 26 percent for those from the high average temperature, with a 9 percent difference.

[Figure 2]

Table 2 reports the main results of our empirical specification in Equation 3 with varying specifications using stunting and severe stunting as the child growth outcome variables. The robust standard errors clustered at the district level are in parentheses. Columns 1-3 present estimates of the effects of exposure on child stunting growth, and columns 4-6 present the effects of exposure on severe stunting growth. The estimates in columns 1 and 4 present the result excluding survey year, region-by-birth month, region-by-year fixed effects, and climatic variables controls. As expected, the estimated coefficients for stunting and severe stunting (columns 1 and 4) are positive and statistically significant. The results are robust to introducing various fixed effects. In columns 2 and 5, we further control for survey year and region-by-month of birth fixed effects. The estimated coefficients slightly increase to 0.0017 and 0.0011 for stunting and severe stunting and remain statistically significant. The estimates remain virtually unchanged after including the region-by-year fixed effects and climatic factors (columns 3 and 6). In all specifications, the result shows a positive and significant relationship between our measure of early life exposure to cold weather shocks with both stunting and severe stunting incidence.

As expected, the effects of early-life exposure to cold weather shocks (0-15°C range) remain positive and statistically significant in all our specifications. The estimates in columns 3 and 6 with the full set of controls are the most preferred results in our specifications. Overall, the results show that exposure to intense cold weather shocks (temperature below 15°C) is strongly associated with poor childhood growth at an earlier stage. In terms of magnitude, our results show that, on average, the increase in exposure to days with cold weather shocks (temperature below 15°C) by 10 percent is associated with an increase in stunting and severe stunting by 1.8 and 1.2 percent points, respectively. Consistent with our earlier hypotheses and in line with other earlier studies, the finding suggests that early life exposure to intense cold weather shocks is strongly associated with poor early child growth.

[Table 2]

Table 3 repeats the previous analysis with an alternative (aggregated) measure of shocks. We construct two measures of exposure using the average minimum temperature from 2003 to 2015. We define cold shocks if the long-run average is below 15 degrees Celsius. We also include the dummy for the long-run minimum temperature between 15 and 21 degrees Celsius. This analysis ignores the time variation and considers only the spatial variation in minimum temperature. Again, the results are positive and statistically significant in all our specifications. In columns 3 and 6, the result shows that children from areas with low minimum temperature (1 SD below the long-run norm) are relatively 7.9 and 4.8 percent more likely to be stunted and severely stunted, respectively. Though lower in magnitude, the effects of exposure to 15-21 degrees Celsius (1 SD below and above the long-run norm) are also positive and statistically significant.

[Table 3]

In sum, the results in Tables 2 and 3 show a strong effect of early life exposure to cold shocks and child stunting probability of under-five children. Consistent with our earlier hypothesis, the results suggest that exposure to cold weather shocks explains to a large extent the observed child stunting heterogeneity in Tanzania. The findings align with previous studies, which found a strong link between exposure to cold weather shocks and child health outcomes (Ogasawara and Yumitori, 2019; Sanchez, 2018).

5.2 The Heterogeneous Effects

This section presents and discusses the heterogeneous effects of early life exposure to cold weather shocks on child stunting across age, gender, household wealth, and rural-urban location by estimating the following modified econometric specifications, including the interaction terms.

$$Y_{ijrt} = \alpha + \lambda_{rm} + \lambda_{rt} + \mu_b + \sum_{k=1}^{2} \gamma_k Shock^k_{ijrt,\tau t} + \sum_{k=1}^{2} \pi_k (Shock^k_{ijrt,\tau t} * \vartheta) \quad (5)$$
$$+ X'_{ijrt}\xi + C'_{jrt}\rho + \varepsilon_{ijrt}$$

Where ϑ denotes a vector of dummies for age groups, gender, wealth (lower quantile household), and rural location, all other variables are defined in the empirical strategy section. This model permits the effects of exposure to cold weather shocks to vary across age, gender, household wealth level, and location. A vector of interaction coefficients (π_k) measures the heterogeneity effects of exposure to cold weather shocks.

Table 4 reports the heterogeneity effects across age groups (in months). Columns 1-2 report the coefficients of the interaction term between age groups (in months) with exposure to 0-15°C. The results report high and significant effects on both stunting and severe stunting for 13-36 months-old children. Columns 3-4 report the coefficients of interaction between age groups (in months) with exposure to $15-21$°C. We find similar trends with high and significant effects for children above 13 months after birth. Contrary, though smaller in magnitude and declining, the effects for the higher age groups are also statistically significant. Surprisingly, we find no substantial effect of exposure for children under 12 months, suggesting that children from areas with a high frequency of cold weather shocks are not substantially different. The results suggest that exposure effects are more likely to be a cumulative impact during the early life exposure and in-utero exposure.

Figures 3 and 4 depict the previous heterogeneity estimates in Tables 4. We plot the estimates of the interaction (x100) coefficients of age group on exposure to 0-15°C temperature range in Figure 3 and exposure to 15-21°C temperature range in Figure 4. The left plot shows the heterogeneity effects on child stunting and the right plot shows the heterogeneity effects on severe stunting probability. Figure 3 shows that the exposure effects on child stunting probability are positive and higher for 25 to 30 months old children and 19-24 month old for severe stunting. More importantly, in all figures (right and left), we find that the effects increase early after birth and decrease later. We observe a similar trend in Figure 4, with higher effects for children between 19 and 24 months for both stunting and severe stunting. We also find the inverted U-shaped effects, with an increase in effects at an early age and declining later. The estimated results indicate that the effects on child growth due to cold weather shocks are likely to diminish as they grow old, suggesting the possibility of catch-up growth effects later. Comparatively, the study by Desmond and Casale (2017) in South Africa also found similar catch-up growth effects for children aged 2 and 3.

[Figure 2-3]

Table 5 shows the heterogeneity effects on both stunting (columns 1-3) and severe stunting (columns 4-6) across location (columns 1 and 4), gender (columns 2 and 5), and household wealth (columns 3 and 6). The estimates in column 1 show the interaction coefficient between cold weather shocks and rural dummy exposure. The estimate is positive and statistically significant, indicating higher effects on child stunting incidence for rural children. Similar evidence is shown in column 4, the effects of exposure to cold weather shocks on severe stunting for rural children. We find higher and significant location effects for rural children on both stunting and severe stunting. In particular, our estimate shows that children from rural are more vulnerable to cold weather shocks.

Columns 2 and 5 provide the heterogeneity effects across gender. The results show higher effects for female children on stunting probability, and the impact on severe stunting is statistically insignificant. One possible explanation for the observed difference is the parental compensatory investment resulting from gender preferences favoring boys over girls (Nsabimana and Mensah, 2020; Rabassa et al., 2014). The substantial differences imply the difference in intra-household resource allocation, and thus male infants are more protected than girls.

The heterogeneity effects between poor and wealthier households, in columns 3 and 5, also show a positive and significant impact of exposure to cold weather shocks for children from a poor household on severe stunting but insignificant for stunting. The estimates show that children from poor households are more likely to be affected by cold weather shocks. The results reinforce our earlier hypothesis on the potential mechanism linking cold weather shocks and child health outcomes. The observed heterogeneity effects among children from rural and poor households suggest that shocks work through the wealth effects due to rural and resource-constrained families' inability to respond to weather shocks.

[Table 5]

Table 6 reports the effects of exposure to cold shocks on other health outcome variables; height-for-age, weight-for-age, under-weight, and wasting. The results show insignificant effects on weight-for-age, underweight, and wasting. The effect on height-for-age is statistically significant. This is consistent with the finding by Agüero (2014) who argue that future investments can mediate the possible impacts of weather shocks on weight and other health outcomes.

[Table 6]

5.3 The Effects of In-utero Exposure on Child Growth

Tables 7 and 8 report the effects of in-utero/prenatal exposure to cold weather shocks on child stunting probability and other health outcomes (Equation 4) by three trimesters of pregnancy. The fetal exposure to cold weather shocks is the proportional number of days (in percent) with minimum temperature within 0-15°C during the respective trimester. Columns 1-2 in Table 7 present the effects of exposure during the first trimester, columns 3-4 present the effects of exposure during the second trimester, and columns 5-6 show exposure effects during the third trimester. As argued before, the ideal outcome variable of in-utero exposure effects is the health outcomes at birth. Due to the absence of information on these variables, we restrict our estimate to children under 12 months. Therefore our estimates are likely to be biased upward due to contamination with after birth exposure.

The estimated effects of exposure during the first trimester are insignificant for stunting but significant for severe stunting. Contrary, we find high, positive, and statistically significant effects on both stunting and severe stunting during the second trimesters, columns 3-4. Similar to effects during the first trimester, in-utero exposure during the third trimester on stunting is insignificant but statistically significant on severe stunting. Though positive and significant during the first and third trimesters, the magnitudes are very low. The high and significant effects during the second trimester suggest that the effects of in-utero cold shocks on offspring outcomes become more strong during the middle of fetus development. One possible explanation for low and weak impact during the third trimester is that at this stage a child is almost fully grown and thus less affected by the temperature shocks. Our results are consistent with other studies which found adverse effects of negative shocks during the first and second trimester of pregnancy with higher effects during the second trimester, the most critical period [6]. In terms of magnitude, our results indicate that an increase in exposure to a temperature below 15 °C by 10% is associated with an increase in the likelihood of being stunted and severely stunted by 2.8 and 2.4 percentage points during the first 12 months after birth.

[Table 7]

Table 8 reports the estimates of in-utero exposure effects on other child health outcomes; the under-weight and wasting indicators. In all pregnancy periods, we find no effects on underweight outcomes. The estimates show positive and statistically significant effects on wasting during pregnancy first and second trimester, but we observe no effects during the third trimester. Consistent with the previous results, the effects are much higher for the exposure during the second trimester. Again, our results reinforce

[6] See for example Lee (2014) and Sardoschau (2019) on the effects of in-utero exposure to conflicts on health outcomes of child in South Korea and Iraq and Rashid et al. (2017) to lower temperature during pregnancy. The studies found high exposure effects to wars/conflicts and low temperature during the first and second trimester of pregnancy and insignificant effects during the third trimester.

our earlier finding that the effects of in-utero exposure are higher and more significant during the second trimester, a most critical period for offspring development.

[Table 8]

Overall, our estimate suggests that prenatal exposure to cold weather shocks strongly affects later child growth and other health outcomes; stunting and wasting. The effects are high and statistically meaningful if the exposure happens during the second trimester period. Our results align with other studies on fetal exposure to weather shocks on later child growth and health outcomes (Andalón et al., 2016; Lee, 2014; Sardoschau, 2019).

5.4 Robustness Checks

We conduct two sets of robustness checks. First, we perform a sensitivity check by excluding the regions with high annual mean temperatures. The prolonged extreme hot weather conditions are an unusual event in Tanzania. Many empirical studies suggest the strong negative effects of extreme hot weather conditions on child health outcomes. We also perform the sensitivity checks using the alternative and broader definition of the exposure to cold shocks variables.

We present the sensitivity analysis in Tables 9-10. Normally, areas along the coast and offshore islands experience the highest annual mean temperature. In Table 9, we sequentially exclude regions that experience high average temperature to check the sensitivity of our estimated results. Estimates in column 1 show the effects of exposure to cold weather shocks for our under-five children sample, the baseline results. In column 2, we estimate our baseline model for children from Tanzania mainland only by excluding the regions from Zanzibar islands. In column 3, we exclude children from the Zanzibar and the Dar es Salaam region, the more urbanized area. In addition, column 4 excludes all the coastal regions (Mtwara, Lindi, Coastal and Tanga, Dar es Salaam) and Zanzibar. In column

5, we also exclude regions from the lake zone (Mwanza, Mara, Shinyanga, and Geita), which receive fewer cold weather shocks. Even after a series of exclusion restrictions, our estimates remain robust. Surprisingly, the effects of exposure to cold weather shocks increase when we exclude regions that receive higher annual mean temperatures. The last column presents the estimated impact for children from southern highland regions, the regions with significant cold shocks prevalence. As expected, the estimated effect turns statistically insignificant, implying high impacts of temperature variation across time and space on child growth.

[Table 9]

In Table 10, we present a sensitivity analysis using the alternative and broader definitions of the exposure to cold shocks variables. First, we use the cold weather shocks as a proportional number of days for which the minimum temperature is below the long-run mean (shocks^2) of the daily minimum temperature (0-18°C). We also define cold weather shocks as a proportional number of days on which the minimum temperature is below the standard deviation above the mean (0-21°C)-shocks^3. Finally, we use one standard deviation above and below as weather shocks (15-21°C)-shocks^4. Ideally, the reference category for the 15 to 21°C cold weather shocks threshold is below 15°C and above 21°C. We expect that if our original conservative measure reasonably captures the cold weather shocks, then the 15 to 21°C cutoff ranges would be insignificant. As expected, the estimated coefficients are statistically significant when using the first two broader definitions (columns 1-3) and negligible for the 15 to 21°C temperature ranges (column 4). The main conclusion of the results above is that our original measure of intensity reasonably captures the early exposure to cold weather shocks.

[Table 10]

6 Conclusion

This paper examined the nonlinear effects of early life and in-utero exposure to cold weather shocks on the child stunting probability of under-five children in Tanzania by exploiting the spatial and day-to-day variation in temperature. Our study main identifying strategy is that weather shocks are plausibly random and thus orthogonal to other determinant factors. Overall, our findings suggest that exposure to cold weather shocks adversely affects early child growth and largely explains Tanzania's observed stunting growth disparities. We find that children exposed to cold weather shocks are more likely to be both stunted and severely stunted. On average, a 10 percent increase in exposure to days with cold weather shocks increase the probability of being stunted and severely stunted by 1.8 and 1.2 percent, respectively. The results are robust to various specifications and alternative definitions of weather shocks. These results are consistent with other previous studies which found an adverse impact of cumulative exposure to weather shocks on child health outcomes (Agüero, 2014; Dorélien, 2015).

The study found strong evidence of in utero exposure to cold weather shocks on the child's later growth. In particular, we find higher and more significant effects during the second trimester. In terms of magnitude, we find that an increase in exposure to shocks by 10% during the second trimester increases the probability of being stunted and severely stunted by 2.9% and 2.4%. We also find substantial effects on wasting but no impact on being underweight.

Our findings also suggest that exposure to cold weather shocks varies with age groups with the possibility of later recovery. Notably, we find high, positive, and statistically significant effects for children aged 19 to 36 months. The effects also tend to vary across gender, wealth, and locations. We find that the negative effects for children from rural and poor households are stronger than those from urban and wealthy households. The results support the evidence that children from poor and resource-constrained households are more vulnerable to adverse cold weather shocks. Female children are more susceptible to adverse cold weather shocks than males. One possible explanation for such a high difference is parental compensatory investment resulting from gender preferences favoring boys over girls in rural areas. The study concludes that the sustainable multi-sector intervention strategy to reduce child stunting in a developing country, particularly Tanzania, should account for regional weather variations.

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Tables and Figures

Table 1: Descriptive Statistics

	2008/9		2010/11		2012/13		2014/15	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Outcome Variables								
Stunting	0.42	0.49	0.35	0.48	0.36	0.48	0.33	0.47
Severe Stunting	0.18	0.38	0.13	0.34	0.14	0.35	0.14	0.35
Panel B: Child Information								
Sex (1=Female)	0.52	0.50	0.50	0.50	0.50	0.50	0.50	0.50
Age (in Months)	31.52	16.78	27.99	17.24	28.66	17.19	28.34	17.00
Rural	0.74	0.44	0.78	0.42	0.75	0.43	0.69	0.46
Panel C: Household Information								
Head: Age	42.11	13.56	42.70	13.88	42.70	14.40	40.96	12.84
Head: Male	0.83	0.38	0.82	0.38	0.83	0.38	0.79	0.41
Head: No Education	0.19	0.39	0.22	0.41	0.23	0.42	0.23	0.42
Head: Secondary and Above	0.12	0.33	0.12	0.32	0.14	0.34	0.17	0.37
Head: Work in Agriculture	0.70	0.46	0.67	0.47	0.66	0.47	0.60	0.49
Head: Employee	0.12	0.33	0.13	0.34	0.15	0.36	0.19	0.39
Head: Self Employee	0.14	0.34	0.14	0.35	0.15	0.35	0.18	0.39
Household Size	6.90	3.86	7.52	5.07	7.51	5.02	6.81	3.85
Wealth Index	−0.00	2.11	0.60	2.93	−0.28	2.18	−0.17	2.16
Piped Water	0.15	0.35	0.10	0.30	0.10	0.29	0.37	0.48
Drinking Water: Safe	0.31	0.46	0.05	0.21	0.08	0.26	0.11	0.32
Food Assistance	0.03	0.16	0.05	0.22	0.10	0.30	0.04	0.21
Panel D: Weather Information								
Minimum Temperature (°C)	18.87	2.68	18.93	2.58	18.84	2.45	18.95	2.46
Shocks$^{(1)}(-1\sigma)$	12.48	21.15	10.28	18.74	11.40	18.50	10.29	17.58
Shocks$^{(2)}(\pm 1\sigma)$	62.33	27.70	64.25	27.80	66.98	25.49	67.64	27.24
Precipitation mm (SD)	0.09	1.21	0.06	1.03	−0.11	0.87	0.00	0.92
Drought Severity Index	−1.41	2.30	−1.21	2.32	−2.04	1.95	−2.17	1.70

Note: The minimum temperature is the minimum temperature ever recorded from 2003 to 2015, and the mean minimum temperature is the average minimum temperature from 2003 to 2015. Shock^1 is the proportional number of days for which temperature is below 15 degrees Celsius (1 SD below the long-run norm) since birth. Shock^2 is the proportional number of days with minimum temperature between 15 and 21 degrees Celsius (1 SD below and above the long-run norm).

Table 2: Effects of Early Life Exposure to Cold Shocks on Stunting: Baseline Results

	Stunting			Severe Stunting		
	(1)	(2)	(3)	(4)	(5)	(6)
Shocks$^{(1)}(-1\sigma)$	0.0013***	0.0017***	0.0018***	0.0007***	0.0011**	0.0012**
	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0005)	(0.0005)
Shocks$^{(2)}(\pm1\sigma)$	-0.0001	0.0010**	0.0011**	0.0000	0.0006	0.0007*
	(0.0002)	(0.0005)	(0.0005)	(0.0002)	(0.0004)	(0.0004)
Controls	Y	Y	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y	Y	Y
Survey Year FE	-	Y	Y	-	Y	Y
Region x Month of Birth FE	-	Y	Y	-	Y	Y
Region x Survey Year FE	-	-	Y	-	-	Y
Climatic Controls	-	-	Y	-	-	Y
Adjusted R^2	0.039	0.052	0.057	0.022	0.034	0.038
Observations	10561	10561	10561	10561	10561	10561

Note: Shock^1 is the proportional number of days with minimum temperature below one standard deviation from the long-run average since birth. Shock^2 is the proportional number of days with minimum temperature one standard deviation below and above the long-run average since birth. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 3: Effects of Early Life Exposure to Cold Shocks on Stunting: Aggregate Shocks

	Stunting			Severe Stunting		
	(1)	(2)	(3)	(4)	(5)	(6)
Shocks$^{(1)}$(-1σ)	0.1021***	0.0839***	0.0794**	0.0564**	0.0475*	0.0477*
	(0.0298)	(0.0306)	(0.0317)	(0.0216)	(0.0251)	(0.0260)
Shocks$^{(2)}$($\pm1\sigma$)	0.0625***	0.0565***	0.0542***	0.0280**	0.0322*	0.0382**
	(0.0155)	(0.0189)	(0.0197)	(0.0109)	(0.0168)	(0.0176)
Controls	Y	Y	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y	Y	Y
Survey Year FE	-	Y	Y	-	Y	Y
Region x Month of Birth FE	-	Y	Y	-	Y	Y
Region x Survey Year FE	-	-	Y	-	-	Y
Climatic Controls	-	-	Y	-	-	Y
Adjusted R^2	0.041	0.052	0.057	0.023	0.034	0.038
Observations	10561	10561	10561	10561	10561	10561

Note: Shock^1 is the dummy for the average minimum temperature below 15 degrees Celsius from 2003 to 2015. Shock^2 the dummy for the average minimum temperature between 15 and 18 degrees Celsius (1 SD below and above the long-run norm) from 2003 to 2015. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 4: Effects of Early Life Exposure to Cold Shocks on Stunting: Heterogeneity Effects

	Coefficients of Interaction between Shocks$^{(1)}$and Age Group		Coefficients of Interaction between Shocks$^{(2)}$and Age Group	
	(1) Stunting	(2) Severe Stunting	(3) Stunting	(4) Severe Stunting
Age (0-6)	−0.0017**	−0.0006	−0.0008	−0.0002
	(0.0007)	(0.0005)	(0.0005)	(0.0004)
Age (7-12)	0.0003	0.0013	0.0007	0.0004
	(0.0008)	(0.0009)	(0.0005)	(0.0004)
Age (13-18)	0.0029***	0.0017**	0.0027***	0.0016***
	(0.0008)	(0.0007)	(0.0005)	(0.0004)
Age (19-24)	0.0051***	0.0033***	0.0040***	0.0025***
	(0.0009)	(0.0009)	(0.0005)	(0.0004)
Age (25-30)	0.0056***	0.0024***	0.0038***	0.0017***
	(0.0009)	(0.0007)	(0.0005)	(0.0004)
Age (31-36)	0.0041***	0.0028***	0.0031***	0.0019***
	(0.0009)	(0.0009)	(0.0005)	(0.0004)
Age (37-42)	0.0019*	0.0010	0.0023***	0.0014***
	(0.0011)	(0.0006)	(0.0006)	(0.0004)
Age (43-48)	0.0007	0.0006	0.0021***	0.0013***
	(0.0008)	(0.0006)	(0.0005)	(0.0004)
Age (49-54)	0.0001	0.0004	0.0018***	0.0011***
	(0.0010)	(0.0006)	(0.0006)	(0.0004)
Age (55-60)	0.0023**	0.0007	0.0020***	0.0012***
	(0.0011)	(0.0007)	(0.0007)	(0.0004)
Shocks$^{(1)}$(-1σ)	0.0000	0.0000	0.0023***	0.0015***
	(.)	(.)	(0.0005)	(0.0004)
Shocks$^{(2)}$($\pm1\sigma$)	0.0009**	0.0007*	0.0000	0.0000
	(0.0005)	(0.0004)	(.)	(.)
Controls	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y
Mean of Dep. Variable	0.363	0.145	0.363	0.145
Adjusted R^2	0.066	0.042	0.092	0.055
Observations	10561	10561	10561	10561

Note: Shock^1 is the proportional number of days with minimum temperature below 15 degrees Celsius since birth. Shock^2 the proportional number of days with minimum temperature between 15 and 18 degrees Celsius (1 SD below and above the long-run norm) since birth. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectiv

Table 5: Effects of Early Life Exposure to Cold Shocks on Stunting: Heterogeneity Effects

	Stunting			Severe Stunting		
	(1)	(2)	(3)	(4)	(5)	(6)
Rural x Shocks$^{(1)}$(-1σ)	0.0018***			0.0012**		
	(0.0007)			(0.0006)		
Rural x Shocks$^{(2)}$($\pm1\sigma$)	0.0008			0.0001		
	(0.0006)			(0.0004)		
Female x Shocks$^{(1)}$(-1σ)		0.0010*			−0.0002	
		(0.0006)			(0.0005)	
Female x Shocks$^{(2)}$($\pm1\sigma$)		0.0002			−0.0003	
		(0.0004)			(0.0002)	
Poor x Shocks$^{(1)}$(-1σ)			0.0007			0.0008*
			(0.0005)			(0.0004)
Poor x Shocks$^{(2)}$($\pm1\sigma$)			0.0005**			0.0001
			(0.0002)			(0.0001)
Shocks$^{(1)}$(-1σ)	0.0003	0.0013**	0.0014**	0.0002	0.0013**	0.0008*
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0004)
Shocks$^{(2)}$($\pm1\sigma$)	0.0006	0.0010**	0.0008*	0.0007	0.0009**	0.0007*
	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Controls	Y	Y	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y	Y	Y
Mean of Dep. Variable	0.363	0.363	0.363	0.145	0.145	0.145
Adjusted R^2	0.057	0.057	0.057	0.038	0.038	0.038
Observations	10561	10561	10561	10561	10561	10561

Note: Shock^1 is the proportional number of days with minimum temperature below 15 degrees Celsius. If the wealth index is below the median, the household is classified as poor. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Effects of Early Life Exposure to Cold Shocks on Other Health Outcomes

	(1) Height for Age	(2) Weight for Age	(3) Underweight	(4) Wasting
Shocks$^{(1)}(-1\sigma)$	−0.0065*	−0.0005	0.0006	−0.0000
	(0.0034)	(0.0039)	(0.0004)	(0.0003)
Shocks$^{(2)}(\pm1\sigma)$	−0.0008	0.0001	0.0007*	−0.0000
	(0.0035)	(0.0042)	(0.0004)	(0.0003)
Controls	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y
Mean of Dep. Variable	-1.427	-0.692	0.142	0.055
Adjusted R^2	0.043	0.042	0.031	0.022
Observations	10561	10561	10561	10561

Note: Shock^1 is the cumulative number of days with a temperature below one standard deviation from the long-run average. Shock^2 is the cumulative number of days with minimum temperature one standard deviation below and above the long-run average. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Effects of In-utero Exposure to Cold Shocks on Stunting

	First Trimester		Second Trimester		Third Trimester	
	(1) Stunting	(2) Severe Stunting	(3) Stunting	(4) Severe Stunting	(5) Stunting	(6) Severe Stunting
$\text{Shocks}^{(1)}(-1\sigma)$	0.0015	0.0014*	0.0029***	0.0024***	0.0014	0.0012*
	(0.0010)	(0.0008)	(0.0009)	(0.0007)	(0.0010)	(0.0007)
$\text{Shocks}^{(2)}(\pm 1\sigma)$	0.0004	0.0001	0.0011	0.0014***	−0.0000	0.0001
	(0.0008)	(0.0005)	(0.0007)	(0.0005)	(0.0008)	(0.0006)
Controls	Y	Y	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y	Y	Y
Mean of Dep. Variable	0.235	0.107	0.235	0.107	0.235	0.107
Adjusted R^2	0.070	0.046	0.073	0.049	0.071	0.045
Observations	2373	2373	2373	2373	2373	2373

Note: Shock^1 is the proportional number of days with a temperature below 15 degrees Celsius. Shock^2 is the proportional number of days with temperatures between 15 and 21 degrees Celsius (1 SD below and above the long-run norm). Columns 1-2 estimate exposure effects on stunting and severe stunting nine months before birth (fetal period), columns 3-4 during six months before birth (second and third trimesters), and 5-6 for three months before birth (third trimester). The estimation is restricted to children aged less than 12 months at the survey time. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 8: Effects of In-utero Exposure to Cold Shocks on other Health Outcomes

	First Trimester		Second Trimester		Third Trimester	
	(1) underweight	(2) wasting	(3) underweight	(4) wasting	(5) underweight	(6) wasting
$Shocks^{(1)}(-1\sigma)$	−0.0005	0.0013*	0.0004	0.0019**	−0.0004	0.0006
	(0.0009)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0007)
$Shocks^{(2)}(\pm1\sigma)$	−0.0009	0.0003	−0.0002	0.0015**	−0.0010	−0.0000
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)
Controls	Y	Y	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y	Y	Y
Mean of Dep. Variable	0.107	0.112	0.107	0.112	0.107	0.112
Adjusted R^2	0.063	0.006	0.062	0.008	0.063	0.005
Observations	2373	2373	2373	2373	2373	2373

Note: $Shock^1$ is the proportional number of days with a temperature below 15 degrees Celsius since birth. $Shock^2$ is the proportional number of days between 15 and 21 degrees Celsius (1 SD below and above the long-run norm). Columns 1-2 estimate exposure effects nine months before birth (fetal period), columns 3-4 during six months before birth(second and third trimester), and 5-6 for three months before birth (third trimester). The estimation is restricted to children aged less than 12 months at the survey time. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 9: Effects of Early-life Exposure on Stunting: Robustness Check

	Exclude					
	(1) None	(2) ZNZ	(3) ZNZ + DSM	(4) ZNZ + Coastal	(5) ZNZ + Coastal + Lake	(6) All Except Highland
Shocks$^{(1)}(-1\sigma)$	0.0018***	0.0019***	0.0021***	0.0017**	0.0022***	0.0020
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0014)
Shocks$^{(2)}(\pm 1\sigma)$	0.0011**	0.0012**	0.0016***	0.0011	0.0021***	0.0010
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0008)	(0.0018)
Controls	Y	Y	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y	Y	Y
Mean of Dep. Variable	0.363	0.368	0.382	0.381	0.388	0.458
Adjusted R^2	0.056	0.058	0.055	0.056	0.059	0.059
Observations	10561	9461	8354	7086	4530	983

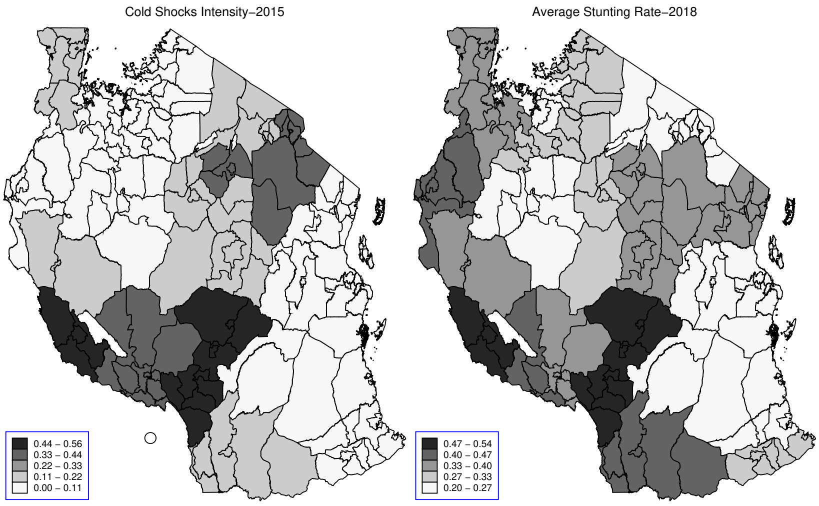
Note: ZNZ-Zanzibar, DSM-Dar es Salaam, Coastal-Coastal Regions, Lake-Lake zone regions, and Highlands-Highland zone regions. The outcome variable is the dummy variable equal to 1 if a child is stunted and 0-otherwise. Shock^1 is the proportional number of days with a temperature below 15 degrees Celsius (1 SD below the long-run norm) since birth. Shock^2 is the proportional number of days between 15 and 21 degrees Celsius (1 SD below and above the long-run norm) since birth. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 10: Effects of Early-life Exposure on Stunting: Sensitivity Check

	(1)	(2)	(3)	(4)
Shocks$^{(1)}$ (-1σ)	0.0009**			
	(0.0005)			
Shocks$^{(2)}$ (-0σ)		0.0008***		
		(0.0003)		
Shocks$^{(3)}$ $(+1\sigma)$			0.0013***	
			(0.0004)	
Shocks$^{(4)}$ $(\pm 1\sigma)$				−0.0001
				(0.0004)
Controls	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y
Adjusted R^2	0.056	0.056	0.056	0.055
Observations	10561	10561	10561	10561

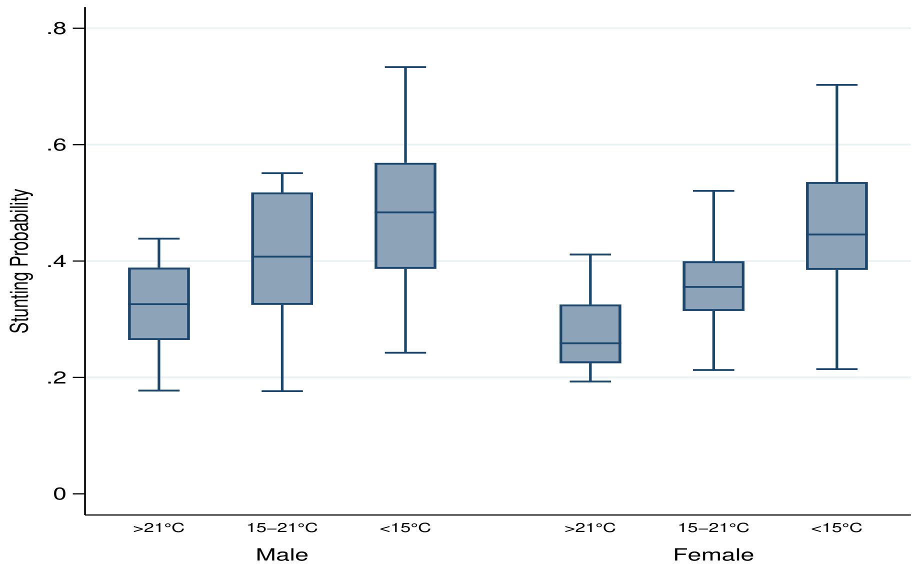
Note: Shocks^1 is the proportional number of days with minimum temperature below 15 degrees Celsius (below 1 SD), Shocks^2 is the proportional number of days with minimum temperature below 18 degrees Celsius (below long-run average), Shocks^3 is the proportional number of days with minimum temperature below 21 degree Celsius (below 1 SD above the mean) and Shocks^4 is the proportional number of days with minimum temperature between 15 and 21 degree Celsius (1 SD below and above the mean). The outcome variable is the dummy variable equal to 1 if a child is stunted and 0-otherwise. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Figure 1: Cold Weather Shocks and Child Stunting in Tanzania



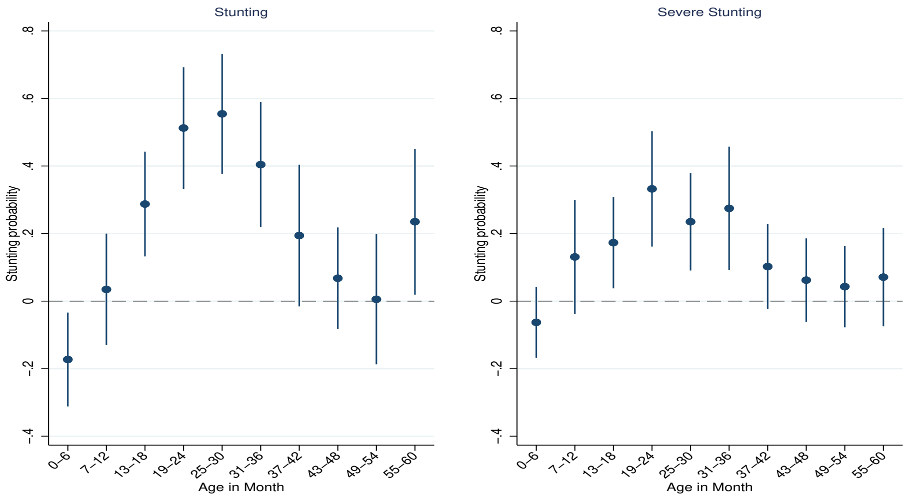
Notes: The left map shows the cold weather intensity in 2015 (proportional number of days for which the minimum daily temperature is below 15°C). The right map shows the region's average stunting rate from the 2018 Nutritional survey.
Source: Author Computation from Global Meteorological Forcing Dataset and 2018 Nutritional survey.

Figure 2: Stunting Heterogeneity by Cold Weather Shocks Intensity



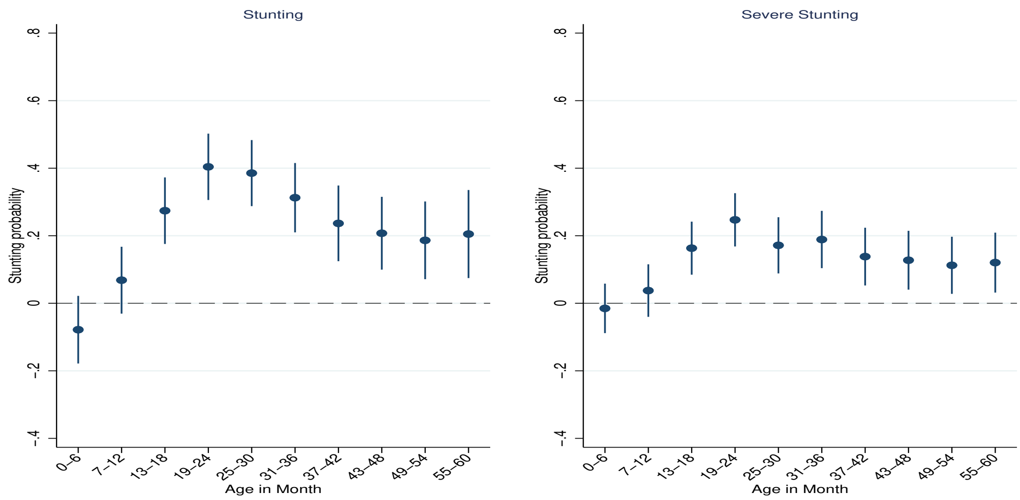
Notes: The horizontal axis shows the range in minimum temperature in degrees Celsius

Figure 3: Effects of Early Life Exposure to Cold Shocks on Stunting Across Age group



Notes: The figure plots coefficient of interaction (x 100) between age group dummy and the intensity of the exposure for 0-15 °C). The left figure plots the heterogeneity effects on stunting, and the right figure plots the effects of severe stunting. All estimates include the demographic and household controls, cohort of birth, survey year, region-by-month of birth and region-by-year fixed results, and other climatic variables controls. The robust standard errors are clustered at the district level. All estimates are at a 95 percent significance level.

Figure 4: Effects of Early Life Exposure to Cold Shocks on Stunting Across Age group



Notes: The figure plots the coefficient of interaction (x 100) between the age group (in months) dummy and the intensity of the exposure for 15-21 °C). The left figure plots the heterogeneity effects on stunting, and the right figure plots the effects of severe stunting. All estimates include the demographic and household controls, cohort of birth, survey year, region-by-month of birth and region-by-year fixed results, and other climatic variables controls. The robust standard errors are clustered at the district level. All estimates are at a 95 percent significance level.

Appendix I

Test for weather shocks endogeneity

The econometric specification presented in section 4.1 provides the causal effects on stunting probability if the weather shocks are purely exogenous. The exogeneity assumption requires that our measure of cold weather shock be orthogonal to other child health determinants. There are three potential sources of violation to this identifying assumption. The first source of violation to the identifying strategy is endogenous migration. Households may migrate from unfavorable to favorable weather conditional on adapting and responding to health outcomes due to weather conditions (Agüero, 2014; Deschênes and Greenstone, 2011). The endogenous migration leads to self-selection, with healthier children staying in the areas with high-frequency cold weather shocks. The TNPS contains information on the year when households started staying in their current location. We utilize this information to test whether estimates suffer from self-selection due to endogenous migration by comparing the effects for non-migrant households and the under-five children sample.

Secondly, child mortality and fetal loss may alter the composition of our sample children in the areas with a high prevalence of cold weather shocks. The child mortality and fetal loss due to cold weather shocks may lead to selection with better health children who survived, leading to biased estimates. We test whether exposure to weather shocks impacts child mortality (24 months or younger at time of death) by utilizing the household death records for the past two years before the survey. Thirdly, due to parental compensatory investment in child health due to cold weather shocks.

Table 11-12 presents the test for the weather shocks endogeneity. As a test for endogenous migration, Table 11 provides the results for the under-five sample (columns 1-2) and non-migrant sub-sample (columns 3-4). We use both child stunting and severe stunting indicators as outcome variables. The results show that the estimated effects are qualitatively and quantitatively similar before and after omitting a migrant sub-sample. This implies that endogeneity due to migration is unlikely and thus does not influence our estimates.

Table 11: Cold Weather Shocks and Endogenous Migration

	Under-five Sample		Non-migrant Sample	
	(1) Stunting	(2) Severe Stunting	(3) Stunting	(4) Severe Stunting
Shocks$^{(1)}(-1\sigma)$	0.0018***	0.0012**	0.0017***	0.0013***
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Shocks$^{(2)}(\pm1\sigma)$	0.0011**	0.0007*	0.0012**	0.0009**
	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Moved Household	−0.0351*	−0.0149		
	(0.0182)	(0.0109)		
Controls	Y	Y	Y	Y
Cohort of Birth FE	Y	Y	Y	Y
Survey Year FE	Y	Y	Y	Y
Region x Month of Birth FE	Y	Y	Y	Y
Region x Survey Year FE	Y	Y	Y	Y
Climatic Controls	Y	Y	Y	Y
Mean of Dep. Variable	0.363	0.145	0.374	0.150
Adjusted R^2	0.057	0.038	0.056	0.037
Observations	10561	10561	8967	8967

Note: Shock^1 is the proportional number of days with a temperature below 15 degrees Celsius (1 SD below the long-run norm) since birth. Shock^2 is the proportional number of days with minimum temperature between 15 and 21 degrees Celsius (1 SD below and above the long-run norm). The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 12 provides the effects of exposure on child mortality. The dependent variable is the child mortality equal 1 for the household that lost a child(ren) aged less than 24 months for the last two years and 0-otherwise. Due to the absence of the month and year of birth of the lost kid, we compute the degree days for the previous 24 months before the survey date. We control for various household covariates and regional-by-year fixed effects. The last two columns, 4 and 5, estimate the impact for rural and urban separately. In all specifications, the results show that exposure to cold weather shocks had an insignificant effect on child mortality. Similar to the previous findings, our results suggest that self-selections due to child survivorship (effects on child mortality) are unlikely. Thus, we conclude that our estimates do not suffer from endogeneity problems.

Table 12: Cold Weather Shocks and Child Mortality

	(1)	(2) Rural	(3) Urban
$\text{Shocks}^{(1)}(-1\sigma)$	−0.0002	0.0001	−0.0017
	(0.0006)	(0.0005)	(0.0016)
$\text{Shocks}^{(2)}(\pm 1\sigma)$	−0.0006	−0.0002	−0.0025
	(0.0006)	(0.0005)	(0.0015)
Controls	Y	Y	Y
Survey Year FE	Y	Y	Y
Region FE	Y	Y	Y
Region x Survey Year FE	Y	Y	Y
Mean of Dep. Variable	0.053	0.048	0.066
Adjusted R^2	0.050	0.061	0.097
Observations	4512	3186	1326

Note: The outcome variable is the dummy variable equal to 1 if the household lost a child aged 0-24 months during the past two years before the survey. Shock^1 is the proportional number of days with a minimum temperature below 15 degrees Celsius (1 SD below the long-run average measured 24 months before the survey month). Shock^2 is the proportional number of days with minimum temperature between 15 and 21 degrees Celsius (1 SD below and above the long-run average) measured 24 months before the survey month. The robust standard errors clustered at the district level are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

제2세션 | 환경과 국제개발

Good Governance and Household Resilience to Natural Disasters: Evidence from Vietnam

발제: **윤 세 미**(서울대 국제대학원)

토론: **정 재 현**(이화여대 국제대학원)

Good governance and household resilience to natural disasters: Evidence from Vietnam

Sungha Jo (Indiana University)
Hyelim Son (University of Seoul)
Semee Yoon (Seoul National University)

KADP
Nov 18, 2022

Motivation

- Need for improving disaster resilience
  - B/t 1960 and 2020, the number of reported natural disasters that caused at least ten deaths and/or 100 affected people has increased more than tenfold (IFRC, 2020).
  - Natural disasters generate socio-economic stressors associated with human survival (IPCC, 2014).
- International community's response to address disaster risk reduction and resilience
  - Adaptation Committee under the United Nations Framework Committee on Climate Change in 2010 (UNFCCC, 2019)
  - SDG 13.1 Climate action "strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries (UN DESA, 2015)"

Motivation

Effects of natural disasters on households in developing countries may be multifaceted:

- governance
  - More resilient households live in villages with more disaster recovery programs (Tan et al. 2020)
  - Households who live in communes with better public infrastructure are more resilient to natural hazards (Arouri et al. 2015; Takahashi, 2020)
- socio-economic variables
  - Female-headed households less resilient to floods in Ghana (Gaisie et al. 2022)
  - Low-income households living in low-lying, flood-prone areas more vulnerable in India (Patankar, 2015)

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This Paper

Question

- Does governance improve households' resilience to floods?
- Are these impacts heterogeneous across different sets of vulnerable groups?

Contribution

- Limited evidence on lower middle-income country context, compared to developed countries
- Understand the dynamics of governance and household-level natural disaster resilience
- Using governance information in a socialist setting

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Literature

- Patterns of natural disaster in developing countries
  - Rise of temperature and precipitation due to climate change will prolong the duration and amplify the magnitude of natural disasters (IPCC, 2012; Eckstein et al. 2020)
  - More people and assets are being concentrated in urban areas that are already at high risk of flooding, storms, typhoons, and hurricanes (Harrison & Williams, 2016; IPCC, 2014)
- Empirical findings on governance and household resilience
  - Most empirical research are based on interviews with government officers and local people
  - Most of quantitative research are based on cross-country analyses
    - Brooks et al. (2005) and Kahn (2015) find that countries with higher World Governance Indicators scores had a smaller number of casualties dues to natural disasters
    - Ferreira et al. (2011) find that governance has a nonlinear effect on the number of fatalities due to floods in developing countries, using the International Country Risk Guide of Political Risk Services

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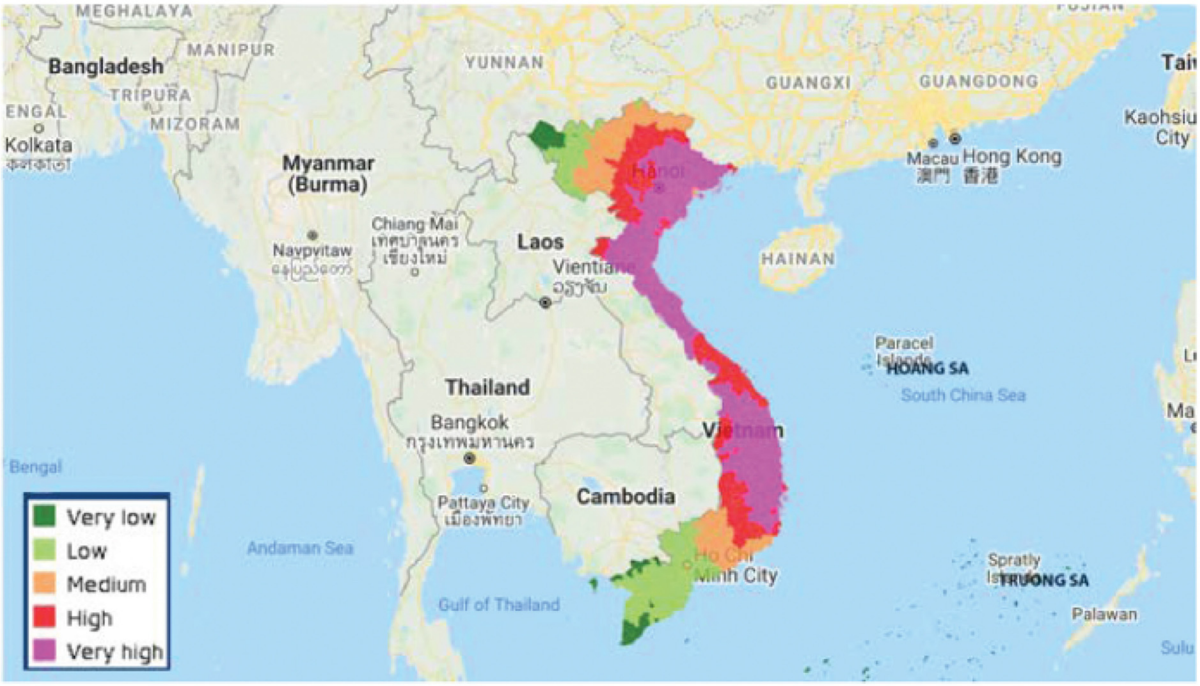
Outline

1. Introduction
   - Motivation
2. Background & Data
   - Data
   - Descriptive stats
3. Estimation Strategy
4. Results
   - Impact of governance on resilience
   - Heterogeneous impacts
5. Take-away

Figure: Storm frequency in Vietnam (UNDP, 2020)



Data

- VHLSS - Vietnam Household Living Standards Survey 2014-2016 (9,396 hh)
- Emergency Events Database (EM-DAT) from the Center of Research on Epidemiology of Disasters
- Vietnam Provincial Governance and Public Administration Performance Index (PAPI) from UNDP
  - 6 dimensions, 92 indicators
  - Participation at local levels, transparency, vertical accountability, control of corruption, public administrative procedures, public service delivery

Descriptive stats

	VHLSS 2014	VHLSS 2016
Ethnic minority	0.17	0.18
	(0.38)	(0.38)
Female household head	0.26	0.25
	(0.44)	(0.43)
HH Head's education level (no. of years)	7.30	7.35
	(3.72)	(3.69)
Ratio of adults aged from 15 to 60	0.65	0.64
	(0.29)	(0.30)
Ratio of members participating in agriculture/aquaculture	0.31	0.29
	(0.33)	(0.33)
Receives remittances	0.030	0.026
	(0.17)	(0.16)
Owns savings account	0.20	0.26
	(0.40)	(0.44)
Membership in an association	0.56	0.57
	(0.50)	(0.50)
Mean value of durables (1,000 dongs)	6.96	7.68
	(38.6)	(43.9)
Crop land area (1,000 m^2)	4504.5	4401.0
	(12054.9)	(12877.4)
Rural	0.70	0.70
	(0.46)	(0.46)
Number of floods	1.34	0.55
	(0.67)	(0.72)
Number of storms	1.45	0.42
	(1.37)	(0.63)
Total PAPI Score	36.5	35.9
	(1.53)	(1.64)

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Estimation Strategy

$$ln(Y_{hpt}) = \alpha_0 + \theta G_{pt} + \delta D_{pt} + \beta DG_{pt} + \mu X_{hpt} + \gamma_p + \eta_t + \epsilon_{hpt} \quad (1)$$

- Y_{hdt}: Log per capita expenditure for household h in province p at time t
- β : the coefficient of interest
- G_{pt} : PAPI score for governance
- D_{pt} : Number of natural disasters in the province
- X_{hpt}: gender of household head, education level of household head, proportion of adults in the household, proportion of hh members working in agriculture, remittance, saving, association membership, ethnic minority, indicator for rural area
- Province and time FE. Standard errors clustered at the province level.

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Governance and household expenditure

	(1)	(2)	(3)
Governance	0.009	0.005	0.005
	(0.006)	(0.006)	(0.005)
Number of floods	-0.016	-1.396**	-1.278**
	(0.013)	(0.632)	(0.598)
Number of storms	0.007	0.801	0.628
	(0.007)	(0.524)	(0.504)
Governance*flood_count		0.384**	0.352**
		(0.175)	(0.166)
Governance*storm_count		-0.221	-0.173
		(0.146)	(0.141)
Ethnic minority			-0.099*
			(0.056)
Female household head			-0.036
			(0.054)
HH Head's education level (no. of years)			0.014**
			(0.006)
Ratio of adults aged from 15 to 60			0.221***
			(0.062)
Ratio of members participating in agriculture/aquaculture			0.130***
			(0.038)
Receives remittances			0.010
			(0.060)
Owns savings account			0.052**
			(0.021)
Membership in an association			0.080***
			(0.020)
Log value of durables			0.008***
			(0.001)
Log(crop land)			0.011**
			(0.005)
Rural			0.098
			(0.108)
Province FE	YES	YES	YES
Observations	18462	18462	18462

Province-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Heterogeneous impact on female-headed households

	Male	Female
Governance	0.008	-0.006
	(0.007)	(0.010)
governance*flood_count	0.185	0.659**
	(0.208)	(0.299)
governance*storm_count	-0.185	-0.076
	(0.162)	(0.284)
Number of floods	-0.674	-2.389**
	(0.751)	(1.080)
Number of storms	0.672	0.264
	(0.581)	(1.024)
HH Head's education level (no. of years)	0.014*	0.006
	(0.007)	(0.012)
Ratio of adults aged from 15 to 60	0.222***	0.241***
	(0.073)	(0.088)
Receives remittances	-0.080	0.097
	(0.071)	(0.083)
Membership in an association	0.107***	0.051
	(0.021)	(0.037)
Rural	0.206*	0.124***
	(0.122)	(0.039)
Province FE	YES	YES
Observations	13785	4677

Province-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Heterogeneous impact by education level of households

	Some secondary education	No secondary education
Governance	0.003	0.001
	(0.007)	(0.007)
governance*flood_count	0.077	0.709***
	(0.288)	(0.235)
governance*storm_count	-0.390	-0.366*
	(0.235)	(0.217)
Number of floods	-0.296	-2.541***
	(1.048)	(0.839)
Number of storms	1.404	1.333*
	(0.844)	(0.778)
Female household head	-0.081	-0.072
	(0.103)	(0.070)
HH Head's education level (no. of years)	0.002	0.021**
	(0.010)	(0.009)
Ratio of adults aged from 15 to 60	0.535***	0.142**
	(0.126)	(0.065)
Receives remittances	-0.172*	0.194**
	(0.087)	(0.084)
Membership in an association	0.078***	0.090***
	(0.028)	(0.022)
Rural	0.862	-0.146
	(0.580)	(0.088)
Province FE	YES	YES
Observations	6948	11514

Province-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Heterogeneous impact by poverty

	Non-poor	Poor
Governance	0.006	0.025
	(0.006)	(0.016)
governance*flood_count	0.344	-0.072
	(0.216)	(0.422)
governance*storm_count	-0.241	-0.224
	(0.159)	(0.455)
Number of floods	-1.246	0.199
	(0.777)	(1.506)
Number of storms	0.871	0.891
	(0.570)	(1.625)
Female household head	-0.080	0.344
	(0.066)	(0.217)
HH Head's education level (no. of years)	0.011*	0.008
	(0.006)	(0.014)
Ratio of adults aged from 15 to 60	0.240***	0.554***
	(0.059)	(0.148)
Receives remittances	-0.012	0.302
	(0.059)	(0.203)
Membership in an association	0.092***	0.034
	(0.021)	(0.054)
Province FE	YES	YES
Observations	16376	2086

Province-clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Take-away

Using a novel index on province-level governance and micro-level evidence on households:

- Good governance remediates impacts of floods, but not storms
- Female-headed households are less resilient to floods but the impact is remediated with better governance
- Households without a single member with secondary education are less resilient, but the impact is remediated with better governance
- Implications on the importance of promoting good governance for disaster risk management

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Thank you!

semee@snu.ac.kr

제2세션 | 환경과 국제개발

Welfare Gains from Trade across Space with Transboundary Air Pollutants

발제: 임 희 현(KDI)

토론: 정 지 원(KIEP)

Welfare gains from trade across space with transboundary air pollutants

Eunhee Lee,
Heehyun Rosa Lim

KADP
Nov 18, 2022

Welfare gains from trade w/ transboundary pollutants

- **Existing understanding of the welfare implications w/ local pollutants**
  - Change in real income → income, price level
  - Change in emission-generating activities
    → location of emission-intensive production
- **Transboundary nature of local pollutants**
  - Nearby: China-Korea (Lee et al., 2017)
  - Long-distance: USA-China (Lin et al., 2014; Zhang et al., 2017)
- **Welfare implications of having large trade partners in proximity**
  - W/o transboundary: lower trade costs
  - W/ transboundary: + large transboundary pollution

Research on trade's impact w/ transboundary pollutants

How would welfare implications change if transboundary nature is considered?

What we do

- Motivational evidence of cross-country transboundary pollution
- Model that adds transboundary nature of local air pollutants
- Quantitative analyses to explore the heterogeneous welfare implications
  - EU enlargement, China shock

Key findings

- Trade shocks affect welfare via changes in
  : real income, own emissions, transboundary pollution from others
- In two shocks, most countries gain, but in heterogeneous magnitude
  - Production and emissions move to liberalized countries
  - Neighboring countries' env. utility decreases due to
    : $\uparrow$ production (input access) and/or $\uparrow$ transboundary pollution
- W/ tighter env. regulation imposed on the liberalized
  : smaller income gains in the liberalized & smaller env. welfare losses in most

Today's presentation

1. Related literature
2. Motivational evidence
3. Quantitative Model
4. Conclusion

Overview

1. Related literature
2. Motivational evidence
3. Quantitative Model
4. Conclusion

Existing research and contributions

Model of trade and the env.: focused on GHG or completely local pollutants

- Copeland and Taylor (2003, 2004), Cherniwchan et al. (2017), Forslid et al. (2018), Shapiro and Walker (2018), Shapiro (2021, 2016), ...
- Transboundary spillovers as another source of environmental externalities

Existence and impact of transboundary pollution spillovers

- Fu et al. (2022), Zheng et al. (2014), Jia and Ku (2019), Jung et al. (2022), Sheldon and Sankaran (2017), ...
- Cross-country pollution transport & Quantitative setting

Pollution haven hypothesis (PHH)

- Branden and Taylor (1998), Chichilnisky (1994), Copeland and Taylor (1994, 1995, 2003), Grossman and Krueger (1993), Taylor (2005), ...
- "Relocated" emissions traveling across borders

Env. impact of EU enlargement and China shock: empirical & decomposition

- Chen et al. (2020), Levitt et al. (2019), de Araujo et al. (2020), Duarte and Serrano (2021), ...
- Decomposition of the change in concentration into own and transboundary

Overview

1. Related literature
2. Motivational evidence
3. Quantitative Model
4. Conclusion

Suggestive link btw concentration & transboundary pollution

$$ln(Concen)_{it} = \psi + \lambda_1 ln(Emi/Land)_{it} + \lambda_2 Meteo_{it} + \kappa \ln(PolTransport)_{it} + \delta_i + \delta_t + \xi_{it}$$

- Country-level panel; i: country (42 cou), t: year (2000-2014)
- $PolTransport_{it} = \sum_{i' \neq i} \frac{Emi_{i't}}{Land_{it'}} \times \frac{1}{Distance^2_{ii't}}$

	(1)	(2) +transboundary	(3) +controls
$ln(Emi/Land)$	0.197***	0.144***	0.177***
	(0.051)	(0.051)	(0.061)
$\ln(PolTransport)$		0.333***	0.291***
		(0.068)	(0.083)
Observations	630	630	429
Within Adj. R^2	0.101	0.131	0.166
YearFE	O	O	O
CountryFE	O	O	O

sample data result

Overview

1 Related literature

2 Motivational evidence

3 Quantitative Model

4 Conclusion

Model of international trade and env. externality

Caliendo and Parro (2015), Shapiro (2016) + traveling local pollutants

- **CES preference**

$$U_i = \underbrace{\left(\prod_j \left(\int_0^1 C_i(e^j)^{\frac{\eta-1}{\eta}\phi_i^j} de^j\right)^{\frac{\eta}{\eta-1}}\right)}_{\text{Utility from consumption}} \underbrace{\left(\frac{1}{1+\left(\frac{1}{\mu_i} g_i(E_1,\ldots,E_N)\right)^2}\right)}_{\substack{\text{Disutility from concentration} \\ \text{(env externality)}}}$$

  - $g_i(\cdot)$: concentration of i resulting from all countries' emissions

- **Perfect competition with Cobb-Douglas production**

$$Q_i^j(e^j) = \left[z_i(e^j)\left(L_i^j\right)^{\gamma_{i,l}^j}\left(K_i^j\right)^{\gamma_{i,k}^j}\left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}\right]^{1-\alpha_i^j}\left[E_i^j(e^j)\right]^{\alpha_i^j}$$

  - $z_i(e^j)$: core productivity $\sim$ Frechet
  - L_i^j, K_i^j, M_i^j, E_i^j: labor, capital, int. input bundle, emission
  - Round-about: final good bundle used for final consumption or as M_i^j

- **Trade**: iceberg trade cost $d_{in}^j \geq 1$

emi

Equilibrium & Quantification

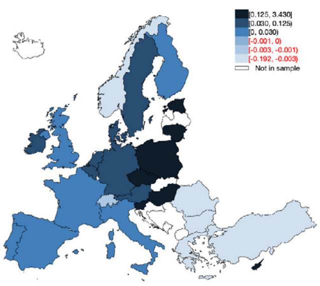
- Goods, labor, and capital market clear
- Solve for the equilibrium in changes (Dekle et al., 2008)
- **Calibration** (to the year 2000)
  - Transboundary travel, $g(\cdot)$: from motivational regression
  - Disutility parameter, μ_i: match $PM_{2.5}$'s marginal social cost
- **Counterfactual scenarios**
  - EU enlargement
  - China's joining the world market (aka. China shock)

sample

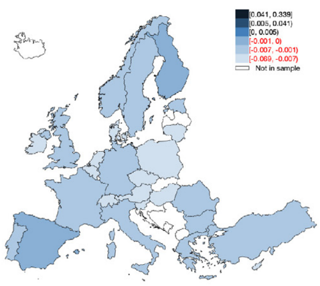
Counterfactual 1. EU enlargement

Actual tariff changes of new EU countries

- Welfare gains in most EU, driven by real income changes
- Spatial heterogeneity in env. changes
  - Higher emission in new members and some existing members (new: market access; existing: cheaper inputs)
  - Higher concentration in most European countries → transboundary pollution



(a) Change in real income (%)

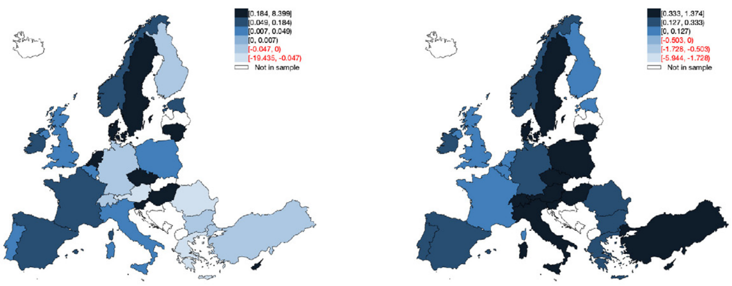


(b) Change in env. ext (%)

Counterfactual 1. EU enlargement

Actual tariff changes of new EU countries

- Welfare gains in most EU, driven by real income changes
- Spatial heterogeneity in env. changes
  - Higher emission in new members and some existing members (new: market access; existing: cheaper inputs)
  - Higher concentration in most European countries → transboundary pollution



(a) Change in emission (%)   (b) Change in concentration (%)

Counterfactual 1. EU enlargement

+ Stricter regulation on new members $\hat{t}_{new} = 1.2$

- New members: smaller welfare gains
  - Limited increase in real income & Gains in env. utility
- Existing members: larger welfare gains
  - Less increase in transboundary pollution

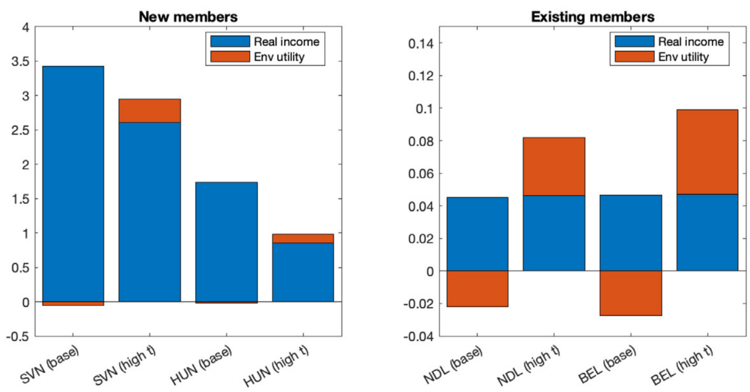


Figure: Welfare changes (%)

china

Overview

1. Related literature
2. Motivational evidence
3. Quantitative Model
4. Conclusion

Conclusions

What are welfare gains from trade when local pollutants travel?

Key findings

- Heterogeneous welfare impact due to changes in
  : real income, own emissions, transboundary pollution from others
- Neighboring countries affected via input access & transboundary pollution
- With stricter env. regulation on the liberalized,
  → Smaller env. welfare losses in most & income gains in the liberalized

Discussions

- Role of incorporating env. policies into trade agreements
- Incentives for the balance between excessive env. harm and economic gains
- General, tractable framework with broad applications
  - A wide range of pollutants (GHG $\sim$ strictly local)
  - Optimal international policies

Additional slides

Motivational evidence – sample countries

Table: Motivational evidene sample countries

AUS	Australia	IND	India
AUT	Austria	IRL	Ireland
BEL	Belgium	ITA	Italy
BGR	Bulgaria	JPN	Japan
BRA	Brazil	KOR	Korea
CAN	Canada	LTU	Lithuania
CHE	Switzerland	LUX	Luxembourg
CHN	China	LVA	Latvia
CYP	Cyprus	MEX	Mexico
CZE	Czech Republic	MLT	Malta
DEU	Germany	NLD	Netherlands
DNK	Denmark	NOR	Norway
ESP	Spain	POL	Poland
EST	Estonia	PRT	Portugal
FIN	Finland	ROU	Romania
FRA	France	RUS	Russia
GBR	United Kingdom	SVK	Slovak Republic
GRC	Greece	SVN	Slovenia
HRV	Croatia	SWE	Sweden
HUN	Hungary	TUR	Turkey
IDN	Indonesia	USA	United States

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Motivational evidence – data & measurement

- **$PM_{2.5}$ emission**: aggregate of country-sector-level emissions (EDGAR)
- **$PM_{2.5}$ concentration**: annual average (Atmospheric Composition Analysis)
- **Trade openness**: ratio of total trade to GDP (WB WDI)
- **Upstreamness**: country-level GVC position (Antras and Chor, 2018)
- **PTA**: share of trade flows made with partner countries of PTAs with env. provisions (WB DTA)
- **Meteorology**: precipitation and temperature (WB CCKP)
- **Env. tech**: # env patents per capita (OECD)
- **Transboundary transport of $PM_{2.5}$**: exposure to other countries' emissions
  - Distance (CEPII GeoDist), land area (WB WDI)

$$PolTransport_{it} = \sum_{i' \neq i} \frac{E_{i't}}{land_{it'}} \times \frac{1}{distance^2_{ii't}}$$

- Others: GDPpc, pop. density, urban pop. share (WB WDI), railway density (OECD)

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Motivational evidence – *PolTransport*

Table: Top and bottom 5 *PolTransport*

	Top 5		Bottom 5
1	Austria	38	Mexico
2	Slovak Republic	39	Canada
3	Germany	40	United States
4	Belgium	41	Australia
5	Netherlands	42	Brazil

back

Motivational evidence – results

Table: Determinants of $PM_{2.5}$ emissions

	(1)	(2)	(3)
GDPpc	30.149***	20.620***	18.867**
	(5.330)	(7.592)	(7.446)
GDPpc^2	-244.977***	-163.162***	-147.311***
	(37.526)	(56.208)	(54.994)
Tech	-33.906***	-27.102**	-28.520**
	(11.311)	(10.944)	(11.128)
Trade	0.073	0.017	0.130
	(0.046)	(0.060)	(0.086)
Upstream	0.300***	0.268**	0.247*
	(0.107)	(0.127)	(0.127)
PTAenv		0.155***	0.323***
		(0.047)	(0.068)
Trade × *PTAenv*			-0.156**
			(0.066)
Number of Observations	630	630	630
Within Adj. R-squared	0.111	0.142	0.151

back

Motivational evidence – results

Table: Determinants of $PM_{2.5}$ emissions

	(1)	(2)	(3)
GDPpc	32.317***	21.339***	20.563***
	(5.408)	(7.820)	(7.729)
GDPpc^2	-257.295***	-168.854***	-157.227***
	(37.848)	(57.355)	(56.719)
Tech	-32.600***	-26.638**	-27.479**
	(11.292)	(10.939)	(11.109)
Export	0.431**	0.270	0.577**
	(0.173)	(0.196)	(0.263)
Import	-0.342*	-0.296	-0.387
	(0.199)	(0.209)	(0.252)
Upstream	0.220*	0.237*	0.193
	(0.113)	(0.142)	(0.144)
PTAenv (ex)		0.290**	0.471**
		(0.120)	(0.221)
PTAenv (im)		-0.151	-0.185
		(0.137)	(0.250)
Export × *PTAenv* (ex)			-0.411
			(0.281)
Import × *PTAenv* (im)			0.113
			(0.247)
Number of Observations	630	630	630
Within Adj. R-squared	0.116	0.148	0.155

back

Motivational evidence – results

Table: Determinants of $PM_{2.5}$ concentration

	(1)	(2)	(3)
ln(emission/land)	0.197***	0.144***	0.177***
	(0.051)	(0.051)	(0.061)
Temp Ave	-0.042***	-0.042***	-0.032*
	(0.015)	(0.015)	(0.018)
Temp SD	0.021	0.022	0.028*
	(0.014)	(0.014)	(0.015)
Rain Ave	-0.003***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)
Rain SD	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)
ln(PolTransport)		0.333***	0.291***
		(0.068)	(0.083)
ln(population density)			0.119
			(0.194)
Share of urban population			1.665*
			(0.911)
ln(rail density)			0.482***
			(0.131)
Technology			-4.216
			(3.490)
Number of Observations	630	630	429
Within Adj. R-squared	0.101	0.131	0.166

back

Emission, tax, and abatement

Follow Copeland and Taylor (2003) for modeling emission from production

- All firms make and abate emissions, which are taxed at country-level (t_i)
- Emission elasticity at α_i^j

$$E_i^j(e^j) = \left(1 - \kappa_i^j(e^j)\right)^{\frac{1}{\alpha_i^j}} F_i^j(e^j)$$

- Use a fraction κ_i^j of potential output for abatement

$$Q_i^j(e^j) = \left(1 - \kappa_i^j(e^j)\right) \underbrace{z_i(e^j)\left(L_i^j\right)^{\gamma_{i,l}^j}\left(K_i^j\right)^{\gamma_{i,k}^j}\left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}}_{\text{Potential output from core inputs} = F_i^j(e^j)}$$

- Equivalent to a production function using emission as Cobb-Douglas factor

$$\begin{aligned} Q_i^j(e^j) &= F_i^j(e^j)^{1-\alpha_i^j}\left[E_i^j(e^j)\right]^{\alpha_i^j} \\ &= \left[z_i(e^j)\left(L_i^j\right)^{\gamma_{i,l}^j}\left(K_i^j\right)^{\gamma_{i,k}^j}\left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}\right]^{1-\alpha_i^j}\left[E_i^j(e^j)\right]^{\alpha_i^j} \end{aligned}$$

back

Firm-level emission intensity

- Abatement fraction

$$\kappa_i^j(e^j) = 1 - \left(\frac{\alpha_i^j p_i^j(e^j)}{t_i}\right)^{\frac{\alpha_i^j}{1-\alpha_i^j}}$$

- Emission per output

$$\varphi_i^j(e^j) \equiv \frac{E_i^j(e^j)}{Q_i^j(e^j)} = \frac{\alpha_i^j p_i^j(e^j)}{t_i}$$

back

International trade

- Unit cost

$$c_i^j = \Upsilon_i^j t_i^{\alpha_i^j}\left(w_i^{\gamma_{i,l}^j} r_i^{\gamma_{i,k}^j} P_i^{(1-\gamma_{i,l}^j-\gamma_{i,k}^j)}\right)^{(1-\alpha_i^j)}$$

- Trade share

$$\pi_{in}^j = \frac{A_i^j\left(c_i^j d_{in}^j\right)^{-\theta^j}}{\sum_{i'} A_{i'}^j\left(c_{i'}^j d_{i'n}^j\right)^{-\theta^j}} = \frac{X_{in}^j}{X_n^j}$$

- Sector-level exact price index

$$P_n^j = \left[\Gamma\left(\frac{\theta^j+1-\sigma}{\theta^j}\right)\right]^{1/(1-\sigma)}\left[\sum_{i'} A_{i'}^j\left(c_{i'}^j d_{i'n}^j\right)^{-\theta^j}\right]^{-1/\theta^j}$$

- Aggregate emissions

$$E_i = \sum_j E_i^j = \sum_j \frac{\alpha_i^j}{t_i}\sum_{n'}\frac{\pi_{in'}^j}{1+d_{in'}^j}X_{n'}^j$$

$X_{n'}^j$: n''s total expenditure in sector j
$\pi_{in'}^j$: trade share of sector j from i to n' in $X_{n'}^j$

back

Market clearing

- Sectoral expenditure

$$X_n^j = \phi_n^j \sum_{j'} (1-\alpha_n^{j'})(1-\gamma_{n,l}^{j'}-\gamma_{n,k}^{j'}) \sum_{n'} \frac{\pi_{nn'}^{j'}}{1+\tau_{nn'}^{j'}} X_{n'}^{j'} + \phi_n^j I_n$$

- Labor and capital market clearing

$$w_n L_n = \sum_{j'} \gamma_{n,l}^{j'} (1-\alpha_n^{j'}) \sum_{n'} \frac{\pi_{nn'}^{j'}}{1+\tau_{nn'}^{j'}} X_{n'}^{j'}$$

$$r_n K_n = \sum_{j'} \gamma_{n,k}^{j'} (1-\alpha_n^{j'}) \sum_{n'} \frac{\pi_{nn'}^{j'}}{1+\tau_{nn'}^{j'}} X_{n'}^{j'}$$

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Quantification sample countries

AUS	Australia	IND	India
AUT	Austria	IRL	Ireland
BEL	Belgium	ITA	Italy
BGR	Bulgaria	JPN	Japan
BRA	Brazil	KOR	Korea
CAN	Canada	LTU	Lithuania
CHE	Switzerland	MEX	Mexico
CHN	China	NLD	Netherlands
CYP	Cyprus	NOR	Norway
CZE	Czech Republic	POL	Poland
DEU	Germany	PRT	Portugal
DNK	Denmark	ROU	Romania
ESP	Spain	ROW	Rest of the World
EST	Estonia	RUS	Russia
FIN	Finland	SVN	Slovenia
FRA	France	SWE	Sweden
GBR	United Kingdom	TUR	Turkey
GRC	Greece	TWN	Taiwan, China
HUN	Hungary	USA	United States
IDN	Indonesia		

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Quantification sample sectors

A	Agriculture/Forestry/Fishing
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31-C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D/E/F	Utilities/Construction
H	Transportation
Other	Other services

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Calibrated parameters

- $g(\cdot)$ parameters

$\hat{\psi}$	$\hat{\gamma}_1$	$\hat{\gamma}_2$				$\hat{\kappa}$	$\hat{\delta}_i$	$\hat{\delta}_{2000}$
		Temp Ave	Temp SD	Rain Ave	Rain SD			
-0.329	0.144	-0.042	0.022	-0.003	0.001	0.333	*varies*	0.12

- Social cost of marginal emission of $PM_{2.5}$
  - US: median of the range from Heo et al. (2016)
  - Non-US countries

$$sc_{i \neq US} = sc_{US} \times \frac{popdensity_i}{popdensity_{US}} \times \left(\frac{GNIpc_i}{GNIpc_{US}}\right)^{\nu}$$

$\nu = 1.103$ from Viscusi and Masterman (2017)

- Disutility parameter

$$\mu_i^2 = -\frac{2g_i l_i}{sc_i} \times \sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k - g_i^2$$

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Social cost estimates

Table: Unit: mn 2005 USD/ton

AUS	Australia	-0.009	IDN	Indonesia	-0.008
AUT	Austria	-0.306	IND	India	-0.019
BEL	Belgium	-1.027	IRL	Ireland	-0.188
BGR	Bulgaria	-0.022	ITA	Italy	-0.499
BRA	Brazil	-0.012	JPN	Japan	-1.098
CAN	Canada	-0.011	KOR	Korea	-0.600
CHE	Switzerland	-1.071	LTU	Lithuania	-0.033
CHN	China	-0.019	MEX	Mexico	-0.029
CYP	Cyprus	-0.212	NLD	Netherlands	-1.603
CZE	Czech Republic	-0.142	NOR	Norway	-0.084
DEU	Germany	-0.630	POL	Poland	-0.072
DNK	Denmark	-0.537	PRT	Portugal	-0.159
ESP	Spain	-0.177	ROU	Romania	-0.035
EST	Estonia	-0.028	RUS	Russia	-0.004
FIN	Finland	-0.054	SVN	Slovenia	-0.138
FRA	France	-0.322	SWE	Sweden	-0.078
GBR	United Kingdom	-0.690	TUR	Turkey	-0.050
GRC	Greece	-0.153	TWN	Taiwan, China	-0.673
HUN	Hungary	-0.084	USA	United States	-0.109

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μ_i^2 estimates

Table: Unit: $\times 10^{-4}$

AUS	Australia	0.0031	IDN	Indonesia	0.0567
AUT	Austria	0.0073	IND	India	1.2518
BEL	Belgium	0.0019	IRL	Ireland	0.0008
BGR	Bulgaria	0.0080	ITA	Italy	0.0261
BRA	Brazil	0.1776	JPN	Japan	0.0034
CAN	Canada	0.0090	KOR	Korea	0.0035
CHE	Switzerland	0.0021	LTU	Lithuania	0.0055
CHN	China	0.3891	MEX	Mexico	0.0373
CYP	Cyprus	0.0008	NLD	Netherlands	0.0026
CZE	Czech Republic	0.0115	NOR	Norway	0.0013
DEU	Germany	0.0237	POL	Poland	0.0540
DNK	Denmark	0.0020	PRT	Portugal	0.0014
ESP	Spain	0.0091	ROU	Romania	0.0208
EST	Estonia	0.0017	RUS	Russia	0.1663
FIN	Finland	0.0061	SVN	Slovenia	0.0031
FRA	France	0.0161	SWE	Sweden	0.0031
GBR	United Kingdom	0.0060	TUR	Turkey	0.0311
GRC	Greece	0.0075	TWN	Taiwan, China	0.0007
HUN	Hungary	0.0169	USA	United States	0.0994

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Counterfactual 2. China shock

- $\hat{d}_{i,China} = \hat{d}_{China,i} = 0.8$, all else equal
  - Welfare gains (albeit heterogeneous size) in most countries
    - Mostly driven by real income changes
  - Increase in env. disutility in some countries
    - China: increased emissions from increased production
    - Neighbors (Japan, Korea, Taiwan, Indonesia)
      : increased emissions $<$ transboundary pollution

- $+$ Stricter regulation on China's emissions $\hat{t}_{China} = 1.2$
  - China: smaller gain in real income & reduction in concentration
  - Neighbors: larger welfare gains from smaller transboundary pollution
    - Ex) Korea -0.14% $\rightarrow$ -0.007% in env. utility

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Welfare Gains from Trade across Space with Transboundary Air Pollutants*

Eunhee Lee†
Heehyun Rosa Lim‡

November 2022

Abstract

This paper re-examines the welfare gains from international trade by incorporating the transboundary nature of air pollutants and studies how various trade policies can shape the spatial distribution of welfare gains from trade and air pollution. We build a general equilibrium model of international trade and environmental externality from local pollutants of transboundary nature, in which the concentration of a country is affected by both its own and other countries' emissions. The model shows that the change in welfare can be decomposed into the change in real income and the change in air pollutant concentration, the latter of which can further be decomposed into that driven by own emissions and by other countries' emissions. We use this model to quantify the welfare implications of two trade shocks, China shock and the EU 2004 enlargement, and show that welfare consequences of a trade shock can be heterogeneous across countries, depending on how the trade shock affects the spatial distribution and the spillover of emissions. We also show that trade policies with stricter environmental regulations can lead to larger welfare gains from trade.

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†University of Maryland, College Park; Federal Reserve Board of Governors Email: eunhee.s.lee@gmail.com
‡Korea Development Institute. Email: heehyun.rosa.lim@kdi.re.kr

1 Introduction

This paper re-examines the welfare gains from international trade by incorporating the transboundary nature of air pollutants and studies how various trade policies can shape the spatial distribution of welfare gains from trade and air pollution. Air pollutants, such as particulate matters, sulfur dioxide, and nitrogen oxides, are called "local pollutants" since they are considered to have localized effects in both environmental and health aspects, unlike "global pollutants" such as greenhouse gases. Thus, it is common that the literature that studies the change in these local air pollutants has focused on the region- or country-level local effects (Duarte and Serrano 2021, He 2005, Vennemo et al. 2008). In other words, the environmental externality of local pollutants is typically assumed to stay entirely at the location of emission. However, these pollutants actually do travel across the border, which is known as their "transboundary" nature. The atmospheric science literature shows that the transboundary air pollution is not just a matter of countries that share borders (Lee et al. 2017) and shows that air pollutants make a long-distance transport, for example between China and the US (Lin et al. 2014, Zhang et al. 2017).

The consideration of transboundary nature is important when we try to understand the welfare implications of trade policies since it affects the level and the dispersion of welfare gains across countries. This feature leads us to think about the so-called gravity relationship in international trade from a different angle from the traditional one. For example, in the gravity model, being close to large trade partners means lower aggregate trade costs and higher gains from trade. With the transboundary nature of air pollutants, however, the welfare implications of proximity to large trade partners can be offset by potentially higher transboundary pollution from them if they rely on relatively dirty production technologies.

In this paper, we build the transboundary nature of local pollutants into a general equilibrium model of trade and the environment. This model allows us to quantify the welfare consequences of trade shocks and decompose the spatially heterogeneous welfare gains into changes in three main sources – real income, own emissions, and transboundary pollution. The quantitative effect of trade shocks on welfare through its impact on tranboundary pollution will be a unique feature that generates interesting spatial heterogeneity. We use the model to investigate the welfare effects of two well-known trade liberalization episodes: China's joining the world market, featuring lower trade costs (henceforth, China shock); the EU 2004 enlargement. We focus particularly on the environmental externality from particulate matter 2.5 ($PM_{2.5}$) pollution. Specifically, we show that there arise not only the relocation of production and emissions to liberalized countries but also heterogeneous welfare implications across countries depending on their economic and geographic proximity to liberalized countries. This result sheds light on the importance of understanding multiple layers of environmental externalities of trade policies. Furthermore, we use our model to simulate the welfare effect of trade liberalization with or without more stringent environmental regulations imposed on liberalized countries.

To motivate our paper's focus on transboundary transport of air pollution, we run a set of multi-country panel regressions that explore the linkage between economic activities, $PM_{2.5}$ emissions, and $PM_{2.5}$ concentration, using a balanced panel on 42 countries from 2000 to 2014. We run two separate regressions: one linking trade and emissions and the other linking concentration with own emissions and transboundary pollution. While this approach is not a two-stage analysis, strictly speaking, by running two separate regressions we can break down how trade and concentration are linked. This link is first established through the response of each country's own emissions to trade, and then through other countries' emissions that may travel across the border. We construct a variable that measures the exposure to transboundary pollution from other countries for each country, by summing up other countries' emissions adjusted by emitting countries' size and the distance between emitting and receiving countries. The regression result shows that a country's $PM_{2.5}$ concentration is correlated with this transboundary transport measure – even after we control for multiple factors that affect concentration, such as meteorology, own emissions, and the density of industrial activities. This result suggests the role of transboundary pollution from other countries in a country's $PM_{2.5}$ concentration level and underlines the need to incorporate it in understanding the role of trade policies on air pollutant concentration.

We then build a general equilibrium model of international trade and environmental externality from local pollutants with transboundary nature. The objective of the model is to introduce a framework to think about how the transboundary nature of local pollutants shapes the heterogeneous welfare effect of trade shocks across countries as well as to lay out a framework for quantifying such relationship. We build on Caliendo and Parro (2015) for multi-country and multi-industry trade framework and introduce environmental externality, similar to that in Shapiro (2016). The novelty of our model is that we allow the concentration of a country to be affected by both its own and other countries' emission, thus incorporating the transboundary nature of local pollutants. The model shows that the change in welfare can be decomposed into the change in real income and the change in air pollutant concentration, the latter of which can be further decomposed into that driven by own emissions and by other countries' emissions.

We use this model to quantitatively assess the welfare implications of trade shocks after taking the environmental externality including transboundary pollution into account. We parametrize the formation of air pollutant concentration, using the estimates from the motivational regression, and calibrate the model to the year 2000's multi-country dataset.

We study two counterfactual exercises: China shock and EU 2004 enlargement. The China shock makes a useful counterfactual scenario since it has been discussed extensively in the literature on its consequences in various aspects and also because there have been discussions on transboundary air pollution within the region. EU enlargement also makes an apposite scenario since both new and existing member countries are all close to each other, so the magnitude of transboundary transport of air pollution would be large. Our focus of the counterfactual exercises is to study the change in welfare and decompose such change into different drivers – including real income, own emissions, and transboundary pollution – and see how they shape heterogeneous welfare consequences across countries. In addition, by running an additional scenario for each event, in which we impose more stringent environmental regulations on China and new EU members, respectively, we investigate the effect and welfare implications of combining trade and environmental policies.

In the China shock exercise, with a cut in trade costs to and from China, most countries experience welfare gains but in a heterogeneous magnitude. The decomposition shows that the gains from the increased real income are partially offset by the rise in concentration in some countries. These countries include not only China, whose comparative advantage improve due to the cut in trade costs and production increase, but also neighboring countries, such as Japan and Korea. The latter group's concentration levels increase due to both increased their own emissions and increased transboundary pollution from countries in proximity including China. When an additional environmental regulation is imposed on China, we see a smaller increase in concentration and, thus, smaller welfare loss from the environmental aspect, in both China and these neighboring countries.

In the EU enlargement counterfactual exercise, we impose the actual decrease in tariff rates between new and existing EU member countries. This counterfactual has a similar set of results to the ones from the China shock. First, while both new and existing members experience welfare gains, the former gains much more than the latter, mostly driven by larger increases in real income. Second, production increases in both new members and the countries that source cheaper inputs from new members. Emissions and concentration increase in these countries, which lowers their environmental utility. The level of concentration increases in many of the existing member countries as well, since the increased emissions from neighboring countries travel across borders, indicating that the effect of pollution relocation is abated. When new members are imposed stricter environmental regulations at joining the EU, the concentration levels of both new and existing members are lower than the scenario without additional regulations, as both the emissions made within borders and that travel across borders decrease. Thus, the overall welfare gains among existing members are larger while the gains among new members are smaller, the latter of which is due to higher production costs and deteriorated competitiveness.

The counterfactual results highlight potentially important policy implications of incorporating environmental policies into trade agreements (or vice versa). Pollution relocation effects of trade agreements are often the subject of heated discussions. In the context of local pollutants, the discussion over pollution relocation centers on the unequal environmental consequences between developed and developing countries, the latter of which usually have laxer regulation and attract emission-intensive industries at the event of trade liberalizations. But our paper shows that due to the transboundary nature of local pollutants, the concentration and, thus, environmental aspect of welfare in developed countries are also affected by the increase in emissions in developing countries that join trade agreements. Thus, there exist incentives among a larger group of countries to consider including environmental provisions in trade agreements to find a balance between excessive environmental harm and economic gains.

Related Literature

This paper is related to several strands of literature. First, this paper builds on a large body of literature on trade and the environment. We follow the model framework from Copeland and Taylor

(2003) in which emissions are generated as a byproduct of production (Cherniwchan et al. 2017, Copeland and Taylor 2004, Forslid et al. 2018, Shapiro 2016; 2021, Shapiro and Walker 2018). It allows us to incorporate emissions into a macro-trade framework in a simple and tractable way to understand the impact of trade liberalization on countries' emission-generating activities and, thus, air pollution. In particular, our paper builds on the recent works that add environmental aspects into a structural gravity framework (Shapiro 2016; 2021, Shapiro and Walker 2018). These works study the impact of trade policies on emissions and welfare in a general equilibrium, quantitative setting, building on either Eaton and Kortum (2002) or Melitz (2003) frameworks. They quantify the change in emissions and welfare driven by either historical or counterfactual trade policies. For example, Shapiro and Walker (2018) decompose the role of trade in the clean-up of US manufacturing air pollutant emissions, and Shapiro (2016) quantifies the change in carbon emissions from international trade liberalizations.

Our contribution is that we consider the transboundary nature of local air pollutants, such as nitrogen oxides (NO_x), sulfur dioxides (SO_2), and particulate matters (PM_{10} and $PM_{2.5}$). In the existing works in this literature, emissions are modeled as either completely local or completely global. On one hand, the papers that study local air pollutants focus on how the change in market size or production cost or both affect emission-generating activities in a country – for example, see Shapiro and Walker (2018). On the other hand, greenhouse gases are completely global; in other words, the impact of emissions on one country does not depend on the source of emissions.[1] Thus, what matters in those papers that study global pollutants is the sum of all countries' emissions (Akerman et al. 2021, Forslid et al. 2018, Shapiro 2016; 2021).

While local air pollutants are 'more local' than global pollutants, they do travel across borders. Thus, it is important to take such transboundary spillovers into account to capture environmental externalities comprehensively. To address this, we estimate the extent of transboundary transport across countries, using a reduced-form regression, and incorporate the estimates into our quantitative analyses to quantify the welfare impact of trade liberalizations via own emissions and transboundary pollution. Especially, we add emissions and transboundary pollution to Caliendo and Parro (2015), which incorporate an input-output linkage in a multi-country, multi-industry setting. Although we use a simplified version of the input-output linkage, having an intermediate input in the model is important since input sourcing and transboundary pollution are closely related to the distance between countries. Countries tend to form a production cluster with those in proximity – for example, think of those in Europe or Asia – and these countries are also more likely to be affected by cross-border pollution.

This paper is not the first paper in the literature to acknowledge and study the transboundary transport of air pollution. Extant work shows that transboundary pollution spillover exists, estimating the change in one region's concentration caused by a change in another region's emissions

[1] But this does not mean that the welfare impact of additional emissions should be the same across countries. The consequences of global warming can be realized in a different manner and magnitude geographically. In addition, countries may experience a heterogeneous degree of disutility from the same environmental shock according to their income level or other elements in the utility function.

or concentration (Fu et al. 2022, Zheng et al. 2014). Moreover, some papers study the impact of such air pollution spillover on economic and health outcomes (Jia and Ku 2019, Jung et al. 2022, Sheldon and Sankaran 2017) or how local governments' pollution regulations respond to such spatial externalities (Boskovic 2015, Wang and Wang 2021).[2] We make two contributions to this body of literature. First, unlike these papers that estimate the transboundary pollution across cities within a country, we find evidence for cross-border pollution transport, using multi-country panel data.[3] Second, our paper complements the existing studies, which focus on empirical evidence, by incorporating the idea of transboundary transport into a tractable, structural model and quantifying the impact of different policy scenarios. To our best knowledge, this paper is the first to apply the transboundary nature in the context of understanding the interaction between trade and the environment in a quantitative setting.

Lastly, this paper contributes to the body of literature that looks at the pollution haven hypothesis (PHH) prediction of trade liberalizations (Brander and Taylor 1998, Chichilnisky 1994, Copeland and Taylor 1994; 1995; 2003, Grossman and Krueger 1993). The PHH claims that pollution-intensive industries would move to countries with lax environmental regulations after trade barriers are reduced. There has been scant evidence and little consensus on the PHH. One reason is that there are other factors that affect countries' comparative advantage, such as factor abundance, which may offset the pollution haven effect (see Taylor (2005) for a more detailed discussion on the PHH).[4] This paper presents another aspect to consider when we discuss potential environmental consequences of trade liberalizations, including the PHH. We show that even if pollution-intensive industries are relocated to those countries with less stringent environmental regulation – that is, *even if* the PHH holds initially – we should take how the "relocated" emissions travel across borders into consideration to capture the ultimate heterogeneous welfare implications across countries.

Specifically, several papers discuss the environmental consequences of two trade liberalization episodes that we look at in our counterfactual: China's WTO accession and EU enlargement. For example, Chen et al. (2020) empirically find that trade expansion increased $PM_{2.5}$ and SO_2 pollution in China, using county-level panel data between 2000 and 2013. They show that trade expansion has contributed to a 60% and 20% increase in those two pollutants' concentration levels, respectively. Levitt et al. (2019) look at the other side of the story by estimating the impact on China's WTO trade partner countries. They find that the consumption-based greenhouse gas (GHG) emissions increased in these countries while the production-based emissions decreased. Specifically, they show that the emissions embodied in imports increased in total and became dirtier, highlighting that this indicates GHG emissions offshoring. Our contribution to these works is that we combine these two

[2]In the science literature, the transboundary nature of air pollution has been heavily discussed (Lin et al. 2014, Liu et al. 2009, Verstraeten et al. 2015, Zhang et al. 2017). They use chemical transport models (CTMs) to relate source emissions and receptor concentrations, which are usually computationally expensive and specific.

[3]Many works in the environmental science literature find evidence of cross-border pollution transport (Akimoto 2003, Jaffe et al. 1999, Lin et al. 2014, Liu et al. 2009, Verstraeten et al. 2015, Zhang et al. 2017). For example, Lin et al. (2014) show that 3-10% of sulfate concentrations in the western US are from the transport of the trade-related Chinese air pollution in 2006.

[4]The pollution haven effect (PHE) argues that less stringent environmental policy improves comparative advantage. The PHE is a necessary condition for the PHH to hold.

sides of a coin by building a tractable quantative model, which allows us to dissect the multi-facted linkages between countries.

In addition, a few papers decompose the actual change in emissions after these trade liberalizations to understand the sources of the change. For instance, de Araujo et al. (2020) divide the change in CO_2 emissions into the change in technology, sourcing, and consumption and show that the sourcing-related emissions increased in the new EU members and China while decreased in the old EU members and the USA between 1995 and 2007. Duarte and Serrano (2021) conduct a similar decomposition but focus on the $PM_{2.5}$ emissions embodied in exports from the new EU member countries to the old EU countries.[5] We complement these works by providing a decomposition of the change in concentration in each country into the change in own emissions and the change in emissions that travel from other countries. By doing so, we highlight that we need to consider the transboundary transport of pollution to truly understand the environmental implications of these liberalization events on both liberalized and partner countries. Moreover, this paper can be used or easily adjusted to study the implications of any future liberalization events.

2 Empirical Evidence

To motivate how we conceptualize the transboundary transport of air pollutants, we establish the relationship between trade and $PM_{2.5}$ concentration by running two panel regressions. First, we establish a linkage between a country's participation in trade and its own emission (step 1). We then show the role of a country's own emissions and that of the emissions traveling from other countries on a country's concentration of $PM_{2.5}$ (step 2). Breaking down our analysis into two steps allows us to understand the separate channels through which trade affects the concentration level of a country – through changing other countries' emissions that may travel across the border as well as its own emission levels. It is important to note that this section is purely motivational and is not making any causal statements. Before going into empirical specifications in more detail, we discuss data and measurements in the following subsection.

2.1 Data and Measurement

We combine multiple data sources to have balanced panel data on $PM_{2.5}$, trade, and other country-level controls. We include not only trade and other economic activities but also several other factors that affect the level of emissions and concentration such as meteorological information. Our sample is a balanced panel of 42 countries from 2000 to 2014.[6] Table A.1 in the Appendix shows the list of sample countries.

[5] In addition, a few papers use an environmental computable general equilibrium (CGE) model to simulate the change in emissions based on scenarios of China's liberalization or EU enlargement (He 2005, Vennemo et al. 2008, Zhu and van Ierland 2006). But these papers do not analyze concentration changes. They also look at the limited set of countries – only China (He 2005, Vennemo et al. 2008) or the EU countries (Zhu and van Ierland 2006) – and, thus, are abstract from heterogeneous consequences across countries.

[6] The sample countries are composed of the countries from the World Input-Ouput Database (WIOD) except for Taiwan which does not have meteorology data.

PM 2.5 First of all, we need the level of both emissions and concentration of $PM_{2.5}$ for each country. Country-level $PM_{2.5}$ emissions are from the Emission Database for Global Atmospheric Research (EDGAR) 5.0 version (Crippa et al. 2020), which provides annual emissions for greenhouse gases and local air pollutants, including $PM_{2.5}$, per sector and country for 1970-2015. EDGAR calculates emissions based on the emission factor approach, using the detailed information on the emission factor of each activity and different emission-reducing technology installations.[7] We aggregate the country-sector-level information to the country-level and convert the unit of emissions from gigagram (gG) to metric ton (ton).[8]

Country-level $PM_{2.5}$ concentration is obtained from Atmospheric Composition Analysis Group's $PM_{2.5}$ Global Estimates (Hammer et al. 2020), which estimates $PM_{2.5}$ concentration by combining Aerosol Optical Depth (AOD) retrievals from satellite with the GEOS-Chem chemical transport model and calibrating to ground-based observations using a Geographically Weighted Regression (GWR).[9] The dataset provides the country-level annual average of concentration measures, measured in microgram per cubic meter ($\mu g/m^3$) at $0.01° \times 0.01°$ resolution from 1998 to 2018 for 238 countries.[10] Figure 1 shows the level of $PM_{2.5}$ concentration (in $\mu g/m^3$) of our sample countries in the year 2000. There is a wide dispersion in the level of concentration across countries. China, India, and South Korea as well as a few Eastern European countries are much more polluted than the other countries in our sample, and even among the more polluted countries, their concentration level ranges a great deal, from $18\mu g/m^3$ to $40.1\mu g/m^3$. In contrast, the level of concentration is low on average in Northern European countries as well as those that have a large share of land area with a relatively low level of industrial activities, including but not limited to Canada, the US, and Australia.

Trade To measure the correlation between a country's participation in trade with its emissions, we first measure the degree of trade openness based on the ratio of exports to GDP and that of imports to GDP, obtained from the World Bank World Development Indicators (WDI) database. For the baseline specification, we use the ratio of total trade to GDP by summing the two ratios. In an additional regression, we use the export ratio and the import ratio as separate controls to explore the potentially heterogeneous roles of the two.

Global Value Chains Not only a country's participation in trade but also its position on the global value chains (GVC, hereafter) determines the country's industry specialization patterns, and thus affects the distribution of emission-intensive industries across the globe. Recent studies find that more upstream industries tend to be more emission-intensive (Copeland et al. 2022, Shapiro

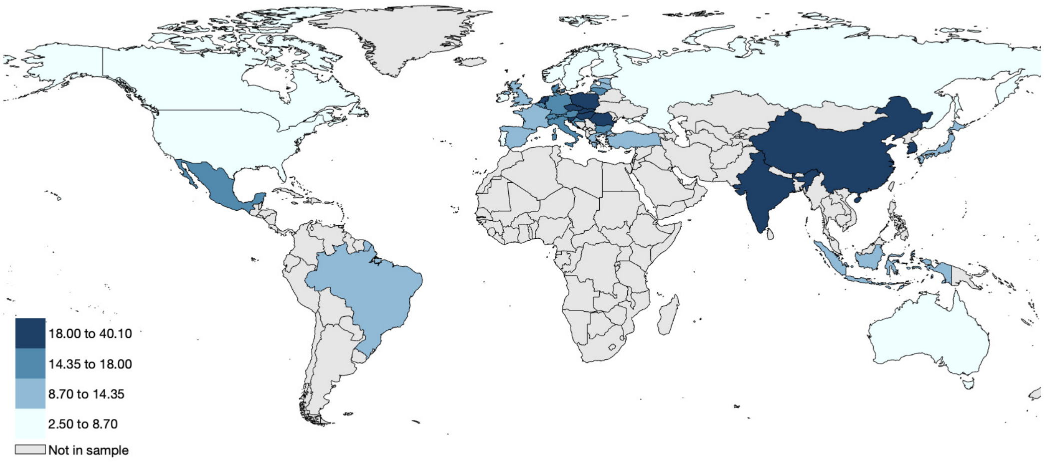
[7] In other words, the database is not direct observations of emissions. See the dataset's web page (https://edgar.jrc.ec.europa.eu/dataset_ap61) for more details.

[8] The conversion is necessary to make the unit consistent with those used in the later quantitative section, in which we use empirical results for calibration.

[9] See the dataset's web page (https://sites.wustl.edu/acag/datasets/surface-pm2-5/) for more details.

[10] We use the estimates that are obtained after removing dust and sea-salt. Annual averages correspond to a simple mean of within-grid values. According to EPA, $PM_{2.5}$ remains airborne for up to weeks, thus the annual measure mostly captures the flow value rather than the stock value.

Figure 1: Level of $PM_{2.5}$ concentration (2000)



Note: This figure illustrates the level of $PM_{2.5}$ concentration for the year 2000. *Source*: Atmospheric Composition Analysis Group.

2021). In order to evaluate the role of country-level upstreamness on emissions – on its own and by interacting with the role of trade – we include a country-level GVC position in our step 1 regression as a control.

We use the World Input-Output Database (WIOD) to construct the country-level upstreamness measure. The database contains the intra- and inter-country input-output information for 56 industries in 44 countries from 2000 to 2014. We follow Antràs and Chor (2018) to calculate the measure of countries' positioning along GVC. Specifically, we collapse the WIOD to the country-by-country level and compute the distance from final use. The country i's upstreamness, U_i, is calculated by the i-th element of

$$\frac{[I - D]Y}{Y_i} \tag{1}$$

where I is an identity matrix, D is an N-by-N matrix whose (i, j) element, d_{ij}, is the dollar amount of country i's output needed to produce one dollar's worth of country j's output. Y is a column matrix with country i's gross output Y_i in row i. The upstreamness is measured year by year using annual data. Table 1 shows the countries with top and bottom 5 upstreamness values in the year 2000. A higher value indicates a more upstream country, which means that the country's overall industry structure is farther from final goods consumers. Our measures are similar with those in Antràs and Chor (2018) in terms of magnitude and ranking, whose measures are 2011 values, indicating that countries' GVC position has not changed much between 2000 and 2011.[11]

Preferential Trade Agreements (PTA) Trade can affect the geographic distribution of emissions by moving the location of production – in particular, emission-generating production – ac-

[11]Both in our paper and Antràs and Chor (2018), the U.S., Greece, and Mexico are in the bottom 5 (i.e., most downstream), and China, Luxembourg, and Czech Republic are in the top 5 (i.e., most upstream).

Table 1: Upstreamness measures by country

Top 5			Bottom 5		
Rank	Country	Upstreamness (2000)	Rank	Country	Upstreamness (2000)
1	China	2.54	38	Lithuania	1.82
2	Luxembourg	2.35	39	India	1.81
3	Russia	2.32	40	United States	1.80
4	Czech Republic	2.23	41	Greece	1.71
5	Australia	2.16	42	Mexico	1.64

Notes: The table presents the top and bottom 5 countries in terms of the upstreamness in year 2000, measured following Antràs and Chor (2018). Only our regression sample countries are included.

tivities across countries. If countries are part of the PTAs that have environmental provisions and thus, aim to address environmental concerns, the impact of trade on the environment would likely to be significantly different for such countries and their neighboring countries. To capture such heterogeneous effects, we control for the information on countries' participation in such PTAs in our regression analysis.

The World Bank's Deep Trade Agreements (DTA) dataset provides detailed information on country-pair-level PTA status and provisions included in each PTAs. One of the provision categories is 'environment' which includes the development of environmental standards, enforcement of national environmental laws, establishment of sanctions for violation of environmental laws, and publications of laws and regulations (Hofmann et al. 2019). To capture the extent of each country to which trade flows are under these environmental provisions, we use the share of trade flows made with partner countries of PTAs that have such environmental provisions.[12]

Meteorology Meteorological factors affect the formation of air pollution concentration, so we include them in the step 2 regression that connects emission and concentration. The information on temperature and precipitation is obtained from the World Bank Climate Change Knowledge Portal (CCKP). The dataset provides temperature and precipitation on a monthly basis for 196 countries. Using the monthly information, we calculate the simple average and standard deviation of temperature and precipitation at the annual level for each country in our sample.

Environmentally-related technology $PM_{2.5}$ has end-of-pipe technologies available, which can reduce the amount of emissions generated from certain economic activities. Thus, the countries with a higher level of such technologies are likely to have lower emissions from the same level of industrial activities. In order to control for such differences across countries, we include the variable that captures the state of technological development of each country.

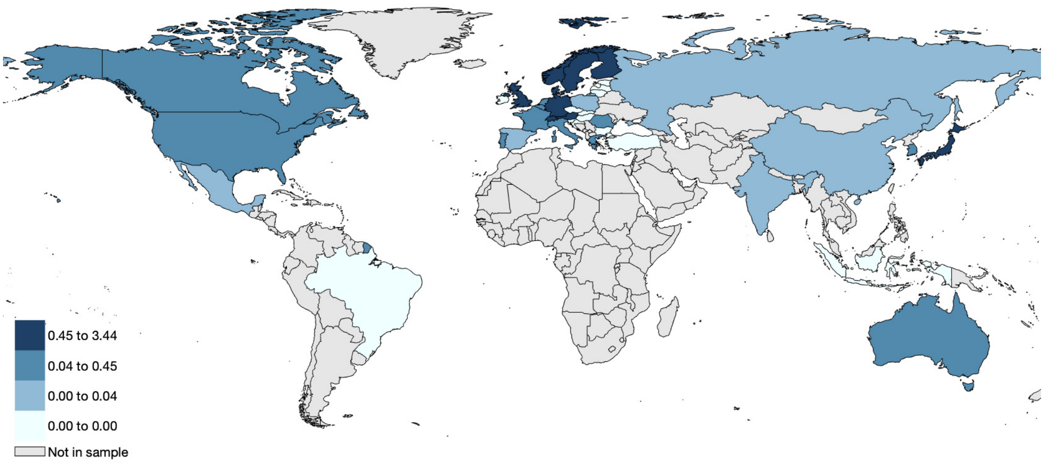
The OECD Environmental Statistics database provides several environment-related patents, including abatement, climate change management, greenhouse gases, and environment monitoring.

[12]We use the bilateral trade flows from the CEPII's Gravity dataset to calculate the share of trade flows with PTA partner countries among the total trade flows.

To control for the difference in patent capacities coming from the size of countries, we use the number of such patents per capita. For the step 1 regression relating economic activities and emissions, we use the number of patents related to the abatement of stationary source emissions to control for the variation in countries' ability to lower emissions produced by the same production processes. For the second regression relating concentration to emissions, we use the number of environmental management patents per capita to proxy the overall development of the technologies relevant to air pollution management.[13]

Figure 2 shows the number of abatement-related patents per capita in the year 2000. European countries are more advanced in the technology related to air pollution abatement than other countries. Especially, Northern European countries have the largest number of such patents per capita.[14] The maximum of the group is Luxembourg, which has 3.44 patents per 1000 persons, although this may be more attributed to its small population size. Figure A.1 in the Appendix shows the number of patents on environmental management, which shows a similar pattern across countries, although the overall level is higher.

Figure 2: Number of patents on abatement (per 1000 persons)



Note: This figure illustrates the number of patents on abatement per 1000 persons for each country.
Source: OECD Environmental Statistics database.

Transboundary transport of $PM_{2.5}$ We include a measure of transboundary transport of $PM_{2.5}$ pollution in order to capture how much each country is exposed to other countries' emissions. By using this measure as a control in the step-2 regression, we can explore how a country's concentration moves with its exposure to other countries' (adjusted) emissions.

The transboundary transport of $PM_{2.5}$ from other countries to country i is measured by the sum of foreign emissions that are adjusted by foreign countries' land area size and the square of the

[13] More ideal would be using patents related to the technologies that dissipate or capture air pollutants after emission, but the such measure is not available in the dataset.
[14] For example, Sweden has 0.79 patents per 1000 persons, Norway 1, and Finland 1.74.

distance between i and each foreign country i'.

$$PolTransport_{it} = \sum_{i' \neq i} \frac{E_{i't}}{land_{it'}} \times \frac{1}{distance^2_{ii't}} \tag{2}$$

Land area is from the World Bank's World Development Indicators (WDI), and the distance between countries is from the CEPII GeoDist dataset. We use the distance between the most populated cities in each of two countries, instead of the simple distance between two countries' center points, to capture the distance from emission sources proxied by the most populated locations.

Two adjustments to foreign emissions are made to capture the degree of transmission from one country to another. Dividing by land area (of an emitting country) captures the degree to which emission is dispersed before crossing the border to other countries. Dividing the emission by the squared term of distance captures the degree of cross-border transport. Intuitively, the farther two countries are apart, the less pollution reaches from one to the other. We choose to use the square term of distance based on the findings from the atmospheric science literature that pollution transport decays faster at a larger distance (Fu et al. 2022, Requia and Koutrakis 2018).[15] We also run a sensitivity analysis regression, using the cubed term.

Table 2 shows the countries with the 5 highest and 5 lowest values for $PolTransport$ of the year 2000. As the countries with higher $PolTransport$ is more exposed to other countries' emissions, $PolTransport$ represents the proximity to foreign emission sources. The list shows that European countries tend to have a higher value of $PolTransport$ while the countries that are relatively distant from the rest of the world – for example, Australia or those in North America– are located at the bottom of the list.

Table 2: Countries with top and bottom 5 $PolTransport$

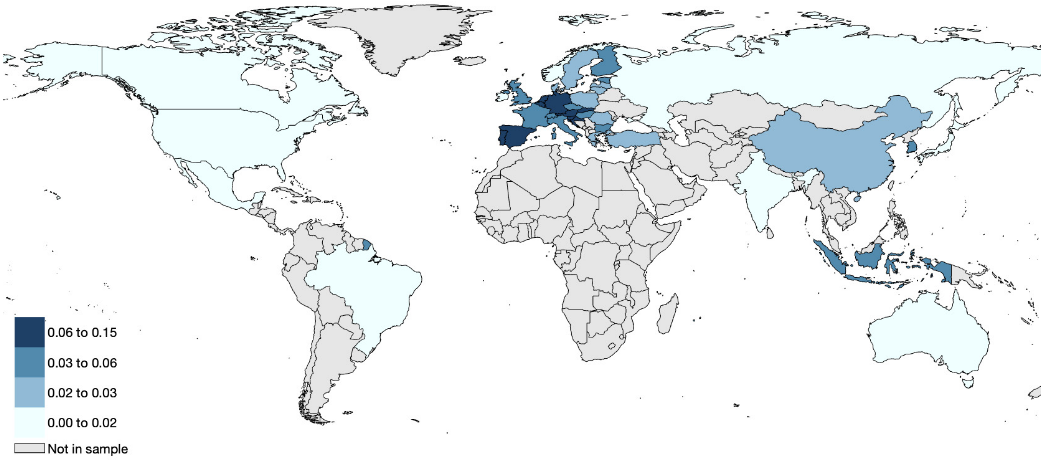
Top 5		Bottom 5	
1	Austria	38	Mexico
2	Slovak Republic	39	Canada
3	Germany	40	United States
4	Belgium	41	Australia
5	Netherlands	42	Brazil

Notes: The table presents the top and bottom 5 countries in terms of $PolTransport$ of 2000. Only our regression sample countries are included.

[15] To the best of our knowledge, there is no existing study that estimates the distance elasticity of transboundary pollutants at the cross-country level. The scientific literature uses chemical transport model, which is based on atmospheric processes in the three-dimension grid models and requires highly disaggregated geographic data (Lin et al. 2014, Liu et al. 2009, Zhang et al. 2017). There are a few papers in the economics literature that estimate the pollution decay function and see how one region's pollution affects the other region (Fu et al. 2022, Zheng et al. 2014). They show that the effect of other cities' (or regions') pollution decreases with distance. But as their analyses are intra-national, thus having shorter distance values only, and high-frequency, it is hard to make direct comparisons with our approach of discounting transboundary transport with distance.

Figure 3 shows *PolTransport* of all of our sample countries. It is noteworthy that the values vary even between the countries that share the same neighbor countries. For example, both India and South Korea are close to China, one of the largest emitters, but South Korea's *PolTransport* is much higher than that of India. The reason is that China is most populated and, thus industrialized, on the east coast, so the distance from the east coast of China matters rather than whether a country shares borders with – or is physically close to – China or not.

Figure 3: Level of *PolTransport*



Note: This figure illustrates the number of patents on abatement per 1000 persons for each country.
Source: Authors' calculation based on the World Bank WDI, CEPII Geo Dist, and EDGAR.

It is crucial to note an important element that is missing from the current specification of *PolTransport*: the role of wind. As wind affects the direction and degree of transboundary pollution, it has been included as a determinant of transboundary pollution in several papers in both economic and atmospheric science literature (Fu et al. 2022, Kim 2019, Reuther 2000, Zheng et al. 2014). Our unit of analysis – annual frequency and country-level – is more aggregate than what is ideal to appropriately use wind direction, which is usually measured at high frequency and varies with distance. In addition, it is not simple to define a dominant wind direction for countries with large land areas, such as Russia, the United States, and Canada. Nonetheless, recognizing the importance of wind as a key factor, we plan to augment the *PolTransport* variable by using wind direction between countries in the next version of the paper.[16] Furthermore, we can crosscheck how *PolTransport* measures the degree of transboundary pollution by comparing it with the source-receptor matrix information in the future.

[16] A few papers incorporate wind in their otherwise-low-frequency analyses. For example, Fu et al. (2022) use the mixed two-stage least square (M2SLS) method to incorporate high-frequency (daily) wind data with low-frequency (annual) economic outcome data. Zheng et al. (2014) use monthly wind direction data and define dominant wind direction as monthly main wind direction(s) that appear the most in 12 months.

Other country-level characteristics

We use several country-level characteristics to capture the size and industrial development of a country – other factors that would affect emissions and concentration – including GDP per capita, population density, urban population share, and rail infrastructure. GDP per capita and population density, and urban population share are from the WDI. The urban population share is measured as the share of the population in urban agglomerations, defined as the areas with more than 1 million people, in total population. We also include the railway density, defined as the length of rail lines (km) per land area (100 km^2), to proxy the dispersion in industrial development within a country.[17] The railway density is obtained from the OECD Infrastructure Transport dataset.

2.2 Empirical Specification

In this section, we introduce two specifications, each of which explores the linkage between trade and emissions and the linkage between emissions and concentrations, respectively. Specifically, we first establish a linkage between a country's participation in trade and its own emission (step 1). Then we show the role of a country's own emissions and the emissions from other countries that travel across borders on a country's concentration (step 2).

While this is not a two-stage analysis, strictly speaking, running two separate regressions allows us to break down how trade and concentration are linked, which are through changing its own emissions and through others' emissions that may travel across the border.

2.2.1 Regression on $PM_{2.5}$ emissions

To test the determinants of $PM_{2.5}$ emission, we estimate the following country-level panel regression:

$$\begin{aligned} ln(Emissionpc)_{it} = \zeta + \chi_1 GDPpc_{it} + \chi_2 GDPpc_{it}^2 + \chi_3 Tech_{it} + \beta_1 Trade_{it} + \beta_2 Upstream_{it} \\ + \beta_3 PTAenv_{it} + \beta_4 Trade_{it} \times PTAenv_{it} + \rho_i + \rho_t + \epsilon_{it} \end{aligned} \quad (3)$$

The dependent variable $\ln(Emissionpc)_{it}$ is the natural log of emission per capita for country i in year$t$. The real GDP per capita ($GDPpc_{it}$) controls the role of economic development and income. Our estimation incorporates the idea of the Environmental Kuznets Curve (EKC) by including the square of $GDPpc_{it}$. The EKC states that economic growth deteriorates the environment during the beginning of industrialization, but after reaching a certain level, further economic development reduces the environmental damage. Thus, $\chi_1 > 0$ and $\chi_2 < 0$ are expected.

The level of emission-reducing technology ($Tech_{it}$) controls for the difference in the amount of emissions resulting from the presence and usage of abatement technologies. Countries with a higher level of such technologies would have a smaller amount of emissions generated from the same economic activities ($\chi_3 < 0$).

[17] The dispersion in industrial activities is controlled to capture potential chemical reactions between pollutants that occur after emissions due to clustered industiral activities (e.g., secondary $PM_{2.5}$ formation).

The main explanatory variables of our interest are a country's trade intensity ($Trade_{it}$) and GVC position ($Upstream_{it}$). As $Trade_{it}$ includes both import and export, its coefficient β_1 represents the net effect of trade on emissions. A large body of literature studies the effect of trade on air pollution, but there is no consensus established, as trade affects a country's emissions (and concentration accordingly) through multiple channels and the net effect is determined by the magnitude of each channel (Antweiler et al. 2001, Frankel and Rose 2005, Grossman and Krueger 1993, Heil and Selden 2001, Li and Reuveny 2006).[18]

Another aspect to consider is a country's position on the global value chain, which determines specialization patterns across countries and, thus, affects emission intensity. Recent studies find that more upstream industries are more emission-intensive (Copeland et al. 2022, Shapiro 2021). The coefficient β_2 tests if such a relationship holds at the country level as well. Positive β_2 means that more upstream countries are dirtier on average after their economic growth and participation in trade are controlled.

Lastly, we explore whether the participation in PTAs with environmental provisions affects the level of emissions as well as how trade affects emissions. With the environmental standards or regulations agreed upon among members, PTAs may mitigate environmental damage that trade brings to some countries – via pollution offshoring, for example. The coefficient on the interaction term, β_4, captures that role and is expected to have the opposite sign to β_2 if PTAs fix some of the environmental externalities.

2.2.2 Role of pollution remoteness on concentration

As the previous section illustrates, we first estimate how a country's emission is associated with its size, level of abatement technology, and participation in trade and GVC position. Then we link country-level emissions with concentrations, which is the mechanism by which emissions affect welfare ultimately. Using Equation 4, we estimate not only the role of a country's own emissions but also those of other countries' $PM_{2.5}$ emissions, the latter of which motivates our focus on transboundary travel of pollutants.

$$ln(concentration)_{it} = \psi + \lambda_1 ln(E/land)_{it} + \lambda_2 Meteo_{it} + \kappa \ln(PolTransport)_{it} + \delta_i + \delta_t + \xi_{it} \quad (4)$$

The right-hand side of Equation 4 shows a few determinants of a country's concentration. First of all, it would increase with its own emission level (normalized by the size of land area), $E_{it}/land_{it}$. In addition, it would also be affected by meteorological factors ($Meteo$), including temperature and precipitation.[19] For example, higher temperature dissipates pollution faster, and more consistent

[18]In a sense, our specification is similar to that of Copeland and Taylor (2003), as we estimate the partial effect of trade intensity when the economy's size, industrial composition, and emission intensity – respectively, scale, composition, and technique aspect – are controlled. Recall that the emission measures are not observations but calculated values. So our specification tests if trade affects any of the factors that are used in the calculation of emissions – for example, share of dirty industries or firms' abatement decisions.

[19]In the atmospheric science literature, air pollutant transport and concentration are simulated based on emissions and meteorological and tropospheric chemical processes (Lin et al. 2014, Liu et al. 2009, Verstraeten et al. 2015, Zhang

precipitation washes down concentration. In order to capture such effects on concentration, we include the average and standard deviation of temperature and precipitation in the $Meteo$ vector.

Lastly, the main variable of interest is $PolTransport$, which measures the degree of transboundary pollution that each country is exposed to. The coefficient on $PolTransport$, κ, tests whether $PM_{2.5}$ emissions travel across border and affect other countries' concentration. For example, if $PM_{2.5}$ travels across the border, κ would be positive.

One limitation of this chapter is that it focuses on the role of primary $PM_{2.5}$ and abstracts from secondary $PM_{2.5}$, which are formed by chemical reactions of precursor gases, including nitrogen oxides (NO_x), ammonia (NH_3), and sulfur dioxide (SO_2), in the atmosphere.[20] As the concentration data includes the pollution formed by secondary processes, the role of secondary formation would be captured in the coefficient of either own emission or transboundary pollution or both as well as the error term in our specification.[21] Thus, we include controls that proxy the dispersion of industrial activities, such as population density, the share of the urban population, and rail density, in the additional specification to capture the degree of secondary formation of $PM_{2.5}$. Alternatively, we could explicitly include the emissions of precursor pollutants, but that would result in including too many regressors that are highly correlated to each other. Also, we would, then, have to take into account the chemical processes of secondary formation of $PM_{2.5}$, which is outside this paper's scope.

2.3 Results

In this section, we present the results from running Equation 3 and 4. These two steps of regressions are useful to understand the linkage between economic activities, including trade, and air pollution. In two steps, we not only check whether our sample shows a similar pattern of the linkage from what the existing literature finds but also highlight the importance of transboundary pollution in air pollution concentration. For all specifications, we use country-level and year-level fixed effects to absorb unobserved factors determining emissions and concentration. We also cluster standard errors at the region-year-level since our dependent variables may not be independent – in particular, concentration in a setting with transboundary spillovers.[22]

2.3.1 Determinants of $PM_{2.5}$ emission per capita

Table 3 reports the step 1 results: the determinants of $PM_{2.5}$ emissions.[23] Column 1 shows that emission increases with economic growth and that the coefficient on the squared GDP is negative, supporting the EKC hypothesis. It also shows the emission-reducing effect of abatement-related

et al. 2017).

[20] EPA (2018) states that a great portion of fine PM ($PM_{2.5}$) contains secondary particles, more than in the case of coarse PM (PM_{10}).

[21] Copeland et al. (2022) find that different pollutants' emissions are highly correlated to each other.

[22] We use the region classification provided by the World Bank, which divides countries into 7 regions, including East Asia and Pacific, Europe and Central Asia, Latin America & the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa.

[23] Appendix Table A.3 shows the summary statistics.

technologies. The role of total trade intensity is positive, but the estimate is not statistically significant, which is consistent with the lack of consensus on the net effect of trade in the literature. Of equal interest is the coefficient on $Upstream$, which shows how a country's positioning in the GVC affects emissions when its trade participation is controlled. The estimate is positive and significant, suggesting that the countries located farther from final consumer demand (i.e., more upstream) are more emission-intensive. This is analogous to the industry-level findings that more upstream industries are dirtier (Copeland et al. 2022, Shapiro 2021).

Columns 2 and 3 add $PTAenv$ and the interaction of $PTAenv$ and $Trade$. The magnitude of coefficient estimates from column 1 decreases overall as PTA terms are added, implying that their roles were absorbed by the existing regressors in column 1. The negative coefficient on the interaction term in column 3 shows that the role of trade on emissions is heterogeneous and depends on a country's participation in PTAs that have environmental provisions. Specifically, countries that are bound by PTA environmental provisions experience less emission-increasing impact from trade.

Table 3: Determinants of $PM_{2.5}$ emissions

	(1)	(2)	(3)
$GDPpc$	30.149***	20.620**	18.867*
	(8.849)	(9.735)	(9.960)
$GDPpc^2$	-244.977***	-163.162**	-147.311**
	(66.072)	(65.267)	(66.497)
$Tech$	-33.906***	-27.102**	-28.520**
	(11.167)	(11.003)	(11.236)
$Trade$	0.073	0.017	0.130
	(0.069)	(0.061)	(0.097)
$Upstream$	0.300***	0.268***	0.247**
	(0.089)	(0.093)	(0.098)
$PTAenv$		0.155***	0.323***
		(0.040)	(0.094)
$Trade \times PTAenv$			-0.156**
			(0.071)
Number of Observations	630	630	630
Within Adj. R-squared	0.111	0.142	0.151

Notes: The dependent variable is the log of emission per capita. All columns use country fixed effects and year fixed effects. Constant estimates are omitted from the table. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *$<$ .1, **$<$ .05, ***$<$ .01.

We also run the regression after separating trade openness into export intensity and import intensity, defined as the ratio of export to GDP and import to GDP respectively. Table 4 shows that the emission-increasing effect of trade openness is driven by the export side of it. In contrast, import is negatively associated with emission. This is not surprising given that exporting requires additional production in a country and importing eliminates the need for emission-generating activities in a country. The emission-increasing and emission-decreasing effects of export and import are muted by PTA, respectively, but the coefficients are insignificant.

Another notable difference is that the coefficient on GVC participation is estimated less significantly while the positive estimate remains. In column 3, it loses significance. One way to interpret this is that splitting trade intensity into export and import sides captures the pattern of specialization of each country, which is closely related to its position in the global value chain. In all columns, the coefficients on $GDPpc$, $GDPpc^2$, and $Tech$ remain similar to those in Table 3.

Table 4: Determinants of $PM_{2.5}$ emissions

	(1)	(2)	(3)
$GDPpc$	32.317***	21.339*	20.563*
	(9.699)	(11.586)	(11.631)
$GDPpc^2$	-257.295***	-168.854**	-157.227**
	(67.695)	(74.844)	(75.833)
$Tech$	-32.600***	-26.638**	-27.479**
	(11.680)	(11.451)	(11.600)
$Export$	0.431*	0.270	0.577**
	(0.231)	(0.238)	(0.254)
$Import$	-0.342	-0.296	-0.387
	(0.296)	(0.282)	(0.277)
$Upstream$	0.220**	0.237**	0.193
	(0.109)	(0.113)	(0.117)
$PTAenv$ (ex)		0.290**	0.471**
		(0.123)	(0.211)
$PTAenv$ (im)		-0.151	-0.185
		(0.123)	(0.213)
$Export \times PTAenv$ (ex)			-0.411*
			(0.244)
$Import \times PTAenv$ (im)			0.113
			(0.214)
Number of Observations	630	630	630
Within Adj. R-squared	0.116	0.148	0.155

Notes: The dependent variable is the log of emission per capita. All columns use country fixed effects and year fixed effects. Constant estimates are omitted from the table. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *$<$ .1, **$<$ .05, ***$<$ .01.

In summary, the results in this section show that the role of trade on emissions is not clear, as it is composed of opposing forces, but that the role is heterogeneous according to countries' participation in PTAs that include environmental provisions. In addition, whether a country is export-intensive or import-intensive also has different implications on its emissions.

2.3.2 Determinants of $PM_{2.5}$ concentration

Table 5 shows the results of the second regression, which tests how each country's $PM_{2.5}$ concentration is determined by its own and others' emissions.[24] The first column shows the role of each country's own emission and meteorological factors on concentration. The coefficients confirm the existing understanding of the impact of temperature and rainfall. Both the increase in average temperature and rainfall decrease concentration (conditional on the emissions from own and foreign countries), and the estimates are significant.

Table 5: Determinants of $PM_{2.5}$ concentration

	(1)	(2)	(3)
ln(emission/land)	0.197***	0.144***	0.177***
	(0.038)	(0.039)	(0.058)
Temp Ave	-0.042*	-0.042*	-0.032
	(0.022)	(0.022)	(0.028)
Temp SD	0.021	0.022	0.028
	(0.025)	(0.024)	(0.025)
Rain Ave	-0.003***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)
Rain SD	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)
ln(PolTransport)		0.333***	0.291***
		(0.087)	(0.088)
ln(population density)			0.119
			(0.173)
Share of urban population			1.665**
			(0.787)
ln(rail density)			0.482***
			(0.101)
Technology			-4.216
			(4.169)
Number of Observations	630	630	429
Within Adj. R-squared	0.101	0.131	0.166

Notes: The dependent variable is log of $PM_{2.5}$ concentration. All columns use country fixed effects and year fixed effects. Constant estimates are omitted from the table. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *<.10, **<.05, ***<.01.

Our main variable of interest, $PolTransport$, is added in the second column. When we include $PolTransport$, the coefficients on the meteorological regressors barely change. But the coefficient on own emissions, $\ln(emission/land)$, decreases. Combining it with a positive and significant coefficient on $\ln(PolTransport)$ indicates that a country's concentration is correlated with other countries' emissions, which was partly absorbed by the coefficient on own emissions in the first

[24] Appendix Table A.4 shows the summary statistics of the regression sample.

column. The coefficients – 0.144 and 0.333 – suggest that a within standard deviation increase in $PolTransport$ is associated with a 2.3% increase in concentration while a within standard deviation increase in own emission is associated with a 1.6% increase in concentration.[25] At the same time, this means that the impact of 1% increase in all other countries' emissions – thereby an 1% increase in $PolTransport$ – is similar with the impact of 2% increase in own emission of a country on average. This suggests that the transboundary transport of foreign emissions has a comparable role to a country's own emissions on its concentration level.[26]

In the third column, we add more controls that may affect $PM_{2.5}$ concentration. Specifically, we add the log of population density, the share of urban agglomeration population, and the log of rail density to capture the density of industrial activities within a country. We also put the level of technology to capture a country's capability to control air pollution. Specifically, we use the number of environmental management patents per capita to proxy the overall development of the technologies relevant to air pollution management.[27] The positive and significant coefficient on $PolTransport$ remains after adding these controls. In the Appendix Table A.5, we present the results obtained from using $PolTransport$ calculated from using cubed distance instead of squared distance to discount the emissions from foreign countries. The results remain similar.

The results of this section show that the role of transboundary pollution is substantial and robust, which motivates us to take the transboundary transport of pollution into consideration when we analyze the impact of trade on air pollution. In addition, the estimates from the regressions are used for calibration in the later quantitative section.

3 Model

Motivated by the empirical evidence presented in the previous section, we build a general equilibrium model of international trade and environmental externality from local pollutants that travel across borders. Our model builds on Caliendo and Parro (2015), a multi-industry extension of Eaton and Kortum (2002) with an input-output linkage. We introduce environmental externality to our multi-country general equilibrium trade model following a similar approach to Shapiro (2016) but allow local pollutants to travel across space. The transboundary nature is an important characteristic for pollutants such as particulate matters. Our model shows how the transboundary nature of local pollutants shapes the heterogeneous welfare effect of trade shocks across countries, when the environmental externality is taken into consideration. Another important advantage of our model is that various aspects of trade policies are parsimoniously captured by a few parameters such as trade costs and environmental tax. As more recent trade agreements tend to cover a broad set of issues beyond tariffs, our model can be used to quantify the welfare effect of such trade agreements,

[25] The within standard deviation of $\ln(emission/land)$ is 0.11, and that of $\ln(PolTransport)$ is 0.07.

[26] Although existing studies use different measures for transboundary pollution, it is useful to compare the magnitude of its role. For example, Zheng et al. (2014) show that the 10% decrease in neighboring cities' smoke emission – weighted by wind direction – reduces the PM_{10} concentration of a country by 1.7%.

[27] Note that this is different from the technology control variable used in the previous section, which is measured as the ratio of the number of patents related to stationary source emission abatement to the total number of patents.

focusing particularly on their environmental consequences.

3.1 Basic Setup

There are N countries in the model, and each country is indexed by either i or n. Consumers in country i have an identical preference summarized by the following utility function which takes into account disutility from concentration of local pollutants:

$$U_i = \left(\prod_j (C_i^j)^{\phi_i^j}\right)\left(\frac{1}{1+\left(\frac{1}{\mu_i} g_i(E_1,\ldots,E_N)\right)^2}\right), \tag{5}$$

where $C_i^j = \left(\int_0^1 C_i(e^j)^{\frac{\eta-1}{\eta}} de^j\right)^{\frac{\eta}{\eta-1}}$ is a consumption bundle for sector j aggregating product varieties $e^j \in [0,1]$ with the elasticity of substitution $\eta > 1$ between them. We assume that there are J industries in this economy, with the expenditure share on each industry from each country is given by $\phi_i^j \in [0,1]$ with $\sum_j \phi_i^j = 1$ for each i.

The term in the second parenthesis of equation (5) describes the disutility from concentration of local pollutants regardless of the origin. In other words, our local pollutants are not entirely local in a sense that we allow these pollutants to travel across space. When we take our model to data, we focus on PM 2.5 as the measure of local pollutants. We denote the total emission of local pollutants from country i by E_i, and $g_i(\cdot)$ captures the concentration level of the local pollutants. Consistent with the transboundary nature that we allow for the local pollutants, $g_i(\cdot)$ is a function of the emission level from all countries around the world. We will parametrize this function when we quantify the model in the next section. Lastly, μ_i is the parameter that captures the social cost of emission of transboundary pollutants. Following Shapiro (2016), we assume that consumers consider concentration of transboundary pollutants as a pure externality which they take as given in their utility maximization problem.

We assume perfect competition for both goods and factor markets as in Eaton and Kortum (2002, EK, hereafter). The producer of a product e^j of sector j uses labor, capital, and intermediate goods as core production inputs. Production process leads to emission of transboundary pollutants for which producers in country i have to pay an environment tax to the government with the rate t_i set by country i's government. Following Copeland and Taylor (2003), we assume that the production technology for a variety e^j in country i has the following Cobb-Douglas form which combines the potential output from core inputs with emission:

$$Q_i^j(e^j) = \left[E_i^j(e^j)\right]^{\alpha_i^j}\left[z_i(e^j)\left(L_i^j\right)^{\gamma_{i,l}^j}\left(K_i^j\right)^{\gamma_{i,k}^j}\left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}\right]^{1-\alpha_i^j}, \tag{6}$$

where L_i^j, K_i^j, and M_i^j are labor, capital, and intermediate input bundle, respectively. We assume that both labor and capital is perfectly mobile across varieties and sectors. The cost shares for labor and capital are given by $\gamma_{i,l}^j, \gamma_{i,k}^j \in (0,1)$, respectively. These cost shares are assumed to vary by country and sector, since we relate the capital intensity to the emission intensity when quantifying the model. The emission level from production of variety e^j is denoted by $E_i^j(e^j)$, and α_i^j stands for the emission elasticity of sector j in country i. Following EK, we assume that the factor neutral productivity for variety e^j in country i, $z_i(e^j)$, is randomly drawn from a Fréchet distribution specified as $F_i^j(z) = \exp\left(-A_i^j z^{-\theta^j}\right)$. In this distribution function, $A_i^j > 0$ denotes country i's absolute advantage in sector j, and $\theta^j > 0$ captures the degree of the Ricardian comparative advantage for sector j. As in variations of EK, θ^j is essentially a sector-specific trade elasticity.

3.2 Emission, Environmental Tax, and Abatement

Producers' decision on the emission level is tied with how much to abate and also internalizes the environmental tax they have to pay for their emission of local pollutants. We follow Copeland and Taylor (2003) to model how these decisions are related. First, we denote the potential output from core inputs by $F_i^j(e^j) \equiv z_i(e^j)\left(L_i^j\right)^{\gamma_{i,l}^j}\left(K_i^j\right)^{\gamma_{i,k}^j}\left(M_i^j\right)^{1-\gamma_{i,l}^j-\gamma_{i,k}^j}$ for notational simplicity. The producer of variety e^j can use a fraction $\kappa_i^j(e^j) \in [0,1]$ her potential output for abatement. Then, the net output in equation (6) can be re-written as

$$Q_i^j(e^j) = \left(1 - \kappa_i^j(e^j)\right) F_i^j(e^j). \tag{7}$$

We denote the emission intensity of the producer of variety e^j in country i with respect to the potential output by $\tilde{\varphi}_i^j(e^j)$, and by using equation (7), we can derive $\tilde{\varphi}_i^j(e^j)$ as follows:

$$\tilde{\varphi}_i^j(e^j) \equiv \frac{E_i^j(e^j)}{F_i^j(e^j)} = \left(1 - \kappa_i^j(e^j)\right)^{\frac{1}{\alpha_i^j}}. \tag{8}$$

The emission elasticity α_i^j captures the responsiveness of emission with respect to abatement. The emission intensity with respect to potential output is larger if producers devote a smaller fraction of their potential output for abatement conditional on the emission elasticity. Denoting the marginal emission tax rate in country i by t_i, the emission intensity can be also written with respect to the net output,

$$\varphi_i^j(e^j) \equiv \frac{E_i^j(e^j)}{Q_i^j(e^j)} = \frac{\alpha_i^j p_i^j(e^j)}{t_i}. \tag{9}$$

We assume that the environmental tax rate for emission varies by country but not by sector within a country. The emission intensity with respect to the net output increases in the emission elasticity and decreases in the environmental stringency of the country which is captured by a higher environmental tax rate.

Combining equations (7)-(9), we can derive the optimal abatement decision of producers as follows:

$$\kappa_i^j(e^j) = 1 - \left(\frac{\alpha_i^j p_i^j(e^j)}{t_i}\right)^{\frac{\alpha_i^j}{1-\alpha_i^j}}, \tag{10}$$

and thus the optimal abatement cost is given by

$$\left(\frac{\alpha_i^j p_i^j(e^j)}{t_i}\right)^{\frac{\alpha_i^j}{1-\alpha_i^j}} F_i^j(e^j). \tag{11}$$

Intuitively, producers devote a larger fraction of their potential output for abatement if the environmental tax rate is higher and the emission decreases more with abatement.

3.3 International Trade

All product varieties are tradable between countries subject to iceberg trade costs $d_{in}^j \geq 1$ for products in sector j shipped from country i to country n. It means that firms need to produce extra units to deliver goods to markets, which also implies they need to generate extra amounts of emissions due to iceberg trade costs. One way to interpret this is the emissions arising from global transportation.[28] We make a simplifying assumption on the input-output structure that the final good bundle can be used either for final consumption by consumers or as intermediate input M_i^j in production function (6). With this assumption, the unit price for the intermediate input bundle is equal to the exact price index of the country. From producer's profit maximization, the unit cost of production for all producers in industry j of country i is

$$c_i^j = \Upsilon_i^j t_i^{\alpha_i^j} \left(w_i^{\gamma_{i,l}^j} r_i^{\gamma_{i,k}^j} P_i^{(1-\gamma_{i,l}^j-\gamma_{i,k}^j)}\right)^{(1-\alpha_i^j)}, \tag{12}$$

where Υ_i^j is a Cobb-Douglas constant; w_i is wage; r_i is rental rate of capital; and P_i is the aggregate price index for country i. Following EK, the equilibrium share of trade of sector j goods from country i to country n (X_{in}^j) in country n's total expenditure in sector j (X_n^j) is given by

$$\pi_{in}^j = \frac{A_i^j \left(c_i^j d_{in}^j\right)^{-\theta^j}}{\sum_{i'} A_{i'}^j \left(c_{i'}^j d_{i'n}^j\right)^{-\theta^j}} = \frac{X_{in}^j}{X_n^j}. \tag{13}$$

The sector-level exact price index is

$$P_n^j = \left[\Gamma\left(\frac{\theta^j+1-\sigma}{\theta^j}\right)\right]^{1/(1-\sigma)} \left[\sum_{i'} A_{i'}^j \left(c_{i'}^j d_{i'n}^j\right)^{-\theta^j}\right]^{-1/\theta^j}, \tag{14}$$

for which we assume $\sigma < \theta^j + 1$ for all j. Using the assumption of Cobb-Douglas aggregation across sectors in consumer's utility, the aggregate price index can be derived as $P_n = \prod_{j'} \left(\frac{P_n^{j'}}{\phi_i^{j'}}\right)^{\phi_i^{j'}}$.

[28] Cristea et al. (2013) and Shapiro (2016) explicitly model the emissions of greenhouse gases based on different modes of freight shipping, including both domestic and international. According to the US EPA, transportation (including both freight and personal transport) is responsible for less than 10% of $PM_{2.5}$ emissions.

The effect of international trade on sector-level and aggregate emissions is summarized by

$$E_i^j = \frac{\alpha_i^j}{t_i} \sum_{n'} \pi_{in'}^j X_{n'}^j, \tag{15}$$

where the country i's aggregate emission is simply $E_i = \sum_{j'} E_i^{j'}$. As a country exports more to other countries, its gross output increases, which in turn leads to a higher level of emission conditional on the emission elasticity and the environmental tax rate. Since sectors vary by emission elasticity, the same change of gross output may lead to different degrees of change in emission across sectors. In particular, a sector with a higher emission elasticity sees a larger increase in emission from the same percentage change of gross output. The government of each country collects the environmental tax whose total revenue is $t_i E_i$ for each country i, and we assume that this tax revenue is rebated to the total income of consumers.

3.4 Market Clearing

To close the model for the general equilibrium, we first need to derive the equilibrium expenditure for each sector from each country. The expenditure function also needs to take the intermediate input demand into account. From the production function in equation (6), the sectoral expenditure is derived as

$$X_n^j = \phi_n^j \sum_{j'} (1 - \alpha_n^{j'})(1 - \gamma_{n,l}^{j'} - \gamma_{n,k}^{j'}) \sum_{n'} \pi_{nn'}^{j'} X_{n'}^{j'} + \phi_n^j I_n, \tag{16}$$

where the total income of country n is given by

$$I_n = w_n L_n + r_n K_n + t_n \sum_{j'} E_n^{j'} + D_n. \tag{17}$$

In the total income, the first two terms are incomes of the owners of the core value-added production inputs, labor and capital; $t_n \sum_{j'} E_n^{j'}$ is the total tax revenue that is rebated to consumers; and D_n is the aggregate trade deficit of country n, which we treat as an exogenous policy variable.[29] Finally, the general equilibrium factor prices $\{w_n, r_n\}_{n=1}^N$ solve the following system of market clearing conditions:

$$w_n L_n = \sum_{j'} \gamma_{n,l}^{j'} (1 - \alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} X_{n'}^{j'} \tag{18}$$

$$r_n K_n = \sum_{j'} \gamma_{n,k}^{j'} (1 - \alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} X_{n'}^{j'}. \tag{19}$$

[29] By having exogenous trade deficit, our model underestimates the increases in emissions of those with current account surplus and overestimates the increases in emissions of those with current account deficit. For example, China experienced the continuous rise in trade surplus after joining WTO. This indicates the production activities and, thus, emissions in China have grown more than what is allowed in our model setting.

3.5 Welfare

Our model framework enables us to derive a closed-form expression for the aggregate welfare for consumers of each country and exactly decompose the welfare expression into real income and environmental externality. Consumer's utility maximization with the preference given by equation (5) gives the following expression for indirect utility:

$$W_i = \left(\frac{I_i}{P_i}\right)\left(\frac{1}{1+\left(\frac{1}{\mu_i}g_i(E_1,\ldots,E_N)\right)^2}\right), \tag{20}$$

where the expression in the first parenthesis is real income which is based on the expressions (14) and (17); and the expression in the second parenthesis is the externality from concentration of local pollutants sourced from all countries including its own emission.

A trade shock potentially has two opposite effects on the welfare. A decline in export trade cost for a particular country, for example, is likely to increase the real income of the country by increasing the world demand for the goods produced in that country. The same trade shock, however, would increase the emission from the country, which eventually increases the environmental disutility. In addition, the transboundary nature of the pollutants can show a richer effect of a trade shock on welfare. If a trade shock hits a country, the change in emission of transboundary pollutants induced by the shock in that country affects the level of concentration of the transboundary pollutants in neighboring countries as captured by the function $g(\cdot)$. The exact degree of the spillover effects depends on the functional form of $g(\cdot)$ which we will specify in the next section based on our empirical findings from Section 2. Also, the pattern of intermediate input sourcing matters for the spillover effect. If country A is physically close to country B and country A imports a lot of intermediate inputs from country B, a decline in export trade cost from country B would increase production, and thus emission, from not just country B but also from country A, because producers in country A can source inputs more cheaply and thus increase their production.

4 Quantification

We quantify the model presented in the previous section to understand the effect of changes in trade environment and the stringency of environmental regulations on the spatial distribution of emission, concentration, and welfare. First, we re-write the model in terms of difference between two steady state equilibria. We then calibrate the baseline equilibrium to match the data in 2000. The quantification of the model also relies on the additional parametrization for the transboundary nature of pollutants.

4.1 Model in Changes and the Decomposition of Changes in Welfare

As the first step of the quantification of the model, we re-formulate the model we presented in Section 3 in terms of changes between the initial steady state equilibrium and the new steady state equilibrium after an exogenous shock is introduced to the model in the same spirit as the exact hat algebra of Dekle et al. (2008). For any variable x of the model, we denote the level of x at the new equilibrium after a shock to the baseline economy by x' then define $\hat{x}$ as the ratio of x' to the initial level x, i.e., $\hat{x} \equiv x'/x$. We can then re-write all equilibrium conditions of the model in terms of $\hat{x}$. For example, the sector-level unit cost in change is

$$\hat{c}_i^j = \hat{t}_i^{\alpha_i^j} \left(\hat{w}_i^{\gamma_{i,l}^j} \hat{r}_i^{\gamma_{i,k}^j} \hat{P}_i^{(1-\gamma_{i,l}^j-\gamma_{i,k}^j)} \right)^{(1-\alpha_i^j)}, \tag{21}$$

where $\hat{t}_i$ is an exogenous change in the environmental tax rate which is one of the counterfactual shocks we introduce in the next section. We assume that the cost share parameters and the emission elasticity are both time-invariant. The other hat variables in equation (21) are changes in endogenous variables which respond to the shock introduced to the model.

The sectoral expenditure at the new equilibrium can be written as

$$X_n'^j = \phi_n^j \sum_{j'} (1-\alpha_n^{j'})(1-\gamma_{n,l}^{j'} - \gamma_{n,k}^{j'}) \sum_{n'} \pi_{nn'}^{j'} \hat{\pi}_{nn'}^{j'} X_{n'}'^{j'} + \phi_n^j I_n', \tag{22}$$

where the total income of the new equilibrium is

$$I_n' = w_n \hat{w}_n L_n + r_n \hat{r}_n K_n + t_n \hat{t}_n \sum_{j'} E_n'^{j'} + D_n'. \tag{23}$$

In our counterfactual exercises, we assume that labor and capital endowments as well as the sectoral expenditure shares in consumer's utility do not vary over time. The emission level of sector j of country i at the new equilibrium is then written as

$$E_i'^j = \frac{\alpha_i^j}{t_i'} \sum_{n'} \pi_{in'}^j \hat{\pi}_{in'}^j X_{n'}'^j. \tag{24}$$

The derivation of changes of other model variables including $\hat{\pi}_{in}^j$, $\hat{P}_n^j$, and $\hat{P}_n$ is in the Appendix. Lastly, the labor market and capital market clearing conditions at the new equilibrium are written as

$$w_n \hat{w}_n L_n = \sum_{j'} \gamma_{n,l}^{j'} (1-\alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} \hat{\pi}_{nn'}^{j'} X_{n'}'^{j'} \tag{25}$$

$$r_n \hat{r}_n K_n = \sum_{j'} \gamma_{n,k}^{j'} (1-\alpha_n^{j'}) \sum_{n'} \pi_{nn'}^{j'} \hat{\pi}_{nn'}^{j'} X_{n'}'^{j'}. \tag{26}$$

The welfare equation in (20) is written in changes as follows:

$$\hat{W}_i = \underbrace{\left(\frac{\hat{I}_i}{\hat{P}_i}\right)}_{\text{changes in real income}} \underbrace{\left(\frac{1+\left(\frac{1}{\mu_i}g_i(E_1,\ldots,E_N)\right)^2}{1+\left(\frac{1}{\mu_i}g_i(E_1',\ldots,E_N')\right)^2}\right)}_{\text{changes in environmental utility}}, \tag{27}$$

which is a function of changes in other variables that have been derived above. Equation (27) enables us to conveniently quantify the welfare effect of a counterfactual shock while taking into account the general equilibrium effect of the shock on income and emission as well as the associated environmental externality. For the rest of the paper, we will call the term in the second parenthesis of equation (27) as changes in environmental *utility*, which a slight abuse of language. We can also decompose the change in the environmental utility into changes in utility coming from own emission and changes in utility from the pollutants that travel from other countries around the world. First, denote the initial environmental utility from concentration of transboundary pollutants for country i by W_i^D, i.e., $W_i^D \equiv \frac{1}{1+\left(\frac{1}{\mu_i}g_i(E_1,\ldots,E_N)\right)^2}$. By totally differentiating W_i^D, the change in W_i^D can be decomposed as follows:

$$\begin{aligned}\hat{W}_i^D - 1 = &\underbrace{\frac{\partial}{\partial E_i}\left(1+\left(\frac{1}{\mu_i}g_i(E_1,\ldots,E_N)\right)^2\right)\frac{E_i(\hat{E}_i-1)}{W_i^D}}_{\text{from own emission}} \\ &+ \underbrace{\sum_{i''\neq i}\frac{\partial}{\partial E_{i''}}\left(1+\left(\frac{1}{\mu_i}g_i(E_1,\ldots,E_N)\right)^2\right)\frac{E_{i'}(\hat{E}_{i'}-1)}{W_i^D}}_{\text{from others' emission}}.\end{aligned} \tag{28}$$

The exact functional form of (28) depends on the parametrization of the $g(\cdot)$ function which is discussed in the next subsection. Given the initial emission data, we compute E_i, $g_i(E_1,\ldots,E_N)$, and W_i^D. After solving the model for $\{\hat{w}_n,\hat{r}_n\}_{n=1}^N$ which is the solution of the system of equations (25) and (26), we compute $\hat{E}_i$ by using (24) and the initial emission data.

4.2 Parametrization of the Travel of Local Pollutants

We parametrize the $g(\cdot)$ function, using the empirical results (step 2) from Section 2. Specifically, we use the coefficient estimates from column 2 of Table 5, which is a baseline specification that includes a transboundary transport term. Recall that the empirical specification looks like

$$ln(concentration)_{it} = \psi + \gamma_1 ln(E/land)_{it} + \gamma_2 Meteo_{it} + \kappa \ln(PolTransport)_{it} + \delta_i + \delta_t + \upsilon_{it}$$

Putting both sides as the power to the exponentials, we get the following function for a country's concentration, $g_i(E_1, \ldots, E_N)$.

$$g_{it}(E_1, \ldots, E_N) = e^{\left(\hat{\psi}+\hat{\gamma_1} ln(E/land)_{it}+\hat{\gamma_2} Meteo_{it}+\hat{\kappa}\ln(PolTransport)_{it}+\hat{\delta_i}+\hat{\delta_t}\right)}$$

The meteorological vector $Meteo$ includes the average of temperature, standard deviation of temperature, average of precipitation, and standard deviation of precipitation, and $PolTransport$ is the degree to which a country is exposed to other countries' emissions. As we discussed in Section 2, we use the following functional form for $PolTransport_{it}$.

$$PolTransport_{it} = \sum_{i' \neq i} \frac{E_{i't}}{land_{i't}} \times \frac{1}{distance^2_{ii't}}$$

The division by land area of an emitting country captures the dispersion of its emissions before crossing borders, and the division by the distance between two countries captures the phenomenon that pollution transport decays with distance nonlinearly.

The coefficient estimates obtained from column 2 are illustrated in Table 6. Note that δ_i is country-specific and we use the coefficient of year fixed effects δ_t corresponding to the year 2000 as the model is calibrated to the year 2000's data. Lastly, we use the year 2000's information on country-level temperature, precipitation, land area as well as the distance between countries from our empirical dataset used in Section 2. Emissions E_i are computed from the model.

Table 6: $g(\cdot)$ parameters

$\hat{\psi}$	$\hat{\gamma_1}$	$\hat{\gamma_2}$				$\hat{\kappa}$	$\hat{\delta}_i$	$\hat{\delta}_{2000}$
		Temp Ave	Temp SD	Rain Ave	Rain SD			
-0.329	0.144	-0.042	0.022	-0.003	0.001	0.333	*varies*	0.12

4.3 Calibration

In this section, we introduce the data and methods used for calibrating the model. We combine a few different datasets for calibration, and our base year is 2000, which is before China's accession to WTO and EU 2004 enlargement, our two main counterfactual scenarios. Our sample includes 38 individual countries and the rest of the world (ROW). We started from 43 countries and ROW as presented in the WIOD, which is our main dataset, and merged those 5 countries without much data coverage with ROW. In addition, based on the sector list from the WIOD, we made a few modifications and ended up with 24 sectors. Specifically, we combined A01-A03 into A and merged D, E, and F into one sector. Also, we put other service sectors than D/E/F and H as other services, so we have 3 service sectors, all of which are non-tradable. Sample countries and sectors are presented in Table A.1 and A.2.

The WIOD provides country-sector-level gross output and value-added as well as a multi-country, multi-sector input-output table. We also use the KLEMS for country-sector-level capital and labor expenditures, EDGAR for country-sector-level emissions, and OECD for the country-level ratio of environmental tax revenue to GDP.

4.3.1 Environment-related parameters

In addition to $g(\cdot)$ function as discussed in the previous section, we have three environment-related parameters that need to be calibrated. They are the disutility parameter μ_i, environmental tax t_i and country-sector-level emission intensity α_i^j.

Disutility parameter We calibrate the disutility parameter, μ_i, so that the welfare decrease by a one-ton increase in $PM_{2.5}$ emissions matches the social cost of $PM_{2.5}$ of each country. Specifically, we take the following steps. First, using the US estimate of $PM_{2.5}$'s social cost, we impute the social cost for other countries. Heo et al. (2016) provide the estimated range for the marginal social cost of $PM_{2.5}$ emission, calculated for the US in 2005. We use the median of the range, which is $109,000$ 2005 USD per metric ton.[30] Non-US countries' social costs, $sc_{i \neq US}$, are estimated by adjusting for their relative population density and GNI per capita (with elasticity ν) compared to the US, as shown in Equation 6.

$$sc_{i \neq US} = sc_{US} \times \frac{popdensity_i}{popdensity_{US}} \times \left(\frac{GNIpc_i}{GNIpc_{US}} \right)^{\nu} \tag{29}$$

This is based on the notion that marginal social cost is estimated by measuring the damage incurred by an additional emission through increased mortality risks and expressing it in a monetized value using the value of statistical life (VSL). The implicit assumption is that the demographics composition of each country and the health effect of pollution are common across countries. A higher level of population density increases the degree to which the population is exposed to a marginal emission, thus increasing total mortality risks.[31] In addition, VSL is based on the willingness to pay to reduce mortality risk and increases with income level (OECD 2012, Viscusi and Masterman 2017). We use the income elasticity of VSL $\nu = 1.103$, following (Viscusi and Masterman 2017).[32] The resulting estimated values of the social cost of $PM_{2.5}$ are reported in Appendix Table A.6.

Then we solve for μ_i which makes the marginal social cost of $PM_{2.5}$ emission match each country's estimated social cost, following Bockstael and Freeman (2005). We define the marginal social cost as the willingness to pay to avoid marginal emission as follows with $dE_k = 1$ for all k.[33]

$$sc_i = -\frac{dI_i}{\sum_{\forall k} dE_k} = \frac{\sum_{\forall k} \partial W_i / \partial E_k}{\partial W_i / \partial I_i} = \sum_{\forall k} \frac{\partial W_i}{\partial g_i} \left(\frac{\partial W_i}{\partial I_i} \right)^{-1} \frac{\partial g_i}{\partial E_k} dE_k \tag{30}$$

[30] The minimum is $88,000$ 2005 USD, and the max $130,000$ 2005 USD.

[31] Ideally, we want to use the exact measure of population exposure to $PM_{2.5}$ pollution, which needs information on the location of emission sources and population density within a country.

[32] This is the estimate for non-US countries.

[33] We interpret marginal social cost in a different way from how **?** does. He defines social cost as the change in welfare with respect to the change in (global) CO_2 emission. Following such definition, $sc_i = \frac{\partial W_i}{\partial E}$ where E is the level of global emissions.

It is worth to note that this is a general form that allows a range of assumptions on the degree of transboundary transport. In a model that does not take transboundary pollution into account (equivalently, $\frac{\partial g_i}{\partial E_{k \neq i}} = 0$), the marginal social cost is, and Equation 30 becomes $sc_i = \frac{\partial W_i}{\partial g_i} \left(\frac{\partial W_i}{\partial I_i} \right)^{-1} \frac{\partial g_i}{\partial E_i}$.

Putting Equation 20 and the functional form of $g(\cdot)$ specified in the previous section into Equation 30, we get the following expression for the environmental disutility parameter, μ_i, squared.

$$\mu_i^2 = -\frac{2g_i I_i}{sc_i} \times \sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k - g_i^2 \tag{31}$$

where

$$\sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k = \frac{g_i}{E_i} \hat{\gamma}_1 dE_i + \hat{\eta}_1 \frac{g_i \sum_{i' \neq i} (land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{\sum_{i' \neq i} \frac{E_{i'}/land_{i'}}{d_{i'i}^2}} \tag{32}$$

We assume that μ_i^2 is time-invariant and use the 2005 data to calculate μ_i^2 since the social cost values we take from Heo et al. (2016) are estimated for the year 2005. Putting Equation 32 into Equation 31 and using the data as well as parameter values for $g_i(\cdot)$ as discussed in the previous section, we obtain the values of μ_i^2 for each country. Equation 27 shows that countries with larger μ_i^2 experience a smaller welfare loss from the same increase in concentration. Appendix A.3.1 shows detailed steps for the derivation, and Table A.7 reports the estimated μ_i^2 values.[34]

If $PM_{2.5}$ pollution sources are located mostly in these areas, then they may capture a closer picture of people's exposure to pollution. But some industrial activities are located far from residential areas. In addition, both measures are not available for all of our sample countries.[35] Thus, we present them as robustness checks. Appendix Table A.8 and A.9 report the resulting social cost and μ_i^2 values from these two approaches, showing that the estimates are similar in most countries. One notable exception is Australia, whose urban version has a much smaller μ_i^2 estimate as the population is highly concentrated in urban areas (thus, much higher urban population density compared to overall and rural population density).

Environmental regulation We calibrate the level of emission tax for each country by matching the ratio of emission tax revenue to value-added $\frac{t_i E_i}{VA_i}$ to the data. Specifically, we use the environmental tax revenue per GDP from OECD.[36] As we have the data for E_i and VA_i, we can easily

[34] We also obtain social cost and disutility parameter values by using alternative measures for population exposure. Population density may not perfectly capture the degree of the population's exposure to pollution. Consider an extreme, hypothetical case in which the population is concentrated in one part of a country whereas polluting sources are concentrated at another end of the country. Then using population density may over-capture the exposure of the population to increased emission and concentration. Ideally, we need information on the location of emission sources and population density within each country. But such information is not easy to attain – especially in a multi-country setting. Thus, we use two alternative measures of population density for robustness analysis: population density for urban areas and population density for urban and rural areas combined.

[35] We use the population and surface area of urban and rural areas, obtained from the World Bank's WDI. Austria, the Czech Republic, Hungary, and Taiwan do not have the data.

[36] We use the tax revenue for all categories, which include the tax on energy, transport, resources, and air pollution. For the countries that provide huge subsidies for energy – resulting in a negative value for this ratio – we exclude

solve for t_i for each country.

Emission elasticity The emission elasticity α_i^j captures the responsiveness of emission with respect to abatement. We calibrate the value of emission elasticity α_i^j by using 33, which is obtained from rearranging Equation 9.

$$\alpha_i^j = \frac{E_i^j t_i}{GO_i^j} \tag{33}$$

It shows that emission intensity can be calculated as the share of tax expenditures in gross output. In other words, it is as though emission is a type of input and α_i^j represents a Cobb-Douglas input share for emission, which is consistent with how Equation 6 shows the Cobb-Douglas production technology using emission as an input. As sector-level emissions E_i^j and gross output GO_i^j are observed in the data, we can obtain the value of α_i^j, using the calibrated value of t_i.

4.3.2 Other calibration

We match input expenditure shares ($\gamma_{i,l}^j$, $\gamma_{i,k}^j$, $1-\gamma_{i,l}^j-\gamma_{i,k}^j$) from the WIOD and KLEMS. Specifically, we first obtain the ratio of value-added and intermediate expenditures to gross output from the WIOD. Then, we divide the value-added share into labor and capital expenditure shares, using the information from the KLEMS.

Sectoral expenditure share, trade share, and trade deficit match the data from the WIOD. To calculate the sectoral expenditure share ϕ_i^j, we divide the total final expenditure on sector j goods by country i's total final expenditures.[37] The bilateral trade share π_{in}^j is obtained by dividing n's imports of sector j goods from i by n's total absorption of sector j goods. Trade deficits are given by subtracting total exports from total imports.

Lastly, we use the estimates from Caliendo and Parro (2015) for the sector-level trade elasticity (θ^j).[38] While most sectors correspond 1-to-1 between their and our classifications, three sectors from theirs are matched with one sector in ours.[39] The sector C26 (Manufacturer of computer, electronic, and optimal products) in our sample is matched with Office, Communication, and Medical Manufacturing in their sector list. We use the weighted average of the three elasticities to get the one for C26, using the world total trade flows. The elasticities are presented in the Appendix Table A.10.

energy subsidies and include the tax on the remaining categories. The model does not allow the negative regulation (i.e., subsidies) as Equation 33 does not make sense with $t_i < 0$.

[37] We follow Costinot and Rodriguez-Clare (2014) to eliminate the negative inventories so that both expenditure share and trade share are all nonzero. Specifically, for negative inventories, the authors assume that the products expressed in the negative inventories were produced in the previous period, thus replacing the negative inventory values with zero and adding the absolute value of the negative inventories to the gross output. For a static model setting, like ours, they assume that they were produced in the same, concurrent period.

[38] We use their 99% sample estimates.

[39] We use the ISIC Rev. 4 classification while they use the ISIC Rev. 3 classification.

5 Counterfactuals

What would be the welfare effect of trade liberalization after taking the environmental externality from transboundary pollutants into account? Is that effect quantitatively different if a particular trade liberalization episode involves more stringent environmental regulations for participating countries? We can use our model to answer these policy questions based on counterfactual exercises. These exercises not only shed light on important policy questions about trade and the environment but also highlight the key mechanism of the model.

We study two counterfactual scenarios. First, we quantify the welfare effect of the China shock by exogenously lowering trade costs to and from China by 20% – i.e., $\hat{d}_{i,China} = \hat{d}_{China,i} = 0.8$ for all $i \neq China$. Second, we explore the welfare effect of EU enlargement in 2004 with the actual changes in tariffs between existing and new EU member countries as the exogenous shock of the counterfactual scenario. For each scenario, we compute changes in total welfare for all countries in our sample and decompose them into changes in real income and changes in environmental externality. The former is a conventional measure of welfare gains from trade in a model with identical and homothetic demand, while the latter is the new component in our framework.

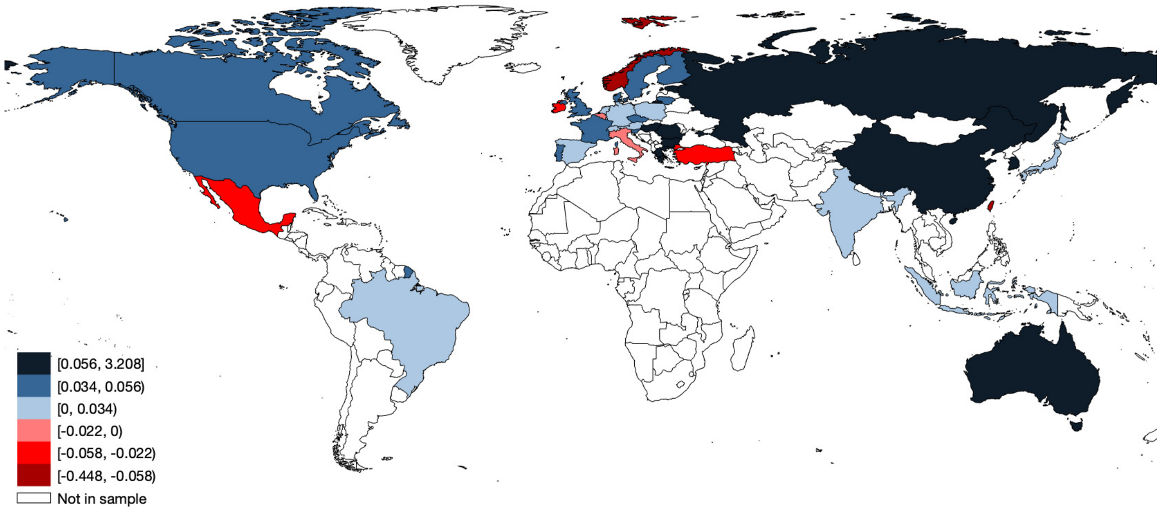
Also, we augment each scenario by introducing hypothetically more stringent environmental regulations. More recent trade agreements tend to include environmental provisions to ensure participating countries' commitment to a clean environment. To study how such provisions may change the welfare effect of trade liberalization, we put an additional shock of a 20% exogenous increase of environmental tax for China in the first scenario, and for new EU member countries in the second scenario. The 20% of increase in the tax is meant to capture the change in regulation stringency in various forms, both tax and non-tax, that may follow the trade liberalization. The additional shock is to highlight the model mechanism but not to exactly capture the actual change in regulation stringency that occurred in China's accession and the EU enlargement.[40]

5.1 China shock

Since China joined the WTO in 2001, most countries around the world have seen a large increase in trade with China, especially imports from China. There has been a lot of research on the welfare consequences of China's joining the world market from various perspectives. Our focus in this paper is to revisit the welfare effect of trade shocks with the environmental externality from transboundary pollutants taken into account. We introduce the so-called China shock to the baseline model by plugging in $\hat{d}_{i,China} = \hat{d}_{China,i} = 0.8$ for all $i \neq China$, which implies that trade costs to and from China are exogenously lowered by 20%. All the other model parameters remain unchanged. This counterfactual shock will affect trade patterns between China and each of the other countries in the sample. Changes in trade patterns will affect each country's production patterns across industries, and depending on each industry's emission intensity, the aggregate emission of

[40] Candidate countries must apply all EU legislation and policy on the environment by their date of accession. For example, they must enforce emission sources to meet EU standards, including but not limited to monitoring and data collection, and reduce emissions. As such, the heightened stringency takes different forms.

Figure 4: Changes in aggregate welfare from the China shock (% change)



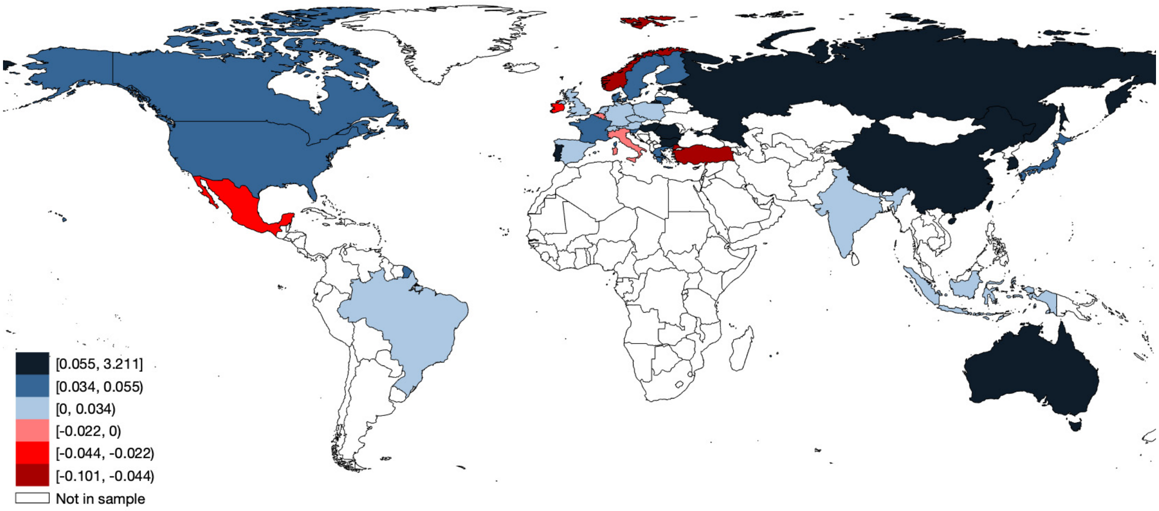
$PM_{2.5}$ will change. While we should expect each country's own emission to be the most important determinant of the concentration level of the same pollutant in the country, changes in the emission level of neighboring countries will also matter due to the transboundary nature of the pollutant. Therefore, the environmental externality is expected to show spatial heterogeneity.

Figure 4 shows the changes in aggregate welfare for each country in our sample from a 20% decrease in trade costs to and from China. The results in numbers are reported in Table A.11 of the Appendix. Not surprisingly, we see that aggregate welfare increases in most countries with the largest increase for China. The results also show that the welfare effect of the China shock is significantly heterogeneous across countries in terms of both directions and magnitudes.

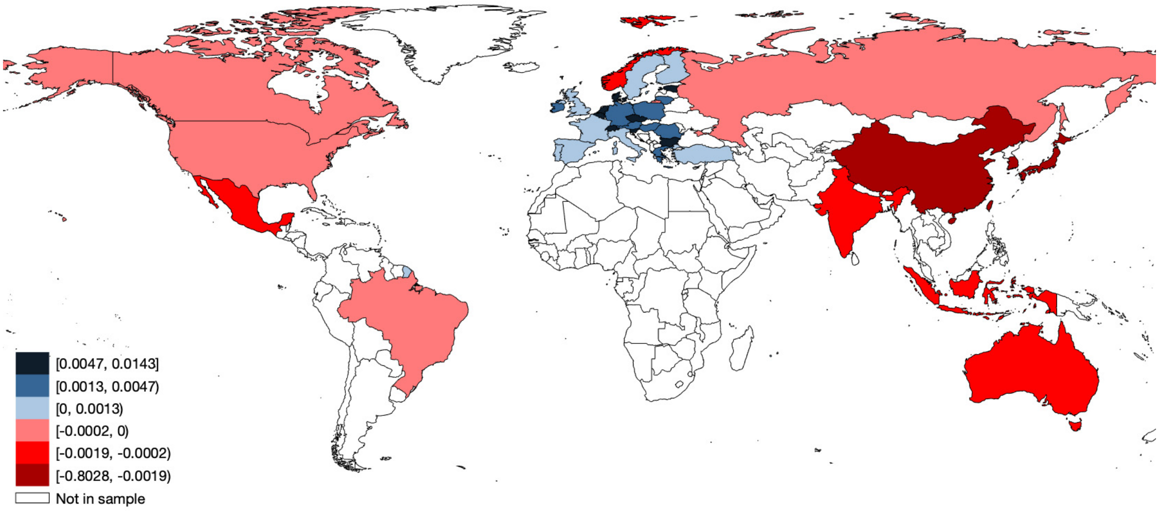
Where does this heterogeneous welfare response across countries come from? A standard trade model without environmental externality would answer this question solely based on changes in real income of each country from the change in trade costs with China. The sign and the magnitude of the changes depend on various factors such as each country's industry composition, China's comparative advantage across industries, and each country's initial trade shares with China. The welfare response in our model, on the other hand, has an additional component that captures changes in environmental externality for each country. As shown in equation (27), the total changes in welfare in response to the China shock can be exactly decomposed into changes in real income as captured in standard trade models, and changes in environmental externality from transboundary pollutants.

Figure 5 shows the decomposition results for each country. Columns (2) and (3) of Appendix Table A.11 report the results in numbers. The first notable pattern is that changes in welfare measures reported in Figure 4 are predominantly determined by changes in real income reported in Figure 5 (a). While there is sizable disutility from transboundary pollutants, the magnitude of the

Figure 5: Decomposition of the welfare effect from the China shock



(a) Changes in real income (%)



(b) Changes from environmental externality (%)

environmental externality is relatively smaller compared to that of changes in real income.[41]

The second pattern to note is that changes in environmental externality,—i.e., changes in utility from the concentration of $PM_{2.5}$ in air,—also contribute to the heterogeneous welfare effects across countries, but that the pattern of heterogeneity is significantly different between changes in real income and changes in environmental externality. In fact, many countries have welfare losses from increases in environmental disutility due to the decrease in trade costs with China, as reported

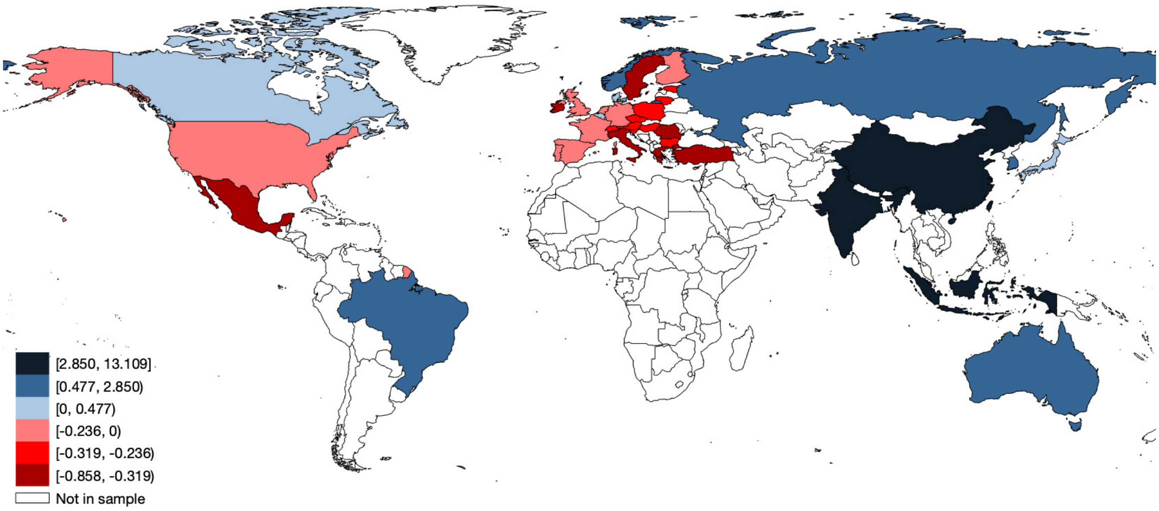
[41]Recent few papers also find that the environmental aspect of welfare changes from trade policies is much smaller than the real-income counterpart (Shapiro 2016; 2021).

in Figure 5 (b). There are three effects combined in this result. First, as China joins the world market, the conventional pollution haven effect would come into play. In other words, production is reallocated from other countries, especially from other developed countries such as North-American or European countries, to China after the shock, which increases the emissions of $PM_{2.5}$ in China and decreases them in those other countries. Second, due to the transboundary nature of $PM_{2.5}$, an increase in emissions from China can have spillover effects on its neighboring countries in East and Southeast Asia. This spillover effect is captured by the decrease in environmental externality in countries like Korea, Japan, India, Taiwan, and Russia in Figure 5 (b). Lastly, the China shock can also increase other countries' own emissions. For example, if country A specializes in the industry X which heavily uses intermediate inputs for which China has a comparative advantage, an increase in trade with China may increase country A's production in industry X. If the technology of country A for industry X has a high emission intensity, an increase in trade with China will increase country A's own emission.

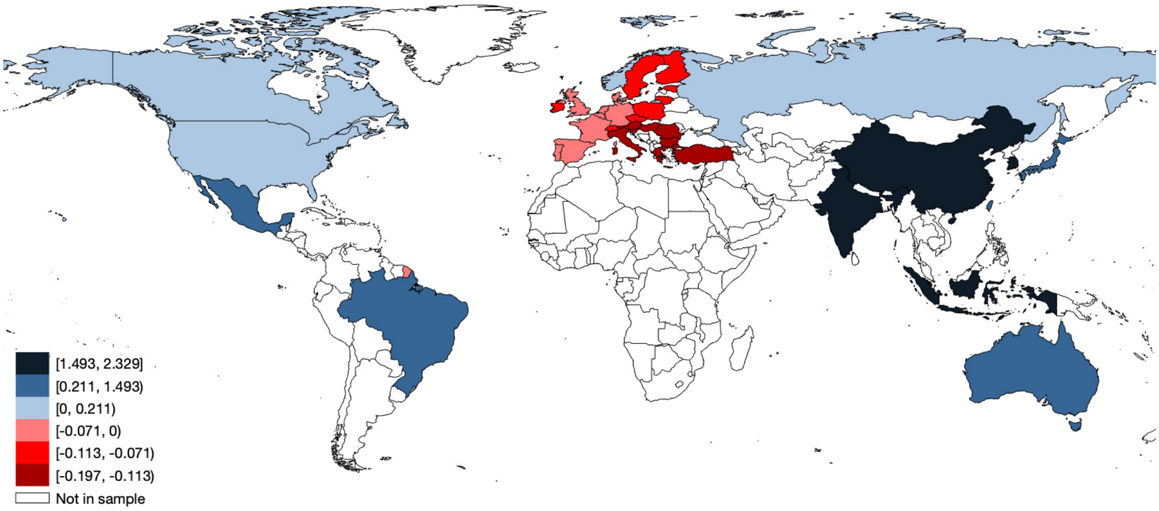
To disentangle these three effects more clearly, we decompose changes in environmental utility into changes in environmental utility from a country's own emission and those from all the other country's emissions, based on the analytical decomposition in equation (28). Columns (4) and (5) of Appendix Table A.11 report the decomposition results. In response to a decrease in trade costs to and from China, the environmental utility from $PM_{2.5}$ in China decreases by 0.0025%, and we show that 84% of that decrease is from an increase in own emission. In other neighbors of China, the patterns are starkly different. In Korea, for example, the China shock decreases the environmental utility by 0.1411%, but only 3.5% of that decrease is from its own emission. The rest of the decrease is from other countries' emissions in which the increase in emissions from China plays a dominant role. The fact that the magnitude of the negative welfare effect from emission is larger in Korea than in China reflects that the marginal disutility from emission can be different across countries, as captured by the country-specific parameter μ_i. In other words, an additional emission brings smaller welfare loss in China given the current calibration of the disutility parameter.

Lastly, our model also shows how much each country's own emission and concentration level of PM2.5 change in response to the China shock. While the emission level depends on each country's own production level, the concentration level of a country depends on how much other countries' emission levels change in addition to the changes in its own emissions, due to the transboundary nature of PM2.5. Figure 6 show changes in emission and concentration in each country in response to an exogenous decrease of trade costs to and from China, and columns (6) and (7) of Appendix Table A.11 report the results in numbers. The results show that both the emission level and the concentration level increase in the neighboring countries of China. A decrease in trade costs with China makes it possible for those countries to import cheaper inputs from China, which would increase their own production level as well. Therefore, the emission level of those countries close to China increases from the increase in their production level. In addition, since China experiences a large increase in production scale and thus a large increase in emission due to their high emission intensity, the neighboring countries of China have spillover effects from the increased emission from

Figure 6: Changes in emission and concentration from the China shock



(a) Changes in emission (%)



(b) Changes in concentration (%)

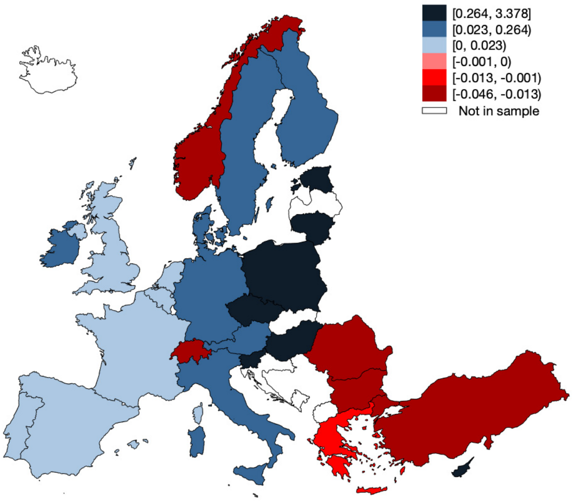
China. As a result, the countries geographically close to China experience increases in both their own emissions and concentration of $PM_{2.5}$ due to their geographical proximity to China. European countries, on the other hand, show a relatively strong pollution haven effect, which is represented by significant decreases in their own emissions. Also, the European countries are relatively further from China compared to their direct neighbors of China. Therefore, they see decreases in both emission and concentration of $PM_{2.5}$ in response to the China shock.

Since different countries have different levels of stringency for environmental regulations, many recent trade agreements try to address this discrepancy with additional provisions related to environmental regulations. These environmental provisions are often a subject of heated debates between developed and developing countries, because more stringent environmental regulations may increase the effective cost of production for developing countries, which would limit the potential benefit from trade liberalization for them. From developed countries' perspectives, they have an incentive to include strict environmental provisions not only to level the playing field but also to reduce future harm to global environmental conditions. In order to assess the welfare effect of trade liberalization accompanied by stricter environmental regulations, we consider a counterfactual scenario where bilateral trade costs to and from China decrease by 20% as in the previous scenario and there is an exogenous 20% increase in the environmental tax rate in China. This scenario characterizes a situation where China is required to implement more stringent environmental regulations when it joins the world market.

Table A.12 in the appendix show the effect of this counterfactual scenario on aggregate welfare, real income, environmental utility, and emission and concentration levels of $PM_{2.5}$. The welfare increase for China is about 3.4% smaller with a higher environmental tax, compared to the first counterfactual scenario without additional environmental regulations. When we decompose the welfare increase, the result shows that the smaller welfare effect is from the smaller increase in real income, as China is not able to expand its production as much as in the first counterfactual scenario with higher effective production costs due to the higher environmental tax. Since producers are required to pay higher environmental tax, the environmental utility in China increases after this counterfactual shock, which is exactly the opposite result of the counterfactual scenario with only trade liberalization without additional environmental regulations. Another thing to note is that even though the concentration level of $PM_{2.5}$ decreases by 0.30% in China with the stricter environmental regulations, the environmental utility increases only by 0.0003%. This result is because the marginal disutility from $PM_{2.5}$ concentration is relatively smaller in China, compared to other developed countries in our sample.

The effects on the other countries' real income do not vary much between the two scenarios. The effects on the other countries' environmental utility, on the other hand, are significantly different depending on whether China's joining the world market is accompanied by stricter environmental regulations imposed on China. In all countries of our sample, the effect of the shock on the environmental utility is larger with a higher environmental tax imposed on China, because fewer emissions of $PM_{2.5}$ from China decrease the concentration level of $PM_{2.5}$ everywhere. This effect is more pronounced in the countries that are geographically close to China. For example, in Korea, the environmental utility decreases by 0.14% in the first counterfactual scenario without environmental regulations for China, but it decreases by only 0.007% with environmental regulations. Therefore, all countries, especially the neighboring countries to China, have a large incentive to actively engage in negotiations about requiring stricter environmental regulations in China. The welfare loss from additional environmental regulations accompanying trade liberalization for China is also not large.

Figure 7: Changes in aggregate welfare from the EU enlargement (% change)



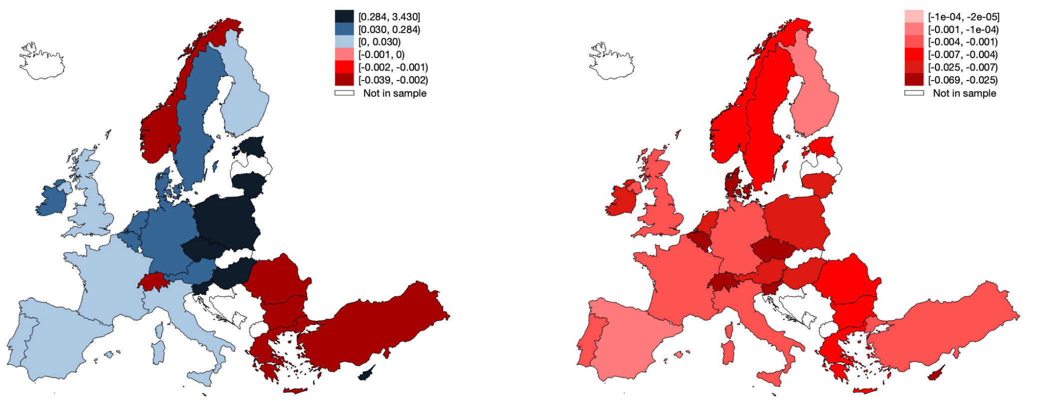
5.2 EU Enlargement

The spillover effect of transboundary pollutants is likely to be more problematic in regions where a large number of countries with potentially different incentives for environmental protection are geographically clustered. The European Union (EU) enlargement that occurred in 2004 is an ideal event to study this effect through the lens of our model since the level of economic development between the new EU member countries and the existing EU member countries was sizable and EU countries are geographically close to one another, which made the spillover effect of transboundary pollutants more important. To study the effect of the trade liberalization that accompanied the EU enlargement on welfare and environmental utility, we introduce the actual changes in tariff rates between new and existing EU member countries between 2000 and 2010 as a counterfactual shock to the model. Other model parameters are assumed to be unchanged.

Figure 7 shows counterfactual changes in aggregate welfare in European countries in response to the trade liberalization that followed the EU enlargement. We report the results in numbers in column (1) of Table A.13 in the appendix. The most notable pattern is that new EU member countries experience larger welfare gains than existing EU member countries. As shown in columns (2) and (3) of Table A.13, this result is driven by larger increases in real income that the new EU member countries experience as a result of their newly acquired access to the larger European market.

As the next step, we decompose the welfare effect of the EU enlargement into changes in real income and changes in environmental utility. Figure 8 show the decomposition results for countries in Europe, and columns (2) and (3) of Table A.13 report the full results in numbers. As discussed previously, the effect of the EU enlargement on real income plays a dominant role in its effect on aggregate welfare. Panel (b) of Figure 8 shows that there is significant spatial heterogeneity in counterfactual changes in environmental utility across European countries and that the pattern is consistent with the pollution haven effect as well as the transboundary nature of $PM_{2.5}$. This pattern can be more easily seen with counterfactual changes in emission and concentration levels of $PM_{2.5}$, which are reported in Figure 9 for European countries. As the new EU member countries gain better access to the large markets of higher-income European countries, their production level increases. Since these countries have a relatively higher level of emission intensity, $PM_{2.5}$ emissions increase significantly in these countries. On the other hand, some existing EU member countries experience a decrease in emissions, as they produce less in dirtier industries and import from new EU member countries instead. For the other existing EU member countries, having new EU member countries may increase their own production due to cheaper input imports, which increases their own emission level. However, in terms of the magnitude, the increase in emission is much larger for the new EU member countries than for the existing members. An increase in $PM_{2.5}$ emissions from new EU member countries increases the concentration level in most European countries due to the transboundary nature of $PM_{2.5}$. For example, in Greece, the own emissions of $PM_{2.5}$ in fact decrease by 0.14% after the EU enlargement, but the concentration level of $PM_{2.5}$ increases by 0.31% as the emission levels increase a lot in the new EU member countries that are geographically close to Greece.

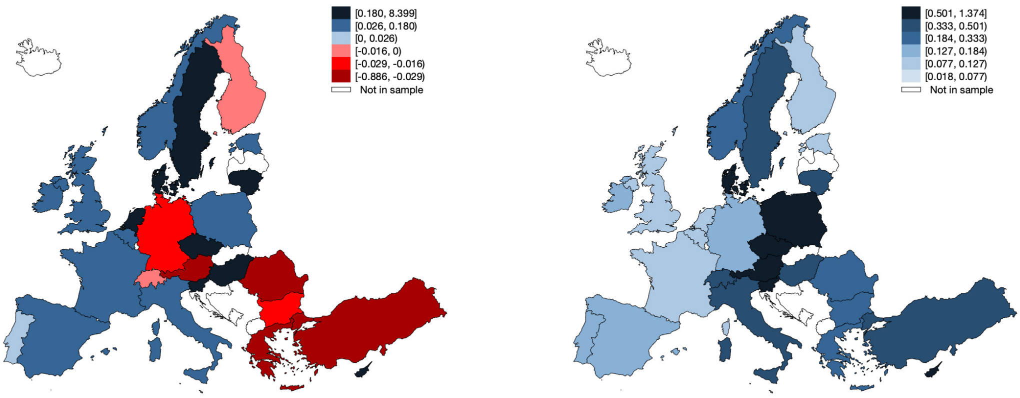
Figure 8: Decomposition of the welfare effect from the EU enlargement



(a) Changes in real income (%)   (b) Changes in environmental externality (%)

Joining the European Union does not only mean that the new member countries must lower trade barriers but also they have to comply with many other rules including environmental regulations. The environmental implication of the EU enlargement discussed above highlights that the existing EU member countries have an incentive to enforce a higher level of environmental regulations on new member countries, especially regarding the air pollutants of transboundary nature, due to their spillover effects. To quantitatively assess how such environmental regulations may change the welfare effect of the trade liberalization that followed the EU enlargement, we add another shock which increases the environmental tax rates for the new EU member countries by 20% from their baseline levels. In other words, this scenario introduces both lower trade costs and higher

Figure 9: Changes in emission and concentration from the EU enlargement



(a) Changes in emission (%) (b) Changes in concentration (%)

environmental tax for the new EU member countries, similarly to the exercise we did for the case of China in the previous subsection.

Table A.14 in the appendix reports the counterfactual results. The results highlight the differential incentives that new and existing EU member countries may have for environmental regulations imposed on the new member countries. Compared to the results from the counterfactual scenario without additional environmental regulations, the welfare gains of the new EU member countries are smaller, and those of the existing member countries are larger. Higher environmental tax rates on the new EU member countries increase the environmental utility for all European countries, but the limited gains in real income for the new member countries partially offset the gains in the environmental utility. With a similar intuition discussed in the case of China, with higher environmental tax rates, the effective production cost increases in the new EU member countries, which limits the expansion of their production in response to the access to the European market. The existing EU member countries benefit from this trade liberalization with new member countries accompanied by stricter environmental regulations because the new member countries need to reduce the emission of transboundary pollutants, which significantly decreases the concentration level of such pollutants in the existing member countries as well.

6 Conclusion

This paper develops a general equilibrium model to quantify the welfare implications of international trade policies incorporating the transboundary nature of air pollutants. As air pollutants travel across borders, the environmental consequences of trade are not solely determined by the location of emission-generating activities; the emissions of neighboring countries are also an important factor. To motivate this paper's focus on transboundary transport of air pollution, we run multi-country panel regressions and find that a country's concentration is correlated with its exposure to other countries' emissions – our measure of transboundary transport of pollution – which is suggestive of the importance of taking this additional externality into account to understand the welfare consequences of trade policies. By building a multi-country general equilibrium trade model with environmental externality, we show how trade shocks affect a country's welfare via changes in real income and its own emissions as well as other countries' emissions that may travel to a country.

We quantify the model to examine how such multiple channels come into play and determine welfare gains from trade shocks. The model is calibrated to the year 2000, and the transboundary travel of local pollutants is parametrized by using the estimates from a multi-country panel regression on the determinants of concentration. We run two counterfactual exercises, using the scenarios that show both large-scale economic integration and potential transboundary spillovers: the China shock and the EU 2004 enlargement. In each of the counterfactuals, we examine the welfare impact of a trade shock only and the welfare impact of a combination of trade shock and tighter environmental regulations. The latter is to explore the welfare implications of combining trade and environmental policies.

Both counterfactual results show a few similar patterns. First, liberalizing countries experience an increase in emissions due to an increase in production. Second, among the rest of countries, some experience decreases in emissions as emission-generating production activities relocate to liberalized countries while others experience increases in production and emissions due to increased access to cheaper inputs from liberalized countries. Third, the levels of concentration increase not only in liberalized countries but also in some other countries, the latter of which are due to the increase in own emissions as well as transboundary pollution. Lastly, the change in real income is much larger than the change in environmental utility, thus determining the overall welfare gains, for most countries. These multiple channels shape heterogeneous welfare consequences across countries. With more stringent environmental regulations imposed on China and new EU members, trade shocks bring smaller environmental welfare losses in both these liberalizing countries and neighboring countries via lower levels of emissions and transboundary pollution. In the meantime, the gains in real income are not reduced much. This additional counterfactual result shows the potential effects of incorporating environmental provisions into trade liberalization agreements or, more broadly speaking, combining international trade and environmental policies.

In summary, this paper provides a general, tractable framework to study spatial heterogeneity in the welfare impact of trade shocks. The general framework of our model can be applied to a wide range of pollutants, from strictly local pollutants to global pollutants, such as greenhouse gases, which makes it a useful tool to study the environmental consequences of trade. For example, we can use the model to look at the effects of the Carbon Border Adjustment Mechanism (CBAM), which aims to tackle carbon leakage by putting a price on the carbon content of imports. Although CBAM focuses on carbon, it would affect a wide range of emissions since many types of pollution are highly correlated (Copeland et al. 2022). One could use this model to study the effects of CBAM across multiple pollutants by considering their different emission intensities as well as the degree of transboundary transport.

In addition, this model can be used to study the optimal trade policy or the optimal combination of trade and environmental policies. For example, if there was no transboundary pollution externality, it would be more beneficial to trade with nearby countries than with countries farther apart. But with transboundary pollution into consideration, there can be a different optimal set of trade partner countries. Moreover, the consequences of a trade war could be smaller for some countries because of the environmental improvement from less transboundary pollution. More broadly, this paper provides a basis to understand the global optimal policy for local pollutants, which has not been studied much unlike the one for carbon (Farrokhi and Lashkaripour 2021), or the linkage between trade and environmental negotiations in the presence of global environmental externalities (Abrego et al. 2001, Limao 2005, Nordhaus 2015, Venables 1999).

Lastly, this model can be extended to incorporate input-output linkages between sectors to study how such linkages amplify the size of environmental externality. If two countries that are geographically close to each other are also linked with tight input-output connections, one's trade policy would affect the other's pollution not only through the channels discussed in this paper but additionally through the amplification effect via sectoral interrelations.

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A Appendix

A.1 Additional tables

Table A.1: Sample countries

AUS	Australia	IRL	Ireland
AUT	Austria	ITA	Italy
BEL	Belgium	JPN	Japan
BGR	Bulgaria	KOR	Korea
BRA	Brazil	LTU	Lithuania
CAN	Canada	LUX	Luxembourg*
CHE	Switzerland	LVA	Latvia*
CHN	China	MEX	Mexico
CYP	Cyprus	MLT	Malta*
CZE	Czech Republic	NLD	Netherlands
DEU	Germany	NOR	Norway
DNK	Denmark	POL	Poland
ESP	Spain	PRT	Portugal
EST	Estonia	ROU	Romania
FIN	Finland	ROW	Rest of the World**
FRA	France	RUS	Russia
GBR	United Kingdom	SVK	Slovak Republic*
GRC	Greece	SVN	Slovenia
HRV	Croatia*	SWE	Sweden
HUN	Hungary	TUR	Turkey
IDN	Indonesia	TWN	Taiwan**
IND	India	USA	United States

Notes: * Croatia, Luxembourg, Latvia, Malta, and Slovak Republic are included in ROW for quantitative analyses. ** Taiwan and ROW are included only in quantitative analyses but not in the empirical section.

Table A.2: Sample sectors

A	Agriculture/Forestry/Fishing
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31-C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D/E/F	Utilities/Construction
H	Transportation
Other	Other services

Notes: We combined A01-A03 into A and merged D, E, and F into one sector. Also, we put other service sectors than D/E/F and H as other services.

Table A.3: Summary statistics for the first specification

		Unit	N	Mean	SD	Min	Max
Baseline regression							
ln($Emissionpc$)	$PM_{2.5}$ emissions per capita	ln(metric ton per capita)	630	-5.568	0.520	-6.869	-4.390
$GDPpc$	GDP per capita	mn 2010 USD per capita	630	0.030	0.023	0.001	0.112
$GDPpc^2$	GDP per capita, squared	(mn 2010 USD per capita)^2	630	0.001	0.002	6.8×10^{-7}	0.013
$Tech$	Number of abatement-tech patents per capita	number per capita	630	.0005	0.001	0	0.006
$Trade$	Ratio of total trade flows to GDP	ratio	630	0.927	0.588	0.198	3.928
$Upstream$	Upstreamness, following Antràs and Chor (2018)	.	630	2.041	0.193	1.609	2.920
$PTAenv$	Share of trade flows with partner countries of PTAs with env. provisions	ratio	630	0.497	0.324	0	0.920
Additional regression							
$Export$	Ratio of export flows to GDP	ratio	630	0.470	0.314	0.090	2.126
$Import$	Ratio of import flows to GDP	ratio	630	0.457	0.278	0.092	1.802
$PTAenv$ (ex)	Share of export flows with partner countries of PTAs with env. provisions	ratio	630	0.508	0.336	0	0.936
$PTAenv$ (im)	Share of import flows with partner countries of PTAs with env. provisions	ratio	630	0.486	0.319	0	0.923

Table A.4: Summary statistics for the second specification

		Unit	N	Mean	SD	Min	Max
Column 1 and 2							
ln(concentration)	$PM_{2.5}$ concentration level (country ave)	ln(metric ton/km^3)[42]	630	-4.525	0.607	-6.502	-2.823
ln(emission/land)	$PM_{2.5}$ emissions per land area	ln(metric ton/km^2)	630	-1.164	1.048	-4.015	1.417
Temp Ave	Simple average of monthly temperature	Celsius	630	10.874	6.857	-7.077	26.427
Temp SD	Standard deviation of monthly temperature	Celsius	630	7.222	2.704	0.216	16.316
Rain Ave	Simple average of monthly preciptation	mm	630	74.682	39.637	21.676	298.390
Rain SD	Standard deviation of monthly precipitation	mm	630	38.722	22.373	8.688	168.389
ln(PolTransport)	Defined as in Eq. 2	.	630	-10.570	1.025	-13.296	-8.713
Column 3							
ln(concentration)	$PM_{2.5}$ concentration level (country ave)	ln(metric ton/km^3)	429	-4.511	0.653	-6.502	-2.823
ln(emission/land)	$PM_{2.5}$ emissions per land area	ln(metric ton/km^2)	429	-1.179	1.018	-4.015	0.821
Temp Ave	Simple average of monthly temperature	Celsius	429	9.860	5.740	-7.077	25.239
Temp SD	Standard deviation of monthly temperature	Celsius	429	7.549	2.405	3.139	16.316
Rain Ave	Simple average of monthly preciptation	mm	429	70.630	27.287	27.227	173.118
Rain SD	Standard deviation of monthly precipitation	mm	429	37.705	24.133	8.688	168.389
ln(PolTransport)	Defined as in Eq. 2	.	429	-10.518	0.893	-12.972	-8.713
ln(pop density)	Population per km^2	ln(persons/km^2)	429	4.479	1.220	0.906	6.227
Share of urban population	Ratio of population in urban agglomerates (>1 mn people) to the total population	ratio	429	0.242	0.139	0.044	0.635
ln(rail density)	Length of rail lines per land area	ln(km/100km^2)	429	1.169	1.007	-2.188	2.511
Technology	Number of env-management patents per capita	number per capita	429	0.007	0.008	0.000	0.033

[42] 1 metric ton/km^3 is equivalent to 1000μg/m^3

Table A.5: Determinants of $PM_{2.5}$ concentration

	(1)	(2)
ln(emission/land)	0.159***	0.196***
	(0.039)	(0.059)
Temp Ave	-0.043*	-0.034
	(0.022)	(0.029)
Temp SD	0.022	0.028
	(0.025)	(0.025)
Rain Ave	-0.003***	-0.001
	(0.001)	(0.001)
Rain SD	0.001	-0.001
	(0.001)	(0.001)
ln(PolTransport)	0.182***	0.132**
	(0.061)	(0.064)
ln(population density)		0.087
		(0.181)
Share of urban agglo. pop		2.155***
		(0.775)
ln(rail density)		0.464***
		(0.099)
Technology		-3.313
		(4.253)
Observations	630	429
Within Adj. R-squared	0.117	0.152

Notes: The dependent variable is the log of $PM_{2.5}$ concentration. All columns use country fixed effects and year fixed effects. Standard errors in parentheses are clustered at the region-year-level. Asterisks denote p-value *< .1, **< .05, ***< .01.

Table A.6: Social cost estimates (unit: mn 2005 USD/ton)

AUS	Australia	-0.009	IDN	Indonesia	-0.008
AUT	Austria	-0.306	IND	India	-0.019
BEL	Belgium	-1.027	IRL	Ireland	-0.188
BGR	Bulgaria	-0.022	ITA	Italy	-0.499
BRA	Brazil	-0.012	JPN	Japan	-1.098
CAN	Canada	-0.011	KOR	Korea	-0.600
CHE	Switzerland	-1.071	LTU	Lithuania	-0.033
CHN	China	-0.019	MEX	Mexico	-0.029
CYP	Cyprus	-0.212	NLD	Netherlands	-1.603
CZE	Czech Republic	-0.142	NOR	Norway	-0.084
DEU	Germany	-0.630	POL	Poland	-0.072
DNK	Denmark	-0.537	PRT	Portugal	-0.159
ESP	Spain	-0.177	ROU	Romania	-0.035
EST	Estonia	-0.028	RUS	Russia	-0.004
FIN	Finland	-0.054	SVN	Slovenia	-0.138
FRA	France	-0.322	SWE	Sweden	-0.078
GBR	United Kingdom	-0.690	TUR	Turkey	-0.050
GRC	Greece	-0.153	TWN	Taiwan, China	-0.673
HUN	Hungary	-0.084	USA	United States	-0.109

Table A.7: μ_i^2 estimates (unit: $\times 10^{-4}$)

AUS	Australia	0.0031	IDN	Indonesia	0.0567
AUT	Austria	0.0073	IND	India	1.2518
BEL	Belgium	0.0019	IRL	Ireland	0.0008
BGR	Bulgaria	0.0080	ITA	Italy	0.0261
BRA	Brazil	0.1776	JPN	Japan	0.0034
CAN	Canada	0.0090	KOR	Korea	0.0035
CHE	Switzerland	0.0021	LTU	Lithuania	0.0055
CHN	China	0.3891	MEX	Mexico	0.0373
CYP	Cyprus	0.0008	NLD	Netherlands	0.0026
CZE	Czech Republic	0.0115	NOR	Norway	0.0013
DEU	Germany	0.0237	POL	Poland	0.0540
DNK	Denmark	0.0020	PRT	Portugal	0.0014
ESP	Spain	0.0091	ROU	Romania	0.0208
EST	Estonia	0.0017	RUS	Russia	0.1663
FIN	Finland	0.0061	SVN	Slovenia	0.0031
FRA	France	0.0161	SWE	Sweden	0.0031
GBR	United Kingdom	0.0060	TUR	Turkey	0.0311
GRC	Greece	0.0075	TWN	Taiwan, China	0.0007
HUN	Hungary	0.0169	USA	United States	0.0994

Table A.8: Alternative social cost estimates (unit: mn 2005 USD/ton)

		Urban	Urban+rural	Baseline
AUS	Australia	-0.168	-0.009	-0.009
AUT	Austria			-0.306
BEL	Belgium	-0.269	-1.042	-1.027
BGR	Bulgaria	-0.028	-0.022	-0.022
BRA	Brazil	-0.068	-0.012	-0.012
CAN	Canada	-0.067	-0.011	-0.011
CHE	Switzerland	-0.431	-1.134	-1.071
CHN	China	-0.022	-0.020	-0.019
CYP	Cyprus	-0.064	-0.217	-0.212
CZE	Czech Republic			-0.142
DEU	Germany	-0.293	-0.633	-0.630
DNK	Denmark	-0.231	-0.550	-0.537
ESP	Spain	-0.107	-0.180	-0.177
EST	Estonia	-0.034	-0.028	-0.028
FIN	Finland	-0.075	-0.054	-0.054
FRA	France	-0.172	-0.330	-0.322
GBR	United Kingdom	-0.249	-0.703	-0.690
GRC	Greece	-0.087	-0.153	-0.153
HUN	Hungary			-0.084
IDN	Indonesia	-0.017	-0.008	-0.008
IND	India	-0.008	-0.018	-0.019
IRL	Ireland	-0.152	-0.192	-0.188
ITA	Italy	-0.148	-0.505	-0.499
JPN	Japan	-0.347	-1.106	-1.098
KOR	Korea	-0.236	-0.598	-0.600
LTU	Lithuania	-0.032	-0.033	-0.033
MEX	Mexico	-0.046	-0.030	-0.029
NLD	Netherlands	-0.382	-1.614	-1.603
NOR	Norway	-0.128	-0.100	-0.084
POL	Poland	-0.049	-0.073	-0.072
PRT	Portugal	-0.072	-0.163	-0.159
ROU	Romania	-0.030	-0.035	-0.035
RUS	Russia	-0.031	-0.005	-0.004
SVN	Slovenia	-0.063	-0.141	-0.138
SWE	Sweden	-0.095	-0.078	-0.078
TUR	Turkey	-0.065	-0.051	-0.050
TWN	Taiwan, China			-0.673
USA	United States	-0.109	-0.109	-0.109

Table A.9: Alternative μ_i^2 estimates (unit: $\times 10^{-4}$)

		Urban	Urban+rural	Baseline
AUS	Australia	0.0002	0.0031	0.0031
AUT	Austria			0.0073
BEL	Belgium	0.0078	0.0019	0.0019
BGR	Bulgaria	0.0063	0.0079	0.0080
BRA	Brazil	0.0315	0.1744	0.1776
CAN	Canada	0.0014	0.0091	0.0090
CHE	Switzerland	0.0056	0.0020	0.0021
CHN	China	0.3374	0.3741	0.3891
CYP	Cyprus	0.0028	0.0008	0.0008
CZE	Czech Republic			0.0115
DEU	Germany	0.0512	0.0236	0.0237
DNK	Denmark	0.0048	0.0019	0.0020
ESP	Spain	0.0150	0.0089	0.0091
EST	Estonia	0.0014	0.0017	0.0017
FIN	Finland	0.0044	0.0061	0.0061
FRA	France	0.0301	0.0157	0.0161
GBR	United Kingdom	0.0169	0.0059	0.0060
GRC	Greece	0.0133	0.0075	0.0075
HUN	Hungary			0.0169
IDN	Indonesia	0.0261	0.0577	0.0567
IND	India	2.9303	1.3213	1.2518
IRL	Ireland	0.0010	0.0008	0.0008
ITA	Italy	0.0886	0.0258	0.0261
JPN	Japan	0.0109	0.0033	0.0034
KOR	Korea	0.0096	0.0035	0.0035
LTU	Lithuania	0.0056	0.0055	0.0055
MEX	Mexico	0.0235	0.0364	0.0373
NLD	Netherlands	0.0119	0.0026	0.0026
NOR	Norway	0.0008	0.0010	0.0013
POL	Poland	0.0801	0.0532	0.0540
PRT	Portugal	0.0032	0.0014	0.0014
ROU	Romania	0.0243	0.0208	0.0208
RUS	Russia	0.0236	0.1641	0.1663
SVN	Slovenia	0.0071	0.0030	0.0031
SWE	Sweden	0.0026	0.0032	0.0031
TUR	Turkey	0.0240	0.0304	0.0311
TWN	Taiwan, China			0.0007
USA	United States	0.0994	0.0994	0.0994

Table A.10: Trade elasticity

Tradable sectors		θ^j
A	Agriculture/Forestry/Fishing	9.11
B	Mining and quarrying	13.53
C10-C12	Manufacture of food products, beverages and tobacco products	2.62
C13-C15	Manufacture of textiles, wearing apparel and leather products	8.10
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	11.50
C17	Manufacture of paper and paper products	16.52
C18	Printing and reproduction of recorded media	16.52
C19	Manufacture of coke and refined petroleum products	64.85
C20	Manufacture of chemicals and chemical products	3.13
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	3.13
C22	Manufacture of rubber and plastic products	1.67
C23	Manufacture of other non-metallic mineral products	2.41
C24	Manufacture of basic metals	3.28
C25	Manufacture of fabricated metal products, except machinery and equipment	6.99
C26	Manufacture of computer, electronic and optical products	7.52
C27	Manufacture of electrical equipment	12.91
C28	Manufacture of machinery and equipment n.e.c.	1.45
C29	Manufacture of motor vehicles, trailers and semi-trailers	1.84
C30	Manufacture of other transport equipment	0.39
C31-C32	Manufacture of furniture; other manufacturing	3.98
C33	Repair and installation of machinery and equipment	1.45

Notes: The values are from Caliendo and Parro (2015)'s 99% sample estimates. We calculate the weighted average of Office, Communication, and Medical Manufacturing for the value of C26, using the global total trade flows in 2000. Service sectors are nontradable thus are omitted from the table.

Table A.11: The effects of the China shock

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	0.3075	0.3084	-0.0010	-0.0003	-0.0007	2.7492	1.2960
Austria	0.0221	0.0190	0.0031	0.0009	0.0023	-0.2372	-0.1249
Belgium	-0.0045	-0.0189	0.0143	-0.0001	0.0144	0.0037	-0.0657
Bulgaria	0.0846	0.0795	0.0051	0.0013	0.0038	-0.3029	-0.1734
Brazil	0.0338	0.0339	-0.0001	0.0000	-0.0001	0.4875	0.2956
Canada	0.0358	0.0360	-0.0001	-0.0001	0.0000	0.4382	0.0948
Switzerland	0.0218	0.0095	0.0123	0.0057	0.0066	-0.3089	-0.0955
China	3.2081	3.2106	-0.0025	-0.0021	-0.0005	13.1091	2.3286
Cyprus	0.0810	0.0774	0.0035	0.0036	0.0000	-0.5036	-0.0720
Czech Republic	0.0369	0.0311	0.0057	0.0024	0.0033	-0.3176	-0.1097
Germany	0.0338	0.0324	0.0014	0.0007	0.0007	-0.2337	-0.0683
Denmark	0.0503	0.0455	0.0048	-0.0006	0.0054	0.0387	-0.0454
Spain	0.0252	0.0249	0.0003	0.0001	0.0002	-0.1723	-0.0684
Estonia	0.0770	0.0683	0.0087	0.0034	0.0053	-0.2845	-0.1037
Finland	0.0365	0.0356	0.0009	0.0002	0.0006	-0.2110	-0.1128
France	0.0438	0.0431	0.0007	0.0004	0.0003	-0.2133	-0.0578
United Kingdom	0.0347	0.0337	0.0011	0.0002	0.0009	-0.0468	-0.0440
Greece	0.0569	0.0546	0.0023	0.0010	0.0013	-0.3899	-0.1310
Hungary	0.0752	0.0718	0.0035	0.0012	0.0022	-0.3183	-0.1279
Indonesia	0.0167	0.0176	-0.0009	-0.0003	-0.0006	3.7936	1.5681
India	0.0306	0.0316	-0.0010	-0.0006	-0.0004	7.0015	1.7023
Ireland	-0.0356	-0.0389	0.0033	0.0021	0.0012	-0.3198	-0.0720
Italy	-0.0063	-0.0072	0.0009	0.0004	0.0005	-0.3409	-0.1135
Japan	0.0186	0.0469	-0.0283	-0.0010	-0.0274	0.1834	0.7675
Korea	0.0755	0.2166	-0.1411	-0.0050	-0.1373	0.4982	2.0002
Lithuania	0.0397	0.0351	0.0046	0.0019	0.0027	-0.2993	-0.1027
Mexico	-0.0260	-0.0258	-0.0002	0.0001	-0.0002	-0.5472	0.2252
Netherlands	0.0177	0.0064	0.0113	0.0061	0.0052	-0.2053	-0.0543
Norway	-0.1030	-0.1012	-0.0017	-0.0024	0.0006	0.8885	0.0938
Poland	0.0318	0.0303	0.0015	0.0006	0.0009	-0.3153	-0.1101
Portugal	0.0558	0.0551	0.0007	0.0004	0.0003	-0.2072	-0.0555
Romania	0.1574	0.1537	0.0037	0.0023	0.0014	-0.8583	-0.1968
Russia	0.0567	0.0568	-0.0001	-0.0001	0.0000	1.0063	0.1556
Slovenia	0.0436	0.0341	0.0095	0.0033	0.0062	-0.2879	-0.1201
Sweden	0.0491	0.0483	0.0009	0.0006	0.0003	-0.4068	-0.0845
Turkey	-0.0480	-0.0489	0.0009	0.0003	0.0005	-0.4119	-0.1558
Taiwan	-0.4481	0.3547	-0.8028	-0.2546	-0.5520	3.2314	1.4725
United States	0.0340	0.0341	0.0000	0.0000	0.0000	-0.2009	0.1472

Table A.12: The effects of the China shock with additional environmental regulations

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	0.3078	0.3085	-0.0007	-0.0003	-0.0004	2.7600	0.9376
Austria	0.0221	0.0190	0.0032	0.0009	0.0023	-0.2369	-0.1275
Belgium	-0.0042	-0.0188	0.0146	-0.0002	0.0148	0.0056	-0.0670
Bulgaria	0.0850	0.0796	0.0054	0.0013	0.0041	-0.3027	-0.1818
Brazil	0.0338	0.0338	0.0000	0.0000	0.0000	0.4883	0.1718
Canada	0.0358	0.0359	-0.0001	-0.0001	0.0000	0.4395	0.0411
Switzerland	0.0223	0.0094	0.0128	0.0057	0.0071	-0.3089	-0.0994
China	3.0984	3.0981	0.0003	0.0008	-0.0005	-5.2080	-0.3016
Cyprus	0.0829	0.0775	0.0054	0.0036	0.0018	-0.5037	-0.1095
Czech Republic	0.0371	0.0311	0.0060	0.0024	0.0036	-0.3175	-0.1140
Germany	0.0338	0.0324	0.0014	0.0007	0.0007	-0.2337	-0.0693
Denmark	0.0510	0.0454	0.0056	-0.0006	0.0062	0.0388	-0.0529
Spain	0.0253	0.0249	0.0003	0.0001	0.0002	-0.1718	-0.0790
Estonia	0.0774	0.0684	0.0090	0.0034	0.0056	-0.2849	-0.1074
Finland	0.0365	0.0355	0.0009	0.0002	0.0007	-0.2101	-0.1169
France	0.0438	0.0430	0.0008	0.0004	0.0004	-0.2131	-0.0597
United Kingdom	0.0348	0.0337	0.0011	0.0002	0.0010	-0.0450	-0.0463
Greece	0.0573	0.0547	0.0026	0.0010	0.0016	-0.3902	-0.1466
Hungary	0.0753	0.0717	0.0036	0.0012	0.0023	-0.3185	-0.1321
Indonesia	0.0170	0.0177	-0.0007	-0.0003	-0.0003	3.8050	1.1596
India	0.0311	0.0318	-0.0007	-0.0006	-0.0001	7.0237	1.1477
Ireland	-0.0355	-0.0392	0.0037	0.0021	0.0016	-0.3204	-0.0806
Italy	-0.0062	-0.0072	0.0010	0.0004	0.0006	-0.3407	-0.1223
Japan	0.0352	0.0469	-0.0117	-0.0010	-0.0107	0.1863	0.3175
Korea	0.2094	0.2166	-0.0072	-0.0050	-0.0022	0.5041	0.1036
Lithuania	0.0403	0.0352	0.0051	0.0019	0.0032	-0.2997	-0.1143
Mexico	-0.0258	-0.0258	0.0000	0.0001	-0.0001	-0.5472	0.0318
Netherlands	0.0178	0.0063	0.0114	0.0061	0.0053	-0.2051	-0.0552
Norway	-0.1027	-0.1012	-0.0015	-0.0024	0.0009	0.8900	0.0816
Poland	0.0320	0.0303	0.0017	0.0006	0.0010	-0.3153	-0.1184
Portugal	0.0562	0.0552	0.0009	0.0004	0.0005	-0.2071	-0.0727
Romania	0.1574	0.1535	0.0039	0.0023	0.0016	-0.8578	-0.2072
Russia	0.0566	0.0567	-0.0001	-0.0001	0.0000	1.0095	0.1126
Slovenia	0.0441	0.0342	0.0099	0.0033	0.0066	-0.2883	-0.1244
Sweden	0.0492	0.0482	0.0010	0.0006	0.0004	-0.4063	-0.0962
Turkey	-0.0479	-0.0489	0.0010	0.0003	0.0006	-0.4119	-0.1719
Taiwan	0.1399	0.3545	-0.2146	-0.2558	0.0376	3.2459	0.3968
United States	0.0341	0.0341	0.0000	0.0000	0.0000	-0.2008	0.0424

Table A.13: The effects of the EU enlargement

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	-0.0010	-0.0010	-0.0001	0.0000	-0.0001	0.0014	0.0762
Austria*	0.1001	0.1238	-0.0237	0.0032	-0.0271	-0.8856	0.9363
Belgium*	0.0193	0.0468	-0.0275	-0.0012	-0.0263	0.0368	0.1260
Bulgaria	-0.0187	-0.0122	-0.0065	0.0001	-0.0067	-0.0286	0.2192
Brazil	-0.0011	-0.0010	-0.0001	0.0000	-0.0001	-0.0084	0.2276
Canada	-0.0004	-0.0003	-0.0001	0.0000	-0.0001	-0.0021	0.0778
Switzerland	-0.0460	-0.0024	-0.0436	0.0003	-0.0440	-0.0144	0.3366
China	-0.0011	-0.0011	0.0000	0.0000	0.0000	0.0017	0.0184
Cyprus**	1.6990	1.7676	-0.0686	-0.0620	-0.0083	8.3987	1.3744
Czech Republic**	1.5310	1.5847	-0.0536	-0.0556	0.0005	7.1331	1.0150
Germany*	0.0801	0.0830	-0.0029	0.0001	-0.0030	-0.0172	0.1432
Denmark*	0.0400	0.0938	-0.0538	-0.0048	-0.0491	0.3139	0.5056
Spain*	0.0109	0.0116	-0.0007	0.0000	-0.0006	0.0684	0.1667
Estonia**	0.5970	0.6040	-0.0070	-0.0021	-0.0049	0.1733	0.0827
Finland*	0.0233	0.0241	-0.0008	0.0000	-0.0008	-0.0155	0.1022
France*	0.0190	0.0205	-0.0015	-0.0001	-0.0014	0.0539	0.1154
United Kingdom*	0.0123	0.0149	-0.0027	-0.0001	-0.0025	0.0429	0.1108
Greece*	-0.0097	-0.0042	-0.0055	0.0004	-0.0059	-0.1383	0.3092
Hungary**	1.7182	1.7317	-0.0135	-0.0008	-0.0128	0.1992	0.4969
Indonesia	-0.0021	-0.0021	0.0000	0.0000	0.0000	-0.0181	0.0682
India	-0.0016	-0.0015	-0.0001	0.0000	-0.0001	0.0105	0.1848
Ireland*	0.0235	0.0308	-0.0073	-0.0003	-0.0070	0.0517	0.1604
Italy*	0.0264	0.0295	-0.0031	-0.0001	-0.0031	0.0461	0.3841
Japan	-0.0008	-0.0001	-0.0007	0.0000	-0.0006	0.0072	0.0182
Korea	-0.0022	-0.0009	-0.0014	0.0000	-0.0013	0.0035	0.0196
Lithuania**	0.3885	0.4054	-0.0169	-0.0030	-0.0139	0.4653	0.3748
Mexico	-0.0006	-0.0005	-0.0001	0.0000	-0.0001	0.0061	0.1789
Netherlands*	0.0233	0.0452	-0.0219	-0.0055	-0.0164	0.1838	0.1056
Norway	-0.0198	-0.0142	-0.0056	-0.0004	-0.0052	0.1440	0.3027
Poland**	0.9144	0.9242	-0.0098	-0.0001	-0.0098	0.0303	0.6943
Portugal*	0.0080	0.0104	-0.0024	0.0000	-0.0023	0.0227	0.1832
Romania	-0.0441	-0.0395	-0.0046	0.0003	-0.0049	-0.1004	0.2401
Russia	0.0015	0.0017	-0.0002	0.0000	-0.0001	0.2447	0.3345
Slovenia**	3.3775	3.4304	-0.0529	-0.0114	-0.0415	0.9940	0.6616
Sweden*	0.0910	0.0952	-0.0042	-0.0016	-0.0027	1.0210	0.4011
Turkey	-0.0135	-0.0116	-0.0019	0.0000	-0.0020	-0.0289	0.3423
Taiwan	-0.0172	-0.0018	-0.0154	-0.0011	-0.0143	0.0141	0.0285
United States	-0.0006	-0.0006	0.0000	0.0000	0.0000	0.0060	0.1677

Notes: The countries indexed with * are existing EU member countries before 2004, and the countries indexed with ** are new EU members of the 2004 enlargement.

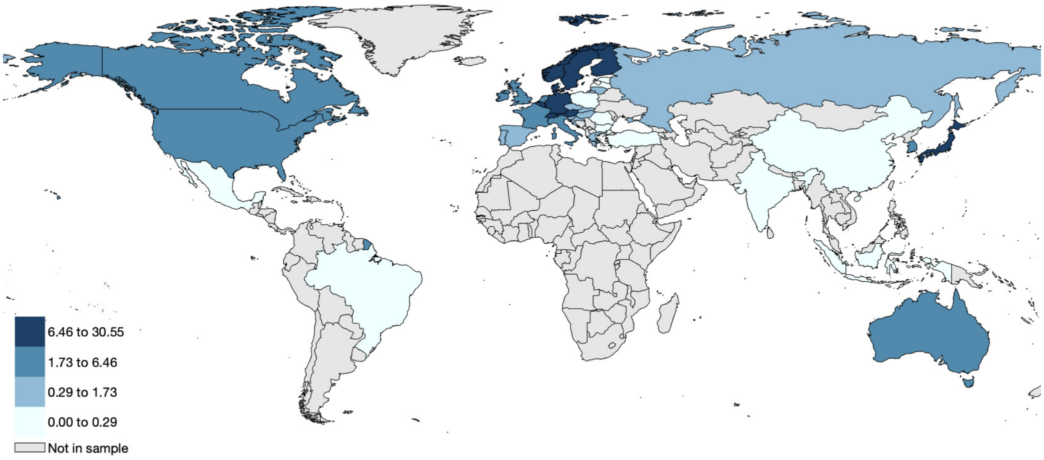
Table A.14: The effects of the EU enlargement with additional environmental regulations

(% change)	(1) Welfare	(2) Real income	(3) Environmental utility	(4) Environmental utility (own)	(5) Environmental utility (others)	(6) Emission	(7) Concentration
Australia	-0.0007	-0.0009	0.0002	0.0000	0.0002	0.0033	-0.3150
Austria*	0.2253	0.1247	0.1005	0.0027	0.0960	-0.7644	-4.1763
Belgium*	0.0991	0.0470	0.0521	-0.0023	0.0543	0.0726	-0.2396
Bulgaria	0.0284	-0.0124	0.0408	0.0001	0.0404	-0.0152	-1.3912
Brazil	-0.0008	-0.0010	0.0002	0.0000	0.0002	-0.0059	-0.9549
Canada	0.0002	-0.0002	0.0005	0.0000	0.0005	0.0001	-0.3281
Switzerland	0.1504	-0.0027	0.1531	0.0001	0.1520	-0.0048	-1.1985
China	-0.0011	-0.0012	0.0001	0.0000	0.0001	0.0021	-0.0691
Cyprus**	1.1121	0.9884	0.1237	0.0711	0.0511	-10.5771	-2.5743
Czech Republic**	0.9650	0.7846	0.1804	0.0909	0.0876	-12.8810	-3.5681
Germany*	0.0891	0.0832	0.0060	-0.0001	0.0060	0.0281	-0.2948
Denmark*	0.2761	0.0952	0.1809	-0.0052	0.1841	0.3395	-1.7351
Spain*	0.0144	0.0121	0.0024	-0.0001	0.0024	0.0920	-0.5928
Estonia**	0.3967	0.1485	0.2482	0.2038	0.0321	-18.4821	-3.0417
Finland*	0.0644	0.0243	0.0401	0.0000	0.0390	0.0030	-5.4150
France*	0.0243	0.0206	0.0037	-0.0001	0.0038	0.0740	-0.2898
United Kingdom*	0.0213	0.0150	0.0063	-0.0002	0.0065	0.0533	-0.2621
Greece*	0.0195	-0.0037	0.0232	0.0003	0.0227	-0.1252	-1.3178
Hungary**	0.9876	0.8578	0.1298	0.0688	0.0586	-19.4351	-5.0286
Indonesia	-0.0019	-0.0021	0.0002	0.0000	0.0002	-0.0161	-0.2843
India	-0.0010	-0.0015	0.0004	0.0000	0.0004	0.0122	-0.7538
Ireland*	0.0531	0.0303	0.0227	-0.0003	0.0230	0.0523	-0.4991
Italy*	0.0478	0.0301	0.0177	-0.0001	0.0176	0.0739	-2.2433
Japan	0.0022	-0.0001	0.0024	0.0000	0.0024	0.0080	-0.0644
Korea	0.0039	-0.0009	0.0048	-0.0001	0.0049	0.0051	-0.0696
Lithuania**	0.0595	-0.1921	0.2516	0.1099	0.1391	-18.6888	-5.9444
Mexico	0.0000	-0.0005	0.0006	0.0000	0.0006	0.0064	-0.7684
Netherlands*	0.0821	0.0462	0.0359	-0.0063	0.0421	0.2100	-0.1732
Norway	0.0078	-0.0132	0.0211	-0.0004	0.0214	0.1611	-1.1561
Poland**	0.3710	0.3007	0.0702	0.0349	0.0343	-19.0277	-5.2815
Portugal*	0.0191	0.0105	0.0086	-0.0001	0.0086	0.0294	-0.6775
Romania	-0.0100	-0.0394	0.0295	0.0002	0.0291	-0.0651	-1.5700
Russia	0.0027	0.0015	0.0011	0.0000	0.0012	0.2825	-2.3543
Slovenia**	2.9453	2.6064	0.3389	0.1892	0.1428	-18.1261	-4.4543
Sweden*	0.1160	0.0963	0.0196	-0.0016	0.0210	1.0586	-1.9015
Turkey	-0.0041	-0.0115	0.0074	0.0000	0.0073	-0.0231	-1.3209
Taiwan	0.0563	-0.0019	0.0582	-0.0013	0.0595	0.0173	-0.1080
United States	-0.0004	-0.0006	0.0002	0.0000	0.0002	0.0072	-0.7163

Notes: The countries indexed with * are existing EU member countries before 2004, and the countries indexed with ** are new EU members of the 2004 enlargement.

A.2 Additional figures

Figure A.1: Number of patents on env. management (per 1000 persons)



A.3 Derivations

A.3.1 Solving for the environmental disutility parameter

We solve for the μ_i^2, the square of the environmental disutility parameter μ_i, since that is how it enters the utility function anyway. And for simpler notation, I omit the subscript t, as the calibration of μ_i^2 uses only 2005 information and estimates. From Equation 30,

$$\begin{aligned} sc_i &= \sum_{\forall k} \frac{\partial W_i}{\partial g_i} \left(\frac{\partial W_i}{\partial I_i} \right)^{-1} \frac{\partial g_i}{\partial E_k} dE_k \\ &= - \left(\frac{2 g_i I_i}{\mu_i^2 + g_i^2} \right) \times \sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k \end{aligned}$$

Since

$$\sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k = \frac{\partial g_i}{\partial E_i} dE_i + \sum_{i' \neq i} \frac{\partial g_i}{\partial E_{i'}} dE_{i'} \tag{34}$$

using the functional form of $g_i(\cdot)$ and $PolTransport$

$$\begin{aligned} \ln g_i &= \hat{\psi} + \hat{\gamma}_1 \ln \left(\frac{E_i}{land_i} \right) + \hat{\gamma}_2 Meteo_i + \hat{\kappa} \ln PolTransport_i + \hat{\delta}_i + \hat{\delta}_t \\ PolTransport_i &= \sum_{i' \neq i} \frac{E_{i't}}{land_{i'}} \times \frac{1}{distance_{ii'}^2} \end{aligned}$$

From the regression estimate on own emission,

$$\hat{\gamma}_1 = \frac{\partial \ln g_i}{\partial \ln E_i} = \frac{\partial g_i}{\partial E_i}\frac{E_i}{g_i}$$

we have the first term of Equation 34, given by

$$\frac{\partial g_i}{\partial E_i} dE_i = \hat{\gamma}_1 \frac{g_i}{E_i} dE_i \tag{35}$$

Also, using the estimate on the pollution transboundary term,

$$\begin{aligned}\hat{\kappa} &= \frac{\partial \ln g_i}{\partial \ln PolTransport_i} \\ &= \frac{\partial g_i}{\partial PolTransport_i}\frac{PolTransport_i}{g_i}\end{aligned}$$

so for $i' \neq i$, we have the second term of Equation 34 as in Equation 36.

$$\begin{aligned}\frac{\partial g_i}{\partial E_{i'}} &= \frac{\partial g_i}{\partial PolTransport_i} \times \frac{PolTransport_i}{\partial E_{i'}} \\ &= \hat{\kappa}\frac{g_i}{PolTransport_i} \times (land_{i'} d_{i'i}^2)^{-1} \\ \sum_{i' \neq i} \frac{\partial g_i}{\partial E_{i'}} dE_{i'} &= \hat{\kappa}\frac{g_i \sum_{i' \neq i}(land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{PolTransport_i} \end{aligned} \tag{36}$$

Putting Equation 35 and Equation 36 into Equation 34, we get

$$\begin{aligned}\sum_{\forall k} \frac{\partial g_i}{\partial E_k} dE_k &= \frac{\partial g_i}{\partial E_i} dE_i + \sum_{i' \neq i} \frac{\partial g_i}{\partial E_{i'}} dE_{i'} \\ &= \hat{\gamma}_1 \frac{g_i}{E_i} dE_i + \hat{\kappa}\frac{g_i \sum_{i' \neq i}(land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{PolTransport_i} \\ &= \hat{\gamma}_1 \frac{g_i}{E_i} dE_i + \hat{\kappa}\frac{g_i \sum_{i' \neq i}(land_{i'} d_{i'i}^2)^{-1} dE_{i'}}{\sum_{i' \neq i} \frac{E_{i'}/land_{i'}}{d_{i'i}^2}}\end{aligned}$$

세션3 보건과 국제개발

- Costing the Implementation of Public Health Interventions in Resource-limited Settings
  발제: 손호준(서울대 의과대학) | 토론: 이석원(서울대 행정대학원)

- Strengthening Health Systems in Resource-constrained Settings: A Case of mHealth-based Health Information System Implementation in Ghana
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제3세션 | 보건과 국제개발

Costing the Implementation of Public Health Interventions in Resource-limited Settings

발제: 손 호 준(서울대 의과대학)

토론: 이 석 원(서울대 행정대학원)

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Implementation Science

COMMENTARY Open Access

Costing the implementation of public health interventions in resource-limited settings: a conceptual framework

Hojoon Sohn*†, Austin Tucker†, Olivia Ferguson†, Isabella Gomes† and David Dowdy†

Abstract

Background: Failing to account for the resources required to successfully implement public health interventions can lead to an underestimation of costs and budget impact, optimistic cost-effectiveness estimates, and ultimately a disconnect between published evidence and public health decision-making.

Methods: We developed a conceptual framework for assessing implementation costs. We illustrate the use of this framework with case studies involving interventions for tuberculosis and HIV/AIDS in resource-limited settings.

Results: Costs of implementing public health interventions may be conceptualized as occurring across three phases: design, initiation, and maintenance. In the design phase, activities include developing intervention components and establishing necessary infrastructure (e.g., technology, standard operating procedures). Initiation phase activities include training, initiation of supply chains and quality assurance procedures, and installation of equipment. Implementation costs in the maintenance phase include ongoing technical support, monitoring and evaluation, and troubleshooting unexpected obstacles. Within each phase, implementation costs can be incurred at the site of delivery ("site-specific" costs) or more centrally ("above-service" or "central" costs). For interventions evaluated in the context of research studies, implementation costs should be classified as programmatic, research-related, or shared research/program costs. Purely research-related costs are often excluded from analysis of programmatic implementation.

Conclusions: In evaluating public health interventions in resource-limited settings, accounting for implementation costs enables more realistic estimates of budget impact and cost-effectiveness and provides important insights into program feasibility, scale-up, and sustainability. Assessment of implementation costs should be planned prospectively and performed in a standardized manner to ensure generalizability.

Keywords: Implementation strategies, Costs of implementation, Economic evaluation, Decision-making, Tuberculosis

* Correspondence: hsohn6@jhu.edu
†Hojoon Sohn, Austin Tucker, Olivia Ferguson, Isabella Gomes and David Dowdy contributed equally to this work.
Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, 615 N. Wolfe Street E6531, Baltimore, MD 21205, USA

Contributions to the literature

- Economic evaluations have long been used to prioritize health interventions in resource-limited settings. However, these analyses often fail to capture the resources required to successfully implement interventions and thus may greatly underestimate the actual economic costs of the intervention.
- Most existing studies in the health economics literature in the context of implementation science are retrospective or 'ex-post' in nature; methods and examples of evaluating these costs prospectively are limited, particularly in resource limited settings.
- Using recent examples from the literature, we highlight the importance and potential magnitude of costs associated with implementation of public health interventions in resource constrained settings.
- We also provide a conceptual framework that details the types of economic resources utilized during the design, initiation, and maintenance phases of implementation and the implications of neglecting implementation costs in evaluating the cost-effectiveness of interventions in resource-limited settings.
- Such a framework provides greater insight into the need for implementation costing practices for more accurate economic evaluation and budget impact analysis as well as insights into program feasibility, scale up and sustainability.

Introduction

Economic evaluations are frequently used to inform prioritization of health interventions and resource allocation for public health [1]. Unfortunately, most existing economic evaluations of public health interventions have done so retrospectively [2], thereby limiting their ability to fully assess the costs of implementation, especially during the early stages of design and initiation. A growing number of studies are exploring these implementation costs, but many continue to do so in retrospective fashion, and interventions in resource-limited settings—where implementation costs may represent a disproportionate fraction of total intervention costs—are sorely under-represented [2]. As such, most published economic evaluations may have greatly underestimated the costs of public health interventions, particularly those studied in resource-limited settings. A framework for considering and prospectively collecting implementation costs could therefore greatly improve economic evaluations of public health interventions in the coming years.

To illustrate, the Avahan initiative was a complex intervention to prevent HIV transmission across six Indian states that included peer outreach, clinical services, condom distribution, safe needle exchange, and community mobilization [3]. A cost-effectiveness analysis estimated that Avahan cost $46 per disability-adjusted life year (DALY) averted [4]. However, approximately two thirds of overall costs were incurred at the "above-service" level—involving institutions above or ancillary to the provision of care (e.g., government, non-governmental organization (NGO), or multilateral institution support or infrastructure for facilitating provision of care). Had these costs of implementation not been counterbalanced by four years of service delivery, the cost per person reached could have been four times higher—with qualitatively important cost-effectiveness implications [5]. Such implementation costs are frequently neglected in economic evaluations, leading to underestimated costs, optimistic cost-effectiveness estimates, and a disconnect between published evidence and public health decision-making. This disconnect is particularly stark in settings where resources are most constrained.

Another illustration of the importance of implementation costing is the recently published PopART (HPTN 071) trial of universal testing and treatment for HIV in South Africa and Zambia [6]. This trial, conducted over 5 years, mobilized 740 community HIV care providers working in pairs (each pair covering approximately 500 households) to provide comprehensive health services—from HIV counseling and rapid testing to screening for tuberculosis (TB) and sexually transmitted infections—during annual household visits. This multifaceted intervention reduced HIV infection by 30% but required extensive programmatic coordination and administrative management, including rigorous re-training and human resource management, planning of daily household visits and periodic community engagement campaigns, HIV testing drives, and centralized coordination of study activities (e.g., obtaining regulatory approvals, provision of security, and maintenance of a stable procurement and supply chain) [7]. Costs associated with the implementation of these complex and comprehensive activities—often neglected in cost-effectiveness analyses—may make the start-up of health interventions unaffordable or infeasible. This, in turn, would result in substantial waste of resources if interventions are poorly maintained or not sustained.

To provide decision-makers with an honest appraisal of the potential costs and benefits of any health intervention, it is critical to document the full range of costs required for programmatic implementation, including the costs of intervention design and local adaptation, initiation and scale-up, and maintenance/sustainability. While consideration of implementation costs is universally relevant, these costs may be proportionally more important in settings where resources are highly constrained. Here, we use the example of peripheral diagnostic testing for TB as a case study to illustrate the importance of evaluating costs throughout the implementation process and to propose a structured method for investigating these costs.

Peripheral diagnostic testing for TB: a case study of implementing a novel health intervention in settings of severe resource constraints

An estimated 13–18% of patients diagnosed with TB in Africa and Asia are lost to follow-up before starting treatment [8]. The current standard of care for TB diagnosis involves molecular testing requiring equipment (e.g., four-module GeneXpert® instruments) that often cannot be maintained at the point of care [9]. Novel tests—including more portable devices (e.g., GeneXpert® Edge) and simpler assays (e.g., lateral-flow detection of urine lipoarabinomannan [LF-LAM])—that can diagnose TB at the point of treatment have been prioritized as a means of reducing diagnostic delays and losses to follow-up [10]. Cost-effectiveness analyses of peripherally implemented TB diagnostic tests are emerging [11]; however, existing analyses may not fully account for the costs required to implement these novel assays in practice.

Costing the implementation process: a framework

Similar to many consumer products, public health interventions can be conceptualized as having a "product life cycle," with well-defined stages—design, launch, growth, maturity, and decline—from introduction to removal from the "market" [12]. Considering each of these stages is critical to the financial success of consumer products—and this is equally true for public health interventions. Although the systems required for each product life cycle phase differ, the costing of systems for launch often overlaps with those for design (preparation for launch) or growth (which starts immediately after launch)—and the decline phase acknowledges that every product (or intervention) has a finite time horizon. Thus, in mapping the structure of the product life cycle to the costing of public health interventions, one can delineate three stages: design and adaptation to the local context ("design phase" including preparation for launch), initial implementation and scale-up ("initiation phase" corresponding to launch and growth), and ongoing activities to ensure intervention sustainability ("maintenance phase" corresponding to maturity and forestalling of decline) [13].

As illustrated in Fig. 1a, the implementation process is not necessarily unidirectional. Rather, the various phases of implementation inform one another, especially as interventions are adapted from one context to another or expanded in size or scope. For example, experiential knowledge attained during the initiation phase in one setting may inform the re-design of protocols for the design phase in a different cultural context. Similarly, the maintenance phase of an intervention in an "early adopter" country may inform policymakers and researchers about the potential sustainability of the intervention and influence considerations about design and initiation in other regions or countries. As such, it is important to individually estimate the cost of each stage of the implementation process—and to illustrate how those estimates depend on key assumptions (e.g., scale of implementation, local market rates for human resources and other costs)—so that those estimates can be generalized to other contexts where existing knowledge and infrastructure may be more or less complete.

In addition to the costs incurred at different phases of implementation, costs can be incurred at the site of delivery ("site-specific" costs; containing administrative efforts from the service delivery facility—e.g., clinic or hospital administration) or more centrally ("above-service" or "central" costs; services such as support from a district health office [DHO], NGO, or Ministry of Health [MOH]). Furthermore, health interventions are often evaluated in the context of research studies or evaluation programs, necessitating a differentiation between costs required for programmatic implementation and those incurred purely for the purposes of research or evaluation (the latter being less relevant to the cost-effectiveness of the intervention itself). Importantly, some degree of monitoring and evaluation is necessary for effective implementation and should therefore be included as a programmatic cost; however, the costs incurred by research studies and other knowledge generation activities often exceed this baseline requirement and may vary depending on the type of intervention being considered. As such, it is important to prospectively monitor and categorize costs as purely research-related (i.e., likely not to be incurred during subsequent implementation in other settings) versus necessary for programmatic implementation (even if those costs represent "research" activities) to facilitate subsequent analyses.

Table 1 provides examples of costs that may be incurred across the three phases of implementation, site-specific versus central locations, and programmatic versus research purposes—using the example of an ongoing cluster randomized trial of peripheral versus central molecular TB testing (the Xpert Performance Evaluation for Linkage to Tuberculosis Care [XPEL TB] trial) [14]. As illustrated in panel b of Fig. 1, "above-service" costs in the design and initiation phases tend to represent a greater proportion of total costs. Thus, consideration of these costs—while always important—is most critical when the costs of design and initiation are greater relative to the costs of delivery (e.g., interventions that are scaled-up to a smaller population), when interventions are being considered by decision-makers (e.g., politicians) with shorter time horizons, when interventions are expected to change in scope or cost with time (e.g., through price reductions or release of new competing interventions), or when interventions are not

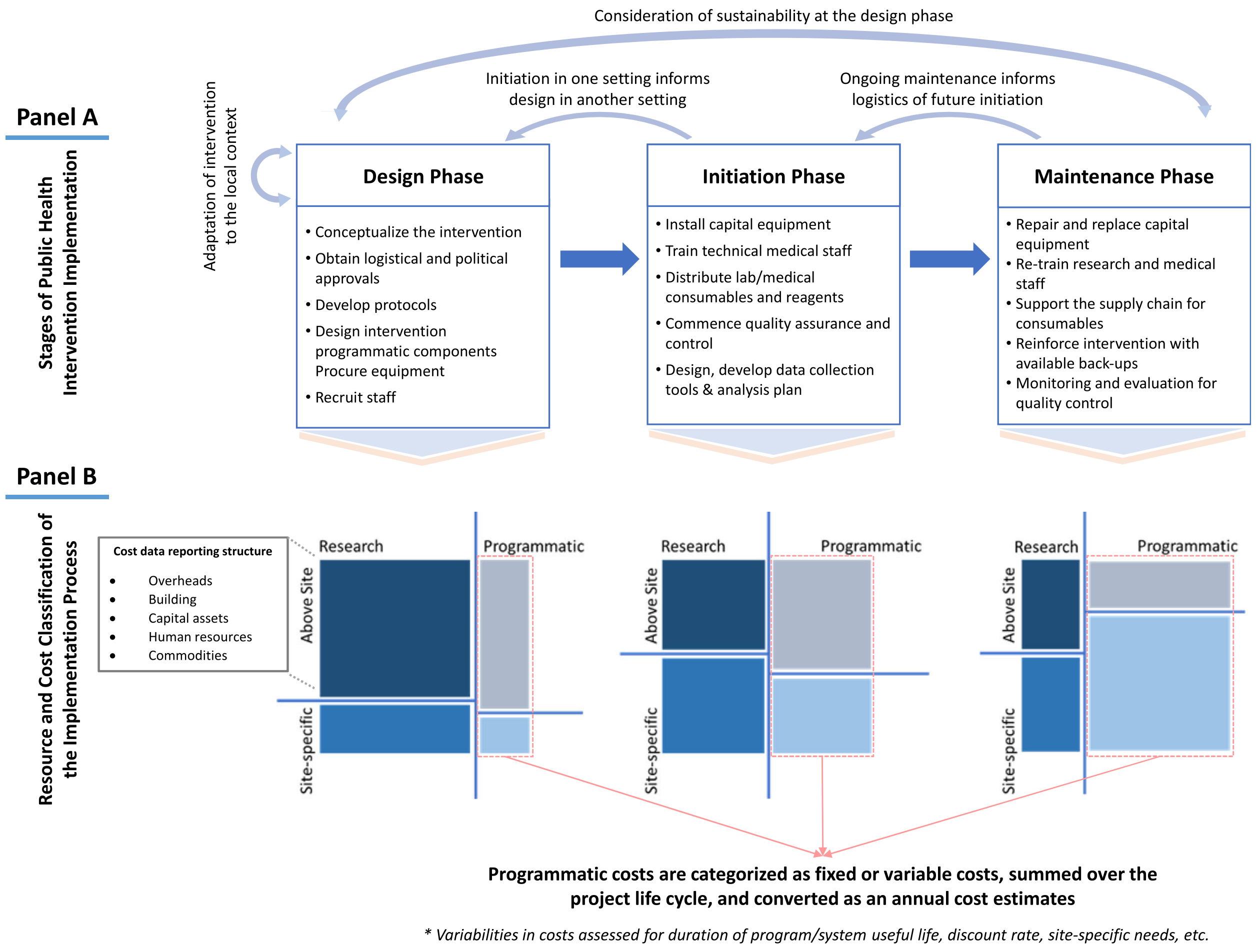

Fig. 1 Simplified illustration of stages, activities, resource classification, and assessment of costs of public health intervention implementation process. **a** A description of the implementation process listing key components of each phase that may carry additional resource requirements is provided. Light blue arrows represent potential feedback loops between phases. **b** An illustration of resource and cost classification of the public health intervention implementation process. At each phase, resource-use for relevant activities is classified based on the location (above site vs. site-specific) of activity and degree to which activities are programmatic versus research specific. Sizes of each square (different shades of blue)—arbitrarily assigned for the purposes of demonstration—represent the corresponding size of each activity category. The increasing size of light-shaded boxes to the right indicate an increasing programmatic component as the study progresses into the maintenance phase

immediately affordable. These situations account for a large fraction of health interventions being considered for implementation in resource-limited settings. Furthermore, most public health interventions in resource-limited settings are not sustained indefinitely. Thus, rigorously measuring the costs of design and implementation and weighing those against the expected duration of the maintenance phase can improve our understanding of the costs and sustainability of public health interventions in terms of their life cycles. We now provide examples of costs that might be incurred at each phase of the implementation process (summarized in Table 2).

Design phase

Implementation costs incurred during the design and adaptation of health interventions may include crafting of appropriate policies and algorithms, obtaining political and administrative approvals, developing necessary infrastructure, engagement of relevant stakeholders, and pilot testing in the local context. Where these costs are large and must be incurred before scale-up is certain, they may represent a majority of the total cost of the intervention. For example, in a trial of mobile Health-facilitated home-based contact investigation for TB in Uganda, a software package was required to generate short messaging service (SMS) reminders to facilitate home-based screening, incurring large up-front costs for an initial service contract and adaptation to the Ugandan telecommunications infrastructure [15]. While this intervention was only delivered to 372 households (919 contacts screened), the cost of designing and developing the intervention ($137 per contact screened, of which $90

Table 1 Descriptions of key activities by study phases (XPEL study example)

Classification of activities	Research or knowledge generation costs[a]	Programmatic costs	Shared research/program costs
Design phase			
Central	• Ministry of Health (MoH), provincial, and district level approvals for the research study • Institutional Review Board approvals • Development of study CRFs (clinical outcomes) • Development of research database (RedCap* program) • Development of study protocols • International collaborator site visits and periodic study calls	• Central procurement of GeneXpert machines, related equipment (e.g., solar panels and external batteries), Xpert Ultra cartridges, and associated supplies • Development of SOPs* for Xpert testing, troubleshooting and QA/QC manuals, and management of testing equipment	• Recruitment of study staff • Focus group discussions
Site-specific	• Site visits for site selection • Review of clinical and laboratory data	• N/A	• Sensitization meetings at district health office and potential study sites • Pilot studies conducted at select potential study sites
Initiation phase			
Central	• Establish clinical and laboratory data monitoring (including National TB Reference Laboratory) • Management of regulatory processes with MoH • Development of data collection plans for health economics study • International collaborator site visits and periodic study calls	• Development of plans and organization of site visit and training • Stock management (medical and laboratory consumables and Xpert cartridges)	• Study database management (clinical and programmatic) • Data quality checks • Weekly study call (implementation issues, study data checks, etc.)
Site-specific	• Management of provincial, district level regulatory processes	• Installation of solar panel and GeneXpert equipment (including GX Alert system) • Distribution of Xpert cartridges and laboratory consumables • Training of laboratory personnel and technical support for Xpert testing	• Site sensitization meetings (w/ routine clinic staff) at both intervention and control sites • Initial participant enrolment • Establishment of data collection and follow-up plans • Interim adjustments in implementation plans (including addition or exclusion of sites) • Recruitment of study contact persons at each site (for data monitoring and study logistics purposes)
Maintenance phase			
Central	• Management and monitoring of study data • International collaborator site visits and periodic study calls • Data analyses and reporting	• Stock management (medical and laboratory consumables and Xpert cartridges) • Site visit organizations and communications	• Study database management (clinical and programmatic) • Central database data review and quality checks • Weekly study call (implementation issues, study data checks, etc.) • Central study team human resource management
Site-specific	• Site-specific data issue troubleshooting	• Ongoing technical support and troubleshooting (for GeneXpert and Solar panel equipment) • Distribution of Xpert cartridges and laboratory consumables • Procurement and replacement of key equipment (if broken) • QA/QC of Xpert testing • Review of GX Alert data • Periodic EQA and re-training for Xpert testing	• Quarterly site visit • Participant enrolment • Adjustments in site-specific operations • Ongoing human resource management at study sites • Data monitoring and quality checks

[a]Research or knowledge generation costs that would be required for programmatic implementation in other settings (for example, ongoing monitoring and evaluation) should be clearly delineated and considered as programmatic costs in most analyses
SOP Standard operation procedure, *QA* Quality assurance, *QC* Quality control, *EQA* External quality control, *GX Alert System* software system to centrally report site-specific Xpert testing statistics, equipment and testing troubleshooting, and testing operations

Table 2 Interventions for peripheral diagnosis of tuberculosis (TB) likely to incur large costs in each phase of implementation

Implementation phase	Application	Example
Design phase	Interventions needing large capital outlay for design and adaptation with uncertain scale-up	Implementation of mHealth-facilitated contact investigation for TB requiring procurement and tailoring of software packages
Initiation phase	Simple interventions with low consumable costs that require changes in policy and workflow	Low-cost lateral-flow LAM assay for TB that necessitates a new supply chain, clinical algorithms, and training of personnel
Maintenance phase	Interventions that require continued infrastructure support and quality control	Molecular diagnosis of TB with equipment (e.g., Xpert MTB/RIF®) that necessitates service contracts for equipment failure and external quality assurance of test results

was for software development) overshadowed the cost of intervention delivery ($54 per contact screened) [16]. This initial outlay for intervention design could be partially counterbalanced by scale-up to a broader population but would probably be incurred again if the intervention were implemented in a different country with a different telecommunications system. Importantly, these costs might vary considerably across countries, regions, and facilities with different levels of underlying infrastructure—and these differences would need to be considered by both researchers (aiming to produce generalizable knowledge) and implementers (aiming to accurately estimate design costs in their unique contexts). Failure to consider the cost of designing the intervention and adapting it to the local context would have resulted in both a dramatic overestimation of cost-effectiveness and an incomplete understanding of the generalizability of cost and cost-effectiveness estimates for implementation of the intervention in other settings.

Initiation phase

As interventions are initially rolled out and scaled-up, many types of implementation costs (e.g., training materials and personnel, infrastructure necessary to launch implementing teams) are incurred up-front. These fixed costs often do not vary with the level of service output. The contribution of up-front costs to the overall cost and cost-effectiveness of a program may vary considerably across implementation sites depending on each site's operational and infrastructural capacity and implementation outcomes such as program reach (i.e., the number and representativeness of people engaged by the program) [17]. These costs are often not adequately considered in traditional cost-effectiveness estimates. This is particularly problematic when variable costs (e.g., medical consumables, test kits, and unit staffing costs) to deliver the intervention are low, but the intervention has high implementation and operating costs. For example, the Alere Determine^{TM} TB LAM Ag assay (LF-LAM) is a simple dipstick-based diagnostic test for TB that costs less than $2 per test kit and requires minimal operator time [18]. Cost-effectiveness analyses have therefore considered the unit cost of LF-LAM to be between $3 and $4 per test [11]. However, this estimate fails to account for the "above-service" (and service-level) costs required to implement LAM—including building costs, staff salaries, utilities, and supplies necessary for such activities as preparing clinics and training clinical staff, coordinating logistics during implementation, assuring fidelity to (often complex) policy guidance, and establishing a reliable supply chain [10]. After incorporating these costs, the unit cost of LF-LAM in South Africa was estimated at over $23 per patient tested—approximately seven-fold higher than the simple estimate based primarily on consumable costs alone [19]. Such underestimates of intervention costs (when costs of implementation and scale-up are not incorporated) are unfortunately very common in the scientific literature and lead to reported cost estimates that do not reflect programmatic realities on the ground.

Maintenance phase

Although implementation costs are often proportionally lower during the maintenance phase (Fig. 1b), they should not be ignored entirely—particularly for interventions that require infrastructure and/or procedures that require ongoing upkeep or quality assurance. For example, in the XPEL trial, single-module GeneXpert devices were installed to enable point-of-treatment diagnosis at 10 peripheral health centers in Uganda. Maintaining these devices requires assurance of a stable electrical supply (e.g., installation and maintenance of solar panels), backup testing systems for when devices temporarily fail (which occurred at 6 sites over a 14-month period), security to prevent theft of computers and other electronics, service contracts to perform repairs, routine monitoring and evaluation, maintenance of a reliable supply chain of diagnostic cartridges, and external quality assurance to ensure ongoing high-quality testing by mid-level staff. Corresponding costs varied from one site to another and when considered in full, costs associated with the maintenance operations accounted for > 12% of the total unit cost of peripheral Xpert testing, even when only considering costs beyond the initiation phase (unpublished data). As the level of technology incorporated in new health interventions often outpaces the establishment of corresponding infrastructure in many global settings, explicitly estimating the costs of maintaining those interventions and ensuring their sustainability will become increasingly important [20].

A way forward

The examples above help illustrate the importance of considering costs at each stage of the implementation process. This structured approach to costing of the implementation process suggests three priorities for improving cost-effectiveness analyses of health interventions in resource-limited settings.

First, cost-effectiveness analyses should not rely entirely on budgetary information but should explicitly consider activities and resources required for successful implementation. Examples of approaches for such implementation costing include collection of routine activity logs of implementing staff, structured discussions with field personnel to enable health economists to understand the extent of resources required for major implementation activities (e.g., trainings, site initiation), and ongoing documentation of specific challenges in implementation (e.g., sites in which implementation failed, staff leaving).

Second, implementation cost data should be classified by resource type, key activities, phase of implementation (e.g., as described in Fig. 1), site level (site-specific vs "above-service"), and as programmatic versus non-programmatic (research) so that implementation costs can be generalized to other settings and key drivers of implementation costs can be identified. In costing the implementation process, assumptions can often be made when empiric data are not immediately available—but appropriate documentation and categorization of data and assumptions are critical if generalizable knowledge is to be generated.

Third, costing activities should generally be planned prospectively before implementation begins (so the process of implementation can be costed). While retrospective estimation of implementation costs is often feasible, such estimates are often subject to recall bias and difficult to appropriately classify retroactively. Early involvement of health economists (with experience in empiric costing activities) can therefore be very useful in evaluating the costs of implementation.

One final consideration is whether detailed measurement of implementation costs is justified for a particular implementation research study. In making this assessment, investigators should consider two questions. First, if the intervention is found to be effective, is implementation likely to be influenced by considerations of cost-effectiveness and/or budget impact? Second, are there sufficient uncertainties in the costs of implementing the intervention that an empiric estimation of costs is warranted (as opposed to simply using pre-existing cost estimates from the literature)? In most cases, the answer to the first question will be yes, and the answer to the second question will be no, meaning that an empiric estimation of costs is scientifically justified. When this is the case, investigators must then evaluate whether the budget exists to measure these costs and (given limited financial resources) whether other scientific questions are more pressing.

Conclusions

In summary, we argue that the costs of implementing health interventions in resource-limited settings are often very substantial, but generally neglected in economic evaluation. We provide a framework for effectively conceptualizing and prospectively measuring these costs, which—if incorporated appropriately—can improve the linkage between published results of cost-effectiveness analyses and the realities of implementation in the field.

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Authors' contributions
HS and DD conceived the idea of the topic of this manuscript. All authors contributed equally in writing the initial draft and revising this manuscript. The author(s) read and approved the final manuscript.

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Publisher's Note

제3세션 | 보건과 국제개발

Strengthening Health Systems in Resource-constrained Settings: A Case of mHealth-based Health Information System Implementation in Ghana

발제: **김 선 영**(서울대 보건대학원)

토론: **신 자 은**(KDI School)

Original Paper

An mHealth-Based Health Management Information System Among Health Workers in Volta and Eastern Regions of Ghana: Pre-Post Comparison Analysis

Young-ji Lee[1], MDP; Seohyun Lee[2], PhD; SeYeon Kim[1], MPH; Wonil Choi[1], MPH; Yoojin Jeong[1], MPH; Nina Jin Joo Rhim[3], MPH; Ilwon Seo[4], BS; Sun-Young Kim[1,5], PhD

[1]Department of Public Health Sciences, Graduate School of Public Health, Seoul National University, Gwanak Campus, Seoul, Republic of Korea

[2]Department of Global Public Administration, Yonsei University Mirae Campus, Wonju, Republic of Korea

[3]Good Neighbors International, Seoul, Republic of Korea

[4]Good Neighbors Ghana, Accra, Ghana

[5]Institute of Health and Environment, Seoul National University, Gwanak Campus, Seoul, Republic of Korea

Corresponding Author:
Sun-Young Kim, PhD
Department of Public Health Sciences, Graduate School of Public Health
Seoul National University
Gwanak Campus
1 Gwanak-ro
Gwanak-gu
Seoul, 08826
Republic of Korea
Phone: 82 28802768
Email: sykim22@snu.ac.kr

Abstract

Background: Despite the increasing attention to electronic health management information systems (HMISs) in global health, most African countries still depend on inefficient paper-based systems. Good Neighbors International and Evaluate 4 Health have recently supported the Ghana Health Service on the rollout of a mobile health–based HMIS called the *e-Tracker* system in 2 regions in Ghana. The e-Tracker is an Android-based tracker capture app that electronically manages maternal and child health (MCH) data. The Ghana Health Service has implemented this new system in Community Health Planning and Services in the 2 regions (Volta and Eastern).

Objective: This study aims to evaluate changes in health workers' capacity and behavior after using the e-Tracker to deliver MCH services. Specifically, the study assesses the changes in knowledge, attitude, and practice (KAP) of the health workers toward the e-Tracker system by comparing the pre- and postsurvey results.

Methods: The KAP of frontline health workers was measured through self-administered surveys before and after using the e-Tracker system to assess their capacity and behavioral change toward the system. A total of 1124 health workers from the Volta and Eastern regions responded to the pre-post surveys. This study conducted the McNemar chi-square test and Wilcoxon signed-rank test for a pre-post comparison analysis. In addition, random-effects ordered logistic regression analysis and random-effects panel analysis were conducted to identify factors associated with KAP level.

Results: The pre-post comparison analysis showed significant improvement in health workers' capacity, with higher knowledge and practice levels after using the e-Tracker system. As for *knowledge*, there was a 9.9%-point increase (from 559/1109, 50.41% to 669/1109, 60.32%) in the proportion of the respondents who were able to generate basic statistics on the number of children born in a random month within 30 minutes. In the *practice* section, the percentage of respondents who had *scheduled clientencounters* increased from 91.41% (968/1059) to 97.83% (1036/1059). By contrast, responses to the *attitude* (acceptability) became less favorable after experiencing the actual system. For instance, 48.53% (544/1121) initially expressed their preferences for an electronic system; however, the proportion decreased to 33.45% (375/1121) after the intervention. Random-effects ordered logistic regression showed that *days of overwork* were significantly associated with health workers' attitudes toward the e-Tracker system.

Conclusions: This study provides empirical evidence that the e-Tracker system is conducive to enhancing capacity in MCH data management for providing necessary MCH services. However, the change in attitude implies that the users appear to feel less comfortable using the new system. As Ghana plans to scale up the electronic HMIS system using the e-Tracker to the national level, strategies to enhance health workers' attitudes are necessary to sustain this new system.

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KEYWORDS

mobile health; mHealth; e-Tracker; health information system; HIS; health information management system; HIMS; District Health Information Management System; DHIMS; maternal and child health; MCH; electronic health record; EHR; health workers

Introduction

Background

A health management information system (HMIS) is a critical component of the health system. According to the World Health Organization, a well-functioning HMIS should "ensure the production, analysis, dissemination, and use of reliable and timely information on health determinants, health systems performance, and health status" [1]. In other words, the key functions of HMIS include the generation, compilation, analysis, synthesis, communication, and use of health information [2]. Among these functions of HMIS, generating health data is particularly crucial as it adds value by providing insights into clinical decision-making and policy implications.

The systematic generation and management of health data in low- and middle-income countries (LMICs) have specific challenges in multiple health focus areas. For example, even the most essential vital statistics such as birth records or maternal and child health (MCH) service provision statistics have not been tracked systematically in many LMICs. In recent years, at least 15,000 newborns died annually, without official records [3]. Similarly, gaps exist between actual service provision and reported data, which makes it difficult for local governments to identify the unmet needs of health services [4]. Health data management is more challenging in resource-constrained settings as the health records are stored in paper-based charts rather than collected electronically. Health workers in such settings generate basic statistics or aggregate the data from paper-based health records and submit the data in person by visiting upper-level facilities such as district or provincial health offices. This manual process is time consuming and often leads to poor data quality [5-8]. In this context, an electronic HMIS has been recognized as an effective and efficient way of addressing this challenge and bridging the quality gap between health care service provision and data management [5,9,10]. Some African countries have recently attempted to implement mobile health (mHealth)–based HMIS as it can be operated using relatively simple software at a lower cost [11,12]. The use of mobile phones or tablet computers for operating HMIS can also address logistic problems, including limited access to fixed broadband internet [13,14], lack of electricity supply [14-17], and financial and human resource deficits in low-resource settings [9,10,18-22].

Ghana is an LMIC that has adopted an mHealth-based HMIS by implementing the MCH data capture app on a tablet computer. Originally, the HMIS in Ghana was initiated as a purely paper-based system in which all stages of data management, from data collection to storage, were performed manually. Once computers became available, the process started transitioning from paper-based to electronic systems at the district level. In 2012, Ghana Health Service (GHS), an implementing agency under the Ministry of Health, implemented the official health service data management software platform, District Health Information Management System, which enabled district health officers to manage health data electronically. However, lower-level health facilities still maintained a paper-based HMIS, which is highly error prone [14,15]. This transition in Ghana was partial as it did not include peripheral community-level health facilities [4]. Community health facilities in Ghana are called Community-based Health Planning and Services compounds and belong to the lowest level of the public health structure in Ghana [23].

In response to the growing demand for an efficient data management system, the GHS implemented the e-Tracker system in 2015, applying it first to family planning and MCH services at the community level for effective and efficient data management of the services [14,24]. The e-Tracker is an Android version of the individual client-based module in the District Health Information System 2. Developed by Oslo University in 2005, this open-source software platform enables the reporting, analysis, and sharing of data for the public health sector. The system is operated on tablet computers to resolve common obstacles such as limited electricity, internet access, lack of financing, and limited human resources by allowing offline data collection and management via portable devices [8,10,14]. GHS is taking the lead to increase health workers' capacity not only for data recordings but also for managing tasks such as *tracking clients who drop out of care*, *scheduling*, *monitoring health services*, and *generating reports* [14,16]. Throughout these transitions, the goal of the HMIS in Ghana has been to support transparent decision-making for nationwide health sector programs [4,21].

For a successful transition from a paper-based health record to an electronic HMIS, the willingness of end users to change their workflow is essential for the sustained use of a new system. In this light, ensuring health workers' acceptability and positive perceptions of the change in practice is one of the key facilitating factors in implementing the e-Tracker, as health workers in community health facilities are frontline workers responsible for managing health data [9,17]. Thus, health workers' acceptability of this new system is considered a prerequisite for the successful implementation of an mHealth-based HMIS [10]. The study by Zargara et al [14] reported that a new system's realignment of work practices is a determinant of MCH service provision quality. The study also reported that the key challenges in transitioning from paper-based to electronic health records were "an increase in workload occurred by double work" and "low computer literacy" [4,9]. A working paper published by the US Agency for International Development and Measure Evaluation showed mixed results in that the health workers from the 4 districts in Ghana's Central Region did not use the full functionality of the new mHealth-based HMIS, such as data analysis. However, most of them were satisfied with the advanced technology for managing health data [24].

Objective

To further investigate the frontline health workers' capacity, perceptions, and practice toward the e-Tracker, this study conducted a pre-post survey to measure knowledge, attitude, and practice (KAP) among the health workers at Community-based Health Planning and Services compounds in the Volta and Eastern regions of Ghana where the e-Tracker was gradually rolled out to all districts within the region. The empirical findings of this study are expected to provide grounds and political implications for the national scale-up of the e-Tracker system.

Methods

Study Sample

This study used a quasi-experimental pre- and postanalysis design. The KAP on MCH data management using the e-Tracker was investigated through paper-based pre-post surveys. The study adopted a purposive sampling method, recruiting respondents during the e-Tracker system training sessions in the Volta (recently renamed the Oti and Volta regions) and Eastern regions in Ghana. Although there were no specific inclusion or exclusion criteria for survey participants, the respondents were presumed to possess qualifications to fulfill the research purpose as the eligible participants of the training session were frontline health workers who were in charge of providing health services and managing patient data.

For the presurvey, respondents were recruited during the initial training session of the e-Tracker system, where they were introduced to the system. The postsurvey was conducted during the refresher training after 3 to 10 months of e-Tracker use. A total of 2396 health workers participated in the presurvey; however, only 46.9% (1124/2396) of respondents who had participated in the initial training (ie, the presurvey) were able to rejoin the refresher training (ie, the postsurvey) as the GHS arranged to place a portion of the initial participants with newly employed health workers who had not received training opportunities. As a result, approximately half of the respondents from the presurvey were replaced with newly participating health workers, shrinking the study sample size (respondents who participated in both pre- and postsurveys) to 1124. The final set of respondents comprised different types of community health workers (community health nurses [CHNs] or community health officers [CHOs], midwives, enrolled nurses, and field technicians) working in the Volta and Eastern regions (Multimedia Appendix 1).

Data Collection and the Questionnaire

The survey was conducted between October 2018 and November 2019. It was designed as a paper-based, self-administered questionnaire collected by staff from Good Neighbors International, the implementing partner of the e-Tracker training program. Responses were entered manually into a Microsoft Excel spreadsheet by the research team. The questionnaire comprised 43 multiple-choice and yes or no questions covering the content domains of demographics and KAP (Multimedia Appendix 2).

First, the *knowledge* section of the questionnaire asked respondents whether they could retrieve specific information on MCH statistics within 30 minutes. The 10 tasks listed in the questionnaire were designed based on observations during the field visit. The questions asked about the respondents' perceived capacity to generate basic statistics (such as the number of children born, stillbirths, and women who came for antenatal care visits in a specific month in the catchment area). The first half of the questions were intended to ask whether aggregate data could be generated for a randomly selected month. The remaining 5 questions asked whether health workers could retrieve aggregate data for the month when the survey was conducted. Second, the section for *attitude* comprised 8 questions with a 5-point Likert scale to identify the level of acceptability of using an electronic device for managing MCH records. The questions asked about the respondents' willingness, perception, and preference for using an electronic device for MCH data management. Third, the *practice* section comprised questions on the practice of 8 specific tasks related to MCH data management and the perceived difficulty in performing those tasks. In addition, the use of a tablet computer for MCH data management and the frequency of electronic devices used for MCH data management were asked. As the data on tablet computer use were systematically inaccessible, self-reported responses were used to assess the practice.

Statistical Analysis

Data from the pre- and postsurveys coded in the spreadsheets were imported into STATA (version 14; StataCorp LLC). Unique identifications were randomly generated for each participant, which allowed each participant's pre- and postsurvey variables to be reliably matched. McNemar chi-square and Wilcoxon signed-rank tests were used for pre-post comparison analyses. In addition, to investigate the factors associated with each KAP component, random-effects ordered logistic regression and random-effects panel analysis were conducted. For the dependent variable, a Cronbach α test was performed for each KAP to test internal consistency for aggregating different responses to a single score. The duration of the intervention (ie, use of the tablet-based e-Tracker system in managing MCH data) was selected as the explanatory variable, and the control variables were categorized into enabling environmental, demographic, and working condition factors. The explanatory variable, represented by the "number of days of using the e-Tracker system for MCH data management," varied as the time points for the presurvey (the initial training workshop) and the postsurvey (refresher training) were different across the districts covered. The variable *days of overwork* was included only in the regression model, as introducing an mHealth-based HMIS may have intensified the health workers' workload, increasing resistance toward the emergent system (Table 1).

Table 1. Analysis framework of regression analysis.

Variables	Description
Dependent variables	
Knowledge	Knowledge of MCH[a] data management (score between 0 and 10)
Attitude	Attitude on using an electronic device to manage MCH data (scaled between 1=most negative and 5=most positive)
Practice	Frequency of using an electronic device to manage MCH data (scaled between 1=never and 5=every time)
Explanatory variable	
Duration of e-Tracker use	Days of using the e-Tracker system via a tablet computer
Control variables	
Environmental factor	Level of internet connection at the health facility
Demographic factors	Age, sex, educational level, working experience, job position, and use of mobile phone
Working condition	Days of overwork

[a]MCH: maternal and child health.

Ethics Approval

This study received ethics approval from the GHS Ethics Review Committee (GHS-ERC009/09/18; Multimedia Appendix 3).

Results

Summary of the Respondents' Characteristics

Table 2 presents descriptive statistics for respondents who participated in the presurvey only (group A) and those who participated in both pre- and postsurveys (group B). The 2 groups of respondents were analyzed to identify any significant differences that might have been caused because of a change in sample size. In group A, approximately 53.23% (676/1272) were from the Volta region, whereas in group B, it was 31.76% (357/1124). Approximately 83.81% (1066/1272) of respondents were female in group A, whereas it was 79.27% (891/1124) for group B. As for education, both groups showed a similar proportion for each academic level; however, group A tended to have a slightly higher educational background. Specifically, the percentages of respondents with diplomas and bachelor's degrees were about 3% points and 2% points higher for group A, respectively. Similarly, group A respondents tended to engage in a higher job position as 28.38% (361/1272) were midwives, whereas 15.84% (178/1124) were midwives in group B. Both groups had a high rate of mobile phone use as >96% indicated the *use of their own mobile phones*. As for internet access, approximately 11.4% (145/1272) and 11.48% (129/1124) of respondents answered that their facilities had no internet access, whereas 31.84% (405/1272) and 31.23% (351/1124) responded with an acceptable level of internet access at work sites groups A and B, respectively. In addition, only 6.21% (79/1272) and 6.14% (69/1124) in groups A and B, respectively, answered that their facilities had very reliable internet access. Regarding the average age and working experience, the average age of group A respondents was approximately 1 year higher than those in group B. The average duration of using an e-Tracker system was 187.55 (51.17) days. The differences between the 2 groups in the chi-square analysis results were statistically significant for all demographic factors. Notably, the results indicated that health workers with a relatively lower educational background and shorter work experience participated in both pre- and postsurveys by rejoining the refresher training.

Table 2. Sociodemographic characteristics of the respondents.

Characteristics	Group A, presurvey only (n=1272)	Group B, matched (n=1124)	*P* value
Region, n (%)			
Volta	676 (53.23)	357 (31.76)	<.001[a]
Eastern	596 (46.86)	767 (68.24)	<.001[a]
Sex, n (%)			
Male	204 (16.04)	233 (20.73)	.004[a]
Female	1066 (83.81)	891 (79.27)	.004[a]
Missing	2 (0.16)	0 (0)	.004[a]
Educational level, n (%)			
Certificate	1051 (82.79)	993 (88.35)	<.001[a]
Diploma	179 (14.13)	121 (10.77)	<.001[a]
Bachelor's degree	37 (2.92)	9 (0.8)	<.001[a]
Master's degree	1 (0.08)	1 (0.09)	<.001[a]
Other	1 (0.08)	0 (0)	<.001[a]
Missing	4 (0.32)	0 (0)	<.001[a]
Job description, n (%)			
Community health nurse or community health officer	901 (70.83)	941 (83.72)	<.001[a]
Enrolled nurse	2 (0.16)	1 (0.09)	<.001[a]
Midwife	361 (28.38)	178 (15.84)	<.001[a]
Field technician	1 (0.08)	2 (0.18)	<.001[a]
Other	3 (0.24)	1 (0.09)	<.001[a]
Missing	4 (0.31)	1 (0.09)	<.001[a]
Use of mobile phone, n (%)			
Yes (use my own mobile phone)	1224 (96.23)	1091 (97.06)	.05[a]
Yes (share a mobile phone with family)	5 (0.39)	0 (0)	.05[a]
No (do not use or have a mobile phone)	2 (0.16)	1 (0.09)	.05[a]
Missing	41 (3.22)	32 (2.85)	.05[a]
Access to the internet, n (%)			
No internet	145 (11.4)	129 (11.48)	.17[a]
Very poor	99 (7.78)	102 (9.07)	.17[a]
Poor	139 (10.93)	113 (10.05)	.17[a]
Acceptable	405 (31.84)	351 (31.23)	.17[a]
Reliable	347 (27.28)	329 (29.27)	.17[a]
Very reliable	79 (6.21)	69 (6.14)	.17[a]
Missing	58 (4.56)	31 (2.76)	.17[a]
Age (years), mean (SD)	32.89 (6.65)	31.45 (5.44)	<.001[b]
Duration of work as a health professional (years), mean (SD)	6.80 (5.74)	5.34 (5.02)	<.001[b]

Characteristics	Group A, presurvey only (n=1272)	Group B, matched (n=1124)	*P* value
Days of using an e-Tracker system, mean (SD)	N/A[c]	187.55 (51.17)	N/A

[a]*P* value derived from chi-square test.

[b]*P* value derived from 1-way ANOVA test.

[c]N/A: not applicable.

Knowledge

The responses were analyzed using the McNemar chi-square test to evaluate the pre- and postlevel knowledge. As shown in Table 3, there were statistically significant improvements for all question items. For example, there was a 9.9%-point increase (from 559/1109, 50.41% to 669/1109, 60.32%) in the proportion of respondents who were able to *generate basic statistics within 30 minutes on the number of children born* for a randomly selected month. In addition, the proportion of respondents who were able to retrieve the *number of pregnant women expected to deliver and those scheduled for their second postnatal care visit* during the month of the survey increased by 8.9% points (from 369/1108, 33.3% to 468/1108, 42.24%) and 8.0% points (from 283/1109, 25.52% to 337/1109, 33.54%), respectively.

After obtaining an aggregated score for the levels of knowledge by summing up the total number of tasks that an individual respondent was capable of, a Cronbach α test was conducted to verify the reliability of the aggregated scores. The scale reliability coefficients of the pre- and postsurvey responses were α=.71 and α=.72, respectively. As the test results showed acceptable reliability, 10 self-reported responses were aggregated into a single score ranging between 0 and 10. A random-effects ordered logistic analysis showed no significant impact of intervention duration on health workers' knowledge (odds ratio [OR] 1.00, 95% CI 0.99-1.00; Table 4). However, respondents' sex, working years, and job positions had a statistically significant association with their level of knowledge. Participants who were female tended to have lower knowledge levels than participants who were male (OR 0.53, 95% CI 0.41-0.70). Moreover, health workers with longer working years had higher knowledge levels (OR 1.06, 95% CI 1.03-1.10), and compared with CHN or CHO, midwives appeared to have higher knowledge levels (OR 2.86, 95% CI 2.03-4.02).

Table 3. Result of pre-post analysis for knowledge (N=1109).

Knowledge on data management	Presurvey	Postsurvey	*P* value[a]
Can retrieve basic statistics on the total number of following items for a random month within 30 minutes, n (%)			
Children born	559 (50.41)	669 (60.32)	<.001
Family planning counseling provided	723 (65.19)	783 (70.6)	.001
Stillbirths	282 (25.43)	354 (31.92)	<.001
Women visiting the facility for postpartum complications	222 (20.02)	272 (24.53)	.003
Women visiting for their first antenatal care	480 (43.28)	544 (49.05)	.001
Can retrieve basic statistics on the total number of following items during the month of the survey within 30 minutes, n (%)			
Defaulters for measles immunization[b]	601 (54.24)	663 (59.84)	.001
Pregnant women who are expected to deliver[b]	369 (33.30)	468 (42.24)	<.001
Children aged <l year	626 (56.45)	665 (59.16)	.05
Women scheduled for their second postnatal care visit	283 (25.52)	377 (33.54)	<.001
Women who are in their first trimester of pregnancy[b]	442 (39.89)	496 (44.77)	.002

[a]*P* value derived from the McNemar chi-square test.

[b]A total of 1108 responses was matched.

Table 4. Result of regression analysis for knowledge.

Characteristics	Odds ratio (95% CI)	SE	*P* value
Days of using the e-Tracker system via tablet computer	1.00 (0.99-1.00)	0.00	.48
Age (years)	0.99 (0.97-1.02)	0.01	.67
Sex (reference: male)	0.53 (0.41-0.70)	0.07	<.001
Education level (reference: certificate)			
Diploma	1.20 (0.87-1.65)	0.20	.27
Bachelor's degree	0.77 (0.26-2.27)	0.42	.63
Master's degree	0.02 (0.00-0.73)	0.04	.03
Other	4.11 (0.12-141.19)	7.42	.43
Working years	1.06 (1.03-1.10)	0.02	.001
Job position (reference: CHN[a] or CHO[b])			
Enrolled nurse	3.54 (0.71-17.64)	2.90	.12
Midwife	2.86 (2.03-4.02)	0.50	<.001
Field technician	0.18 (0.00-16.33)	0.42	.46
Other	1.65 (0.13-21.62)	2.16	.70
Use of mobile phone (reference: use own mobile phone)			
Share mobile phone	0.41 (0.04-4.08)	0.48	.44
Do not use mobile phones	4.09 (0.27-61.14)	5.65	.31
Access to the internet (reference: no internet)			
Very poor	1.30 (0.87-1.96)	0.27	.20
Poor	1.40 (0.93-2.10)	0.29	.10
Acceptable	1.18 (0.84-1.65)	0.20	.34
Reliable	1.15 (0.81-1.63)	0.21	.43
Very reliable	0.78 (0.48-1.28)	0.19	.33

[a]CHN: community health nurse.

[b]CHO: community health officer.

Attitude

The Wilcoxon signed-rank test was conducted to assess the prelevel and postlevel of attitude. The initial results showed that approximately 33.99% (379/1115) were *most willing* to manage electronic MCH records (Table 5). However, the proportion decreased to 21.26% (237/1115), whereas the neutral response increased from 18.03% (201/1115) to 28.43% (317/1115). Regarding the preference for paper-based versus electronic-based management, 48.53% (544/1121) initially expressed their preferences for electronic systems; however, the proportion decreased to 33.45% (375/1121) after the intervention. In contrast, the percentage of respondents indifferent to the 2 options increased from 15.7% (176/1121) to 26.32% (295/1121). Compared with the results of the survey, general ideas on using an electronic system or device became less favorable.

The Cronbach α test was conducted to verify the reliability of the 5-point Likert scale for attitude levels. The scale reliability coefficients of the pre- and postsurvey responses were α=.80 and α=.85, respectively. Given the acceptable Cronbach α test results, each of the 8 answers scoring between 1 and 5 was aggregated and converted into one average value and then analyzed using a random-effect panel analysis. As shown in Table 6, the *duration of using the e-Tracker system* was positively associated with attitude toward electronic MCH data management but to a minor degree (coefficient 0.001; *P* value<.001). On the contrary, *days of overwork* showed a negative relationship with the attitude toward the new system. Regarding demographic factors, female health workers tended to favor the new system less. In addition, health workers with diplomas and bachelor's degrees showed more positive attitudes than those with certificates. In contrast, workers with master's degrees had less favorable attitudes. In terms of job positions, enrolled nurses had less favorable attitudes than CHNs and CHOs. Moreover, health workers who shared mobile phones with their families had less favorable attitudes than those with their own mobile phones, implying that the ownership of personal mobile phones may have equipped the respondents with adaptability to the tablet computer system. Access to the internet was also significantly associated with attitudes toward the new system. Health workers who worked at facilities with *very reliable* internet access had more favorable attitudes than those who did not. In summary, some demographic factors, such as the ownership of personal mobile phones and access to the internet, demonstrated a larger magnitude of effect on attitude than the duration of e-Tracker use.

Table 5. Result of pre-post analysis for attitude.

Attitude toward electronic data management	Presurvey, n (%)	Postsurvey, n (%)	*P* value[a]
Willing to manage MCH[b] records using an electronic system (n=1115)			
1 (least likely)	30 (2.69)	33 (2.96)	<.001
2	41 (3.68)	78 (7)	<.001
3 (neutral)	201 (18.03)	317 (28.43)	<.001
4	464 (41.61)	450 (40.36)	<.001
5 (most likely)	379 (33.99)	237 (21.26)	<.001
Comfortable with managing electronic MCH records (n=1117)			
1 (very uncomfortable)	28 (2.51)	32 (2.86)	<.001
2	46 (4.12)	106 (9.49)	<.001
3 (neutral)	275 (24.62)	383 (34.29)	<.001
4	497 (44.49)	435 (38.94)	<.001
5 (very comfortable)	271 (24.26)	161 (14.41)	<.001
Using an electronic device for managing MCH records is a good idea (n=1120)			
1 (strongly disagree)	6 (0.54)	16 (1.43)	<.001
2	6 (0.54)	34 (3.04)	<.001
3 (neutral)	145 (12.95)	254 (22.68)	<.001
4	398 (35.54)	424 (37.86)	<.001
5 (strongly agree)	565 (50.45)	392 (35)	<.001
Using an electronic device to enter MCH records is difficult for me (n=1116)			
1 (strongly disagree)	419 (37.54)	371 (33.24)	.70
2	171 (15.23)	212 (19)	.70
3 (neutral)	292 (26.16)	354 (31.72)	.70
4	187 (16.76)	145 (12.99)	.70
5 (strongly agree)	47 (4.21)	34 (3.05)	.70
I prefer using an electronic device to manage MCH records than writing them on paper (n=1121)			
1 (strongly disagree)	25 (2.23)	41 (3.66)	<.001
2	25 (2.23)	59 (5.26)	<.001
3 (neutral)	176 (15.7)	295 (26.32)	<.001
4	351 (31.31)	351 (31.31)	<.001
5 (strongly agree)	544 (48.53)	375 (33.45)	<.001
Using an electronic device to enter MCH records is more convenient than writing on paper (n=1120)			
1 (strongly disagree)	13 (1.16)	35 (3.13)	<.001
2	25 (2.23)	57 (5.09)	<.001
3 (neutral)	183 (16.34)	285 (25.45)	<.001
4	371 (33.13)	369 (32.95)	<.001
5 (strongly agree)	528 (47.14)	374 (33.39)	<.001
Using an electronic device to enter MCH records is more accurate than writing on paper (n=1120)			
1 (strongly disagree)	19 (1.70)	39 (3.48)	<.001
2	22 (1.96)	61 (5.45)	<.001
3 (neutral)	185 (16.52)	307 (27.41)	<.001
4	404 (36.07)	355 (31.7)	<.001

Attitude toward electronic data management	Presurvey, n (%)	Postsurvey, n (%)	*P* value[a]
5 (strongly agree)	490 (43.75)	358 (31.96)	<.001
Using an electronic device to enter MCH records is more effective than writing on paper (n=1117)			
1 (strongly disagree)	17 (1.52)	33 (2.95)	<.001
2	14 (1.25)	60 (5.37)	<.001
3 (neutral)	169 (15.13)	295 (26.41)	<.001
4	415 (37.15)	384 (34.38)	<.001
5 (strongly agree)	502 (44.94)	345 (30.89)	<.001

[a]*P* value derived from Wilcoxon signed-rank test.

[b]MCH: maternal and child health.

Table 6. Result of regression analysis for attitude.

Characteristics	Coefficient	SE	*P* value
Days of using the e-Tracker system via a tablet computer	0.001	0.00	<.001
Days of overwork	−0.01	0.00	.002
Age (years)	0.00	0.00	.58
Sex (reference: male)	−0.29	0.04	<.001
Education level (reference: certificate)			
Diploma	0.10	0.05	.04
Bachelor's degree	0.21	0.08	.01
Master's degree	−0.19	0.05	<.001
Other	−0.34	0.07	<.001
Working years	0.00	0.01	.49
Job position (reference: CHN[a] or CHO[b])			
Enrolled nurse	−0.30	0.13	.02
Midwife	0.04	0.06	.45
Field technician	−0.28	0.22	.21
Other	−0.06	0.38	.88
Use of mobile phone (reference: use own mobile phone)			
Share mobile phone	−0.61	0.09	<.001
Do not use mobile phones	0.25	0.22	.25
Access to the internet (reference: no internet)			
Very poor	−0.09	0.07	.20
Poor	−0.07	0.06	.28
Acceptable	0.02	0.05	.70
Reliable	0.12	0.06	.03
Very reliable	0.35	0.07	<.001

[a]CHN: community health nurse.

[b]CHO: community health officer.

Practice

The McNemar chi-square test was conducted for self-reported use of tablet computers for MCH data management and for 8 specific tasks related to MCH data management, such as recording client demographic data or scheduling appointments (Table 7). In addition, the Wilcoxon signed-rank test was performed to assess changes in perceived difficulty in conducting each task following the adoption of the e-Tracker. As expected, the analysis showed that the use of tablet computers for MCH data management increased from 5%

(56/1121) to 81.71% (916/1121). As for the frequency of electronic device use for MCH data management, most respondents (817/1119, 73.01%) answered that they had *never* used an electronic device during the presurvey; however, 26.99% (302/1119) responded that they use it *every time*, 36.73% (411/1119) for *most of the time*, 29.49% (330/1119) for *sometimes*, and 3.75% (42/1119) for *never* after the intervention (ie, during the postsurvey).

In the case of actual practice on 8 specific tasks related to MCH data management, the percentage of respondents who performed 8 tasks showed statistically significant changes after the adoption of the e-Tracker. For example, the percentage of respondents who had *scheduled client encounters* increased from 91.41% (968/1059) to 97.83% (1036/1059). In addition, the percentage of respondents who had *collected individual data into aggregates for the District Health Information Management System 2* increased from 66.04% (702/1063) to 89.93% (956/1063). When asked if they *have ever used statistical data for making a request to the District Health Office*, the percentage of respondents who answered *yes* increased from 52.28% (591/1106) to 70.02% (787/1106). However, no statistically significant changes were found for the percentages of respondents who *produce reports on MCH*, *following up health care defaulters*, and *generate basic statistics other than monthly reports on MCH*. On the one hand, the percentages of respondents who *produce reports on MCH* or *following up health care defaulters* were >97% for both pre- and postsurveys, indicating that the tasks have generally been manageable for the health care workers regardless of the e-Tracker adoption. In contrast, the percentages of respondents who had *generated basic statistics other than monthly reports on MCH* remained at approximately 78.62% (846/1076) and 77.97% (839/1076) throughout the pre- and postsurveys, respectively. This result may imply the limited use of the data aggregation functionality of the e-Tracker.

In terms of perceived difficulty for the 8 tasks, a statistically significant improvement was observed for all 8 tasks after the implementation of the e-Tracker system. For instance, 27.94% (292/1069) responded that *following up with health care defaulters* was *very difficult* before the intervention. However, after using the e-Tracker system, only 6.89% (72/1069) answered that the task was *very difficult*. Moreover, those who found the task *very easy* increased from 7.56% (79/1069) to 15.31% (160/1069).

Unlike the *knowledge* and *attitude* sections, responses from the *practice* section failed to fulfill the acceptable standard through the Cronbach α test. Thus, the practice level for regression analysis was defined as a 5-point Likert scale of the frequency of electronic device use for MCH data management, which was analyzed with random-effects ordered logistic analysis (Table 8). The results showed that health workers with diplomas (OR 1.31, 95% CI 1.02-1.67) had higher practice levels than workers with a certificate educational level. Moreover, respondents with more work experience (OR 1.06, 95% CI 1.03-1.09) tended to show higher practice levels. In the case of environmental factors, internet accessibility was associated with practice level; that is, poor (OR 1.37, 95% CI 0.97-1.93), acceptable (OR 1.61, 95% CI 1.22-2.14), and reliable (OR 1.31, 95% CI 0.98-1.76) internet access showed higher odds than no internet access.

Table 7. Result of pre-post analysis for practice.

Practice on MCH[a] data management	Presurvey, n (%)	Postsurvey, n (%)	*P* value
Use a tablet computer for MCH data management (n=1121)	56 (5)	916 (81.71)	<.001[b]
Frequency of electronic device use for MCH data management (n=1119)			
Every time	15 (1.34)	302 (26.99)	<.001[c]
Most of the time	49 (4.38)	411 (36.73)	<.001[c]
Sometimes	163 (14.57)	330 (29.49)	<.001[c]
Rarely	75 (6.7)	34 (3.04)	<.001[c]
Never	817 (73.01)	42 (3.75)	<.001[c]
The number of respondents who perform the following tasks and the perceived task difficulty			
Recording client demographic data (n=1080)	1028 (95.19)	1062 (98.33)	<.001[b]
Perceived task difficulty			
1 (very difficult)	137 (13.33)	44 (4.14)	<.001[c]
2	179 (17.41)	91 (8.57)	<.001[c]
3	401 (39.01)	395 (37.19)	<.001[c]
4	222 (21.6)	321 (30.23)	<.001[c]
5 (very easy)	103 (10.02)	191 (71.98)	<.001[c]
Scheduling client encounters (n=1059)	968 (91.41)	1036 (97.83)	<.001[b]
Perceived task difficulty			
1 (very difficult)	72 (7.44)	25 (2.41)	<.001[c]
2	153 (15.81)	77 (7.43)	<.001[c]
3	365 (37.71)	349 (33.69)	<.001[c]
4	275 (28.41)	351 (33.88)	<.001[c]
5 (very easy)	122 (12.6)	185 (17.86)	<.001[c]
Tracking client progress over time (n=1064)	992 (93.23)	1027 (96.52)	<.001[b]
Perceived task difficulty			
1 (very difficult)	204 (20.56)	68 (6.62)	<.001[c]
2	211 (21.27)	124 (12.07)	<.001[c]
3	315 (31.75)	372 (36.22)	<.001[c]
4	215 (21.67)	319 (31.06)	<.001[c]
5 (very easy)	54 (5.44)	116 (11.3)	<.001[c]
Following up health care defaulters (n=1069)	1045 (97.75)	1045 (97.75)	.88[b]
Perceived task difficulty			
1 (very difficult)	292 (27.94)	72 (6.89)	<.001[c]
2	264 (25.26)	132 (12.63)	<.001[c]
3	275 (26.32)	349 (33.4)	<.001[c]
4	154 (14.74)	351 (33.59)	<.001[c]
5 (very easy)	79 (7.56)	160 (15.31)	<.001[c]

Practice on MCH[a] data management	Presurvey, n (%)	Postsurvey, n (%)	*P* value
Collecting individual data into aggregates for the District Health Information Management System 2 (n=1063)	702 (66.04)	956 (89.93)	<.001[b]
Perceived task difficulty			
1 (very difficult)	152 (15.70)	45 (4.34)	<.001[c]
2	161 (16.63)	104 (10.04)	<.001[c]
3	213 (22)	277 (26.74)	<.001[c]
4	120 (12.4)	195 (18.82)	<.001[c]
5 (very easy)	55 (5.68)	80 (7.72)	<.001[c]
Producing reports on MCH (n=1088)	1061 (97.52)	1066 (97.98)	.30[b]
Perceived task difficulty			
1 (very difficult)	129 (13.33)	68 (6.56)	<.001[c]
2	215 (22.21)	98 (9.46)	<.001[c]
3	375 (38.74)	403 (38.9)	<.001[c]
4	241 (24.9)	397 (38.32)	<.001[c]
5 (very easy)	103 (10.64)	135 (13.03)	<.001[c]
Generating basic statistics other than monthly reports on MCH (n=1076)	846 (78.62)	839 (77.97)	.70[b]
Perceived task difficulty			
1 (very difficult)	92 (9.50)	41 (3.96)	<.001[c]
2	153 (15.81)	63 (6.08)	<.001[c]
3	264 (27.27)	315 (30.41)	<.001[c]
4	124 (12.81)	190 (18.34)	<.001[c]
5 (very easy)	33 (3.41)	57 (5.5)	<.001[c]
Ever used statistical data for making a request to the District Health Office (n=1106)	591 (52.28)	787 (70.02)	<.001[b]

[a]MCH: maternal and child health.

[b]*P* value derived from the McNemar chi-square test.

[c]*P* value derived from the Wilcoxon signed-rank test.

Table 8. Result of regression analysis for practice.

Practice	Odds ratio (95% CI)	SE	*P* value
Days of using the e-Tracker system via tablet computer	1.00 (1.001-1.004)	0.00	.002
Age (years)	0.98 (0.95-1.00)	0.01	.04
Sex (reference: male)	0.83 (0.68-1.01)	0.08	.06
Education level[a] (reference: certificate)			
Diploma	1.31 (1.02-1.67)	0.16	.03
Bachelor's degree	0.64 (0.27-1.51)	0.28	.31
Master's degree	0.98 (0.13-7.56)	1.02	.98
Other[a]	0	0	0
Working years	1.06 (1.03-1.09)	0.01	<.001
Working position (reference: CHN[b] or CHO[c])			
Enrolled nurse	2.59 (0.70-9.53)	1.72	.15
Midwife	0.92 (0.71-1.18)	0.12	.50
Field technician	0.00 (0.00-0.00)	0.00	.99
Other	1.29 (0.16-10.18)	1.36	.81
Use of mobile phone (reference: use own mobile phone)			
Share mobile phone	2.98 (0.44-20.19)	2.91	.26
Do not use mobile phones	1.22 (0.14-10.43)	1.33	.86
Access to the internet (reference: no internet)			
Very poor	1.21 (0.86-1.70)	0.21	.29
Poor	1.37 (0.97-1.93)	0.24	.07
Acceptable	1.61 (1.22-2.14)	0.23	.001
Reliable	1.31 (0.98-1.76)	0.19	.07
Very reliable	1.11 (0.605-0.74)	0.23	.52

[a]The subcategory of *Other* was removed because of a low number of observations.

[b]CHN: community health nurse.

[c]CHO: community health officer.

Discussion

Principal Findings

This study is the first empirical analysis to explore the change in the KAP of health workers in managing MCH data using the e-Tracker system in Ghana. The pre-post comparison analysis results showed a statistically significant improvement in health workers' knowledge and practice levels of MCH data management. Regarding *knowledge*, the proportion of respondents who reported that they could *retrieve basic MCH statistics* increased after using the e-Tracker system. The changes in the practice level were notable in that there were statistically significant increases in the number of health workers engaging in 8 MCH data management tasks, such as scheduling patients' encounters and tracking patients' progress. Furthermore, a significant improvement was observed in the perceived difficulty of performing these 8 tasks. These results were confirmed by a previous study that reported amelioration in the quality of newborn care of health workers in Malawi after using an mHealth solution called NeoTree [3]. In the case of *attitude*, the level remained positive after using the e-Tracker, which was in line with a previous study that identified high satisfaction with e-Tracker use [24]. However, compared with the results from the presurvey, general ideas on using an electronic system or device became less favorable after experiencing the actual system. An additional regression analysis found that the duration of the intervention (days of using a tablet computer) was positively associated with attitude and practice but to a minor degree. Most importantly, the *days of overwork* showed a statistically significant correlation with attitude level, implying the negative impact of increased workload on health workers' acceptability. This can be explained by the concurrent use of the traditional manual and the new e-Tracker system, which created extra work for health workers, affecting their attitude toward the system. A previous study also identified the realignment of work practice and increased workload because of the introduction of the new system [4]. Furthermore, an environmental factor such as access to the internet was also an essential condition as health workers who worked at facilities with relatively more reliable internet access had more favorable attitudes and higher practice levels. This was confirmed by previous studies, which ascertained limited access to fixed broadband internet [13,14] and lack of electricity supply [14-17] as obstacles to implementing an electronic HMIS.

Limitations

Despite its contributions in providing empirical evidence on KAP for the new technology, this study has several limitations. First, the results of this study are not free of external validity issues. The participants of this study were limited to health workers at community health facilities in Ghana, and the surveys were conducted during the training sessions for the e-Tracker adoption. Furthermore, the unexpected change in participants during the refresher training reduced the sample size, as only 46.9% (1124/2396) of the presurvey respondents responded to the postsurvey. The major problem was the demographic description of the 2 groups, which showed a statistically significant difference for every demographic factor. This implied that those who participated in both presurveys and postsurveys tended to be less experienced, which could have affected the results. Second, this study failed to establish a complete study environment to compare before and after the e-Tracker system because of the concurrent use of traditional paper-based and new electronic methods during the study period. Such a dual system caused a double burden for data management tasks on health workers, which was presumed to be the cause of less favorable responses in the *attitude* section. This was supported by the regression analysis, which found that the *days of overwork* had a negative association with the overall attitude toward the electronic-based system. Finally, this study focused on quantitative analysis and did not identify the contextual factors that could be captured through in-depth interviews. Thus, further assessment is necessary to understand the complex reasons behind the reluctance or preference for the new system.

Policy Implications

Nevertheless, our study provides insights for drawing policy recommendations to settle the mHealth-based HMIS in Ghana. The findings warrant the benefits of the e-Tracker system, an enhancement in health workers' capacity for MCH data management, which provides justification for the scale-up of the system. To achieve a successful adaptation of the new system, it is necessary to establish national, regional, and facility-level strategies to address users' acceptability. First, ensuring health workers' acceptability is pivotal for the sustained use of the advanced system [9,17]. Previous studies have concluded that double work is one of the challenges of the e-Tracker [4,9,21]. Thus, GHS needs to spur the complete replacement of manual-based data management with the e-Tracker system to enhance job efficiency by reducing the double burden at the national level. Moreover, an effort to develop the infrastructure and environment of community health facilities to secure stable internet access is necessary. Second, on-site training for health workers to use the system should be arranged regularly by the District Health Offices. A previous qualitative study on health workers' perceptions reported that workers who were more accustomed to mobile technology tended to have a positive attitude toward an mHealth system [18]. Other studies have also reported *low computer literacy* as one of the key challenges in transitioning from paper-based to electronic health records [4,9]. Thus, training health workers in data management, defined as collecting, recording, analyzing, and reporting health data, is crucial for more accurate and reliable information and sustained system use [19,25,26]. Finally, facilitative supervision and organizational management are essential to increase users' perceived ease and realign health workers' tasks, which are detrimental to the sustained use of the e-Tracker system [24].

Conclusions

Strengthening the HMIS is vital for improving health outcomes, as it facilitates communication within the health system and contributes to sound and evidence-based decision-making in health policy. However, many low-income countries rely on manual-based HMIS, which has many limitations for collecting and managing health data. The introduction of the e-Tracker, an mHealth-based HMIS, is expected to be an innovative attempt to bridge the gap between existing technology and the outdated practice of paper-based health data management. Currently, there are ongoing efforts to scale up the e-Tracker system nationally in Ghana. This context warrants an increased need to evaluate the new system's effectiveness and sustainability by exploring health workers' capacity and behavioral changes in using the e-Tracker system. The findings of this study will contribute to the successful adoption of the e-Tracker system at the national level by providing grounds for national scale-up and schemes to enhance the sustainability of the system.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Number of respondents by region and district.
[DOCX File , 16 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Evaluation of the mobile health program questionnaire.

[DOCX File , 281 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Ethics approval.
[PDF File (Adobe PDF File), 141 KB-Multimedia Appendix 3]

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Abbreviations

CHN: community health nurse
CHO: community health officer
GHS: Ghana Health Service
HMIS: health management information system
KAP: knowledge, attitude, and practice
LMIC: low- and middle-income country
MCH: maternal and child health
mHealth: mobile health
OR: odds ratio

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Rough Assessments of Pandemic Responses and Preparedness in the Age of COVID-19

발제: 김 태 종(KDI School)

토론: 오 주 환(서울대 의과대학)

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Article

A "Ballpark" Assessment of Social Distancing Efficiency in the Early Stages of the COVID-19 Pandemic

Taejong Kim [1] and Hyosun Kim [2,*]

[1] KDI School of Public Policy and Management, Sejong 30149, Korea; tjkim@kdischool.ac.kr
[2] Chung-Ang Business School, Chung-Ang University, Seoul 06974, Korea
* Correspondence: hkim3@cau.ac.kr

Abstract: This paper presents an efficiency assessment of social distancing as an internationally adopted measure to tackle the COVID-19 pandemic in 2020. The simple framework adopted for the assessment accounts for two kinds of costs that a society may bear in a pandemic. The first is welfare loss due to infection and its consequences, and the second is welfare loss resulting from a slowdown in economic transactions. We call the first infection costs, and the second economic costs, for convenience in the paper. Efficient social distancing should minimize the sum of these costs. Infection costs are likely to decrease with social distancing at a decreasing rate as intensified social distancing eases pressure on scarce resources for intensive care. Economic costs on the other hand are likely to increase at an increasing rate as extreme slowdown in economic life may entail job losses and business failures. The resulting U-shaped total costs curve implies parity between infection costs and economic costs as a necessary condition for efficiency. In a simplified implementation of the framework, we approximate infection costs by the value of (statistical) lives lost, and economic costs by the gap between the actual gross domestic product (GDP) in 2020 and the potential GDP as predicted by the within-country growth trend during the preceding decade. The results for 158 countries suggest that the global community perhaps reacted with overly strict social distancing measures. The results for the subgroup of high-income countries, however, suggest that these countries were more successful in maintaining the parity between infection and economic costs.

Keywords: COVID-19; social distancing; welfare loss; pandemics; efficiency

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1. Introduction

The COVID-19 pandemic has claimed more than 5.2 million lives as of the end of November 2021. Economic consequences have also been devastating. The global gross domestic product (GDP) recorded a 3.5% contraction in 2020, and while economic activities have regained some momentum in 2021, the projection for the global GDP in 2021 remains below the pre-pandemic levels across the regions [1]. A key component in global responses to the pandemic has been various measures of social distancing [2–5]. While the remarkably fast development and deployment of vaccines has significantly enhanced the ability of the global community to control the spread of the virus, viral mutations necessitate continued practice of social distancing in emergency situations, even in regions with already high vaccination rates. During the first year of the pandemic, social distancing was the mainstay in public health responses to fight the viral spread across the world, and it remains such in a large swathe of developing countries where vaccine supplies are still slow in arriving.

This paper presents a simple and practical conceptual framework for assessing efficiency in the implementation of social distancing across the countries. The framework recognizes that efficient social distancing should minimize the sum of two distinct costs a society may bear in a pandemic: first, costs due to infection by the virus (infection costs), and second, costs due to the potential slowdown in economic transactions (economic costs). Social distancing will reduce infection costs, while raising economic costs. Figure 1 provides a visual representation of the framework.

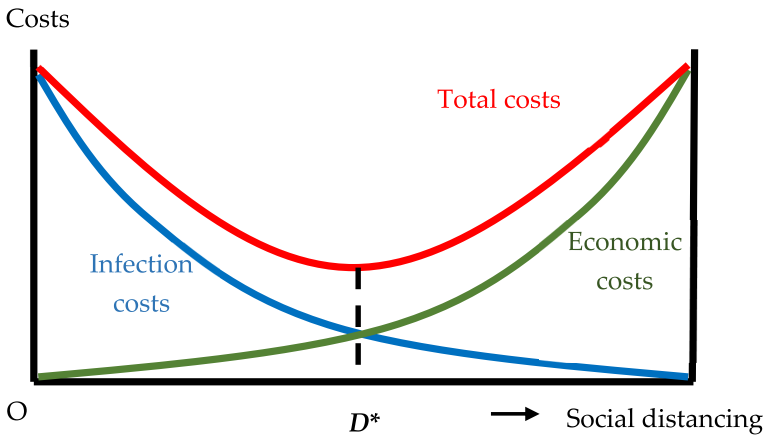

Figure 1. Infection costs, economic costs, and efficient social distancing. (Source: the authors' own conceptualization).

Infection costs are likely to decrease with social distancing at a decreasing rate as intensified social distancing eases pressure on limited resources for intensive care [5]. Due to the capacity ceiling in the public healthcare system for intensive care, modest social distancing may save a lot of lives, whereas public health benefits from further restrictions in mobility are likely to be smaller. Economic costs on the other hand are likely to increase at an increasing rate as the extreme slowdown in economic life entails job losses and business failures [6–8]. As social distancing intensifies, the reduction in business customs will mount. Businesses will be forced to lay-off employees, and even to close down, in case social distancing is strengthened beyond a point, with discrete jumps in implied welfare loss. The resulting U-shaped total costs curve implies parity between infection costs and economic costs as a necessary condition for efficiency. In Figure 1, efficiency is attained at D^*, where infection costs and economic costs match each other, minimizing total costs.

Rigorous measurement of infection and economic costs is not an easy task [9]. In this paper, we attempt a simplified operationalization by approximating infection costs by the value of (statistical) lives lost, and economic costs by the gap between the actual gross domestic product (GDP) in 2020 and the potential GDP as predicted by the within-country growth trend during the preceding decade. These approximations are both likely to understate the true costs, as they leave out obvious items: infection costs should also include costs for treatment for the infected [10], value of labor lost while the infected go through treatment and recovery [11], and long-term adverse health effects of infection known as "long COVID" [12], whereas economic costs should include welfare loss due to negligence in the care of other diseases [13], loss in psychological wellbeing due to imposed loneliness [14], and disruptions in human capital investment, among other things [15].

Our motivation for choosing the simplifying approximations is chiefly practical, as we have no clear methods to estimate the omitted items in a credible and comparable manner across the countries in the world. In the case of the infection costs, however, we believe that our approximation is likely to capture more or less satisfactorily the true extent of the costs, as the value of lives lost will dwarf the other items. We concede that the extent of the underestimation is likely to be more substantial in the approximation we propose for the economic costs. We will discuss the implication of this observation in the discussion of the results.

We followed the recommendation by Viscusi and Masterman [16] to estimate 2020 values of a statistical life (VSL) in different countries, and multiplied these by the number of cumulative deaths due to COVID-19 by the end of year 2020 provided by the World Health Organization (WHO) to estimate country-by-country infection costs. We sourced GDP data for 2020 and the preceding decade from the World Bank.

We have already noted that infection costs should be equal to economic costs, if social distancing is to be efficient and total costs are minimized. Thus, the ratio of infection costs over economic costs should be equal to 1 with efficient social distancing. The value of the ratio over 1 means that infection costs outweigh economic costs, and that social distancing is insufficient in view of efficiency. In the context of Figure 1, social distancing is practiced on the left-hand side of the optimal point D^*. The value of the ratio below 1 means the opposite: economic costs from social distancing outweigh infection costs, and social distancing is overly strict on the right-hand side of the optimal point D^*.

The actual range of the ratio of infection costs over economic costs is widely spread on both sides of the critical value of 1. For our sample of 158 countries, both the mean and the median of the ratios are significantly below 1, suggesting that the vast majority of countries in the global community practiced overly restrictive social distancing. For 34 countries in the sample with per capita income over USD 20,000, however, we cannot reject the null hypothesis that the mean or the median of the ratio is equal to 1.

The rest of the paper proceeds as follows. Section 2 will discuss approximations we used to estimate both infection costs and economic costs. Section 3 will present results from the comparison of infection and economic costs across the countries in the sample, including results from statistical tests. Section 4 will discuss the findings and their implications and present some concluding remarks.

2. Estimation of Infection Costs and Economic Costs

Infection costs comprise costs for medical treatment, value of labor lost by the infected during treatment and recovery, reduction in welfare due to long COVID, and most importantly, value of lives lost. Our "ballpark" estimation focuses on the value of lives lost, ignoring the remaining items. This decision was chiefly forced by the difficulty in estimation for a large number of countries, but may be justified in that the value of lives lost most probably dominates the remaining items by an order of magnitude.

To measure the value of lives lost to the pandemic, we rely on the concept of the value of a statistical life (VSL). The VSL is a measure of life's value derived from the tradeoff rate between fatality risk and money, often observed through choices in product and labor market contexts [17]. Since the 1980s, the VSL has played an increasing role in cost–benefit analyses for regulatory changes affecting mortality risks in the US and other countries. As most estimates of the VSL are concentrated in a relatively small number of mostly high-income countries, mortality valuation in a global context has to estimate the VSL figures for countries through extrapolation from a base country [18]. The extrapolation relies on the following formula:

$$\mathrm{VSL}_{\mathrm{target}} = \mathrm{VSL}_{\mathrm{base}} * \left(\mathrm{Income}_{\mathrm{target}}/\mathrm{Income}_{\mathrm{base}}\right)^{\mathrm{elasticity}} \quad (1)$$

In the equation, elasticity is a positive parameter capturing the empirical pattern among existing VSL estimates, showing higher VSL values for more affluent societies. Following the recommendation by Viscusi and Masterman [16], we used 2015 US as the baseline, with the VSL estimated to be USD 9.6 million and the base income of USD 55,980. Elasticity was assumed to be 1.0 for countries with a per capita income of less than USD 8809 and 0.85 for countries with a higher income.

Estimating economic costs poses an even greater challenge. We estimated economic costs through the difference between the actual 2020 GDP and the predicted 2020 GDP estimated using the average annual growth rate during the previous decade. We are aware that this approximation clearly understates the true value, as it ignores welfare loss due to negligence in the care of other diseases, loss in psychological wellbeing due to imposed isolation, and adverse consequences for disruption in the investment for human capital. While we lack a credible method to estimate the value of the omitted items across a large number of countries, country case studies indicate that the welfare reduction implied by these items is indeed substantial [10–15]. This realization is the main reason why we think of our assessment as a "ballpark" exercise. We will discuss the implication of the relatively more severe underestimation of economic costs versus infection costs later, and note briefly here that a more accurate measurement of both the costs should strengthen our case that social distancing was overly restrictive during the first year of the pandemic.

3. Results

Using data on GDP and COVID-19 deaths sourced, respectively, from the World Bank and the World Health Organization, we have calculated infection costs and economic costs per capita. The summary statistics for these and other related variables are presented in Table 1. From the table, we note that both the mean and, in particular, the median are larger for economic costs than their counterparts for the infection costs.

Table 1. Summary statistics (in USD, 2015 PPP).

Variable	Obs.	Mean	Std. Dev.	Median	Min.	Max.
Infection costs per capita	158	1244	2486	138	0.005	13,150
Economic costs per capita	159	1601	1836	1071	−5114 *	8852
VSL	159	2,411,469	3,325,592	931,999	33,672	1.67×10^7
GDP per capita	159	14,025	19,631	5434	196	107,028

* We counted six countries in our sample where the actual 2020 GDP was higher than the predicted: Iran, Brunei Darussalam, Guyana, Guinea, Central African Republic, and Comoros.

In Table 2, we present the costs and related data for six selected countries, with the same data covering all the countries in the sample provided in the Appendix A. COVID-19 deaths are the number of cumulative deaths by the end of year 2020, and VSL represents our estimates of the VSL based on extrapolation from the 2015 US baseline. Infection costs in the third column were found by multiplying the number of deaths by VSL. Note that the figures in the table are not normalized for population. Infection costs in countries on the top three rows (China, South Korea, and Australia) were relatively small, measured in billions, mainly reflecting fewer deaths registered in these countries. Infection costs were much higher for Germany, the US, and Belgium, as shown in the table, and in the US in particular, the infection costs were beyond 3 trillion dollars. Economic costs were also substantial, and in the countries in the top three rows, they were larger than the infection costs. In the US and Belgium, we see that while economic costs were large, they were smaller than even the larger infection costs these two countries incurred in 2020. China is notable with the economic costs of over 1 trillion dollars, much larger than their infection costs. Reflecting these cross-country variations, the last column reports a fairly wide range of values for the ratio of infection costs over economic costs. For the six countries in consideration, the ratio varies from 0.0057 for China (overly strict social distancing) to 3.3314 for Belgium (overly lax social distancing).

Table 2. COVID-19 deaths, VSL, infection costs, and economic costs in 2020 for selected countries.

Country	COVID-19 Deaths	VSL	Infection Costs in Mil. USD (A)	Economic Costs in Mil. USD (B)	Ratio A/B
China	4634	1,399,381	6485	1,134,762	0.0057
South Korea	917	5,428,300	4978	85,729	0.0581
Australia	909	9,615,503	8740	36,833	0.2373
Germany	33,791	7,903,049	267,974	292,941	0.9148
United States	352,001	9,192,503	3,235,770	1,183,774	2.7334
Belgium	19,528	7,833,682	152,976	45,918	3.3314

Figure 2 presents a scatterplot juxtaposing economic costs against infection costs in the international comparison. Each dot in the plot represents one of 158 countries for which we have been able to estimate these costs. The red straight line superimposed on the plot is the 45-degree line, signifying parity between economic costs and infection costs. The countries above the line suffered infection costs higher than economic costs. Had they been able to be stricter in social distancing, they should have been able to cope with the pandemic with lower total costs. The vast number of countries located below the line incurred economic costs larger than infection costs, meaning that they could have relaxed their measures of social distancing and reduced the total costs.

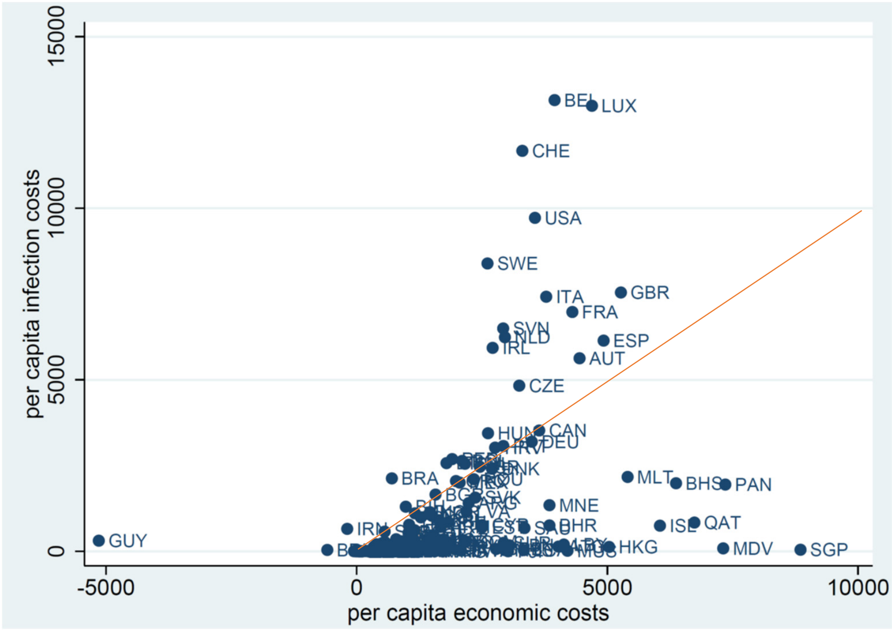

Figure 2. Economic costs versus infection costs: international comparison (in USD).

Figures 3 and 4 are histograms, showing the frequency distributions of the ratio of infection costs over economic costs, for the whole sample (Figure 3) and for the high-income subsample (Figure 4), respectively. The high-income subsample has 34 countries with a per capita GDP over USD 20,000. Figure 3 vividly demonstrates that the global community in general has overreacted to the pandemic scare in terms of social distancing. In more than 50% of countries, the infection costs/economic costs ratio was under 0.25. In 130 countries out of 158, the same ratio was below 1. In the framework of Figure 1, all these countries' practice of social distancing was to the right-hand side of D^*. In Figure 4, the frequency distribution is more closely concentrated around the value of 1 for high-income countries, even though there is no bunching around the value of 1.

We may formally test how successful countries are in efficient practice of social distancing. The variable used in the one-sample *t*-test is the ratio of infection costs over economic costs. If the ratio is at 1 or near 1, we may decide the country was efficient in social distancing in the sense of minimizing the sum of infection and economic costs. Values of the ratio far away from 1 signify failure of efficient social distancing, either overly strict (the ratio much lower than one) or overly lax (the ratio much larger than one). Therefore, we present the null and alternative hypotheses as follows:

H_0: The mean of the ratio of infection costs over economic costs is equal to 1 (efficient social distancing).

H_A: The mean of the ratio is not equal to 1 (inefficiency in social distancing).

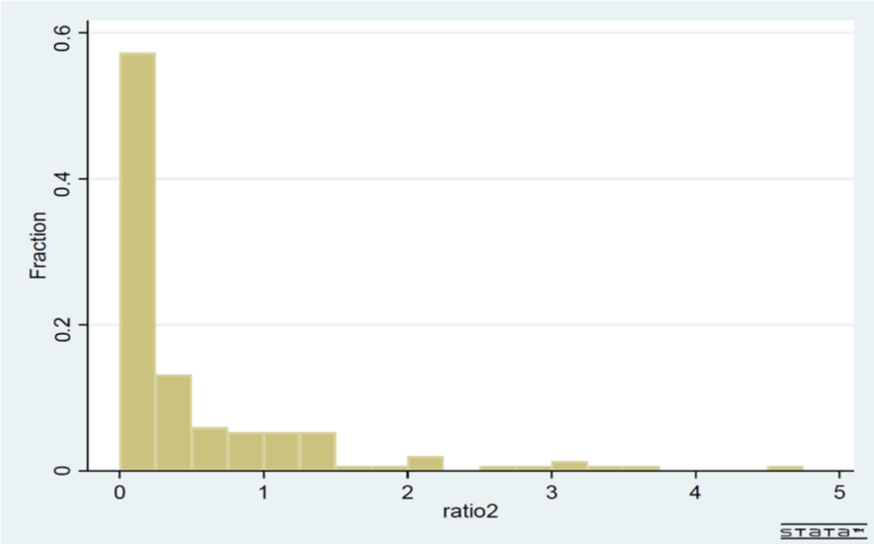

Figure 3. The frequency distribution of the ratio infection costs/economic costs: whole sample (158 countries).

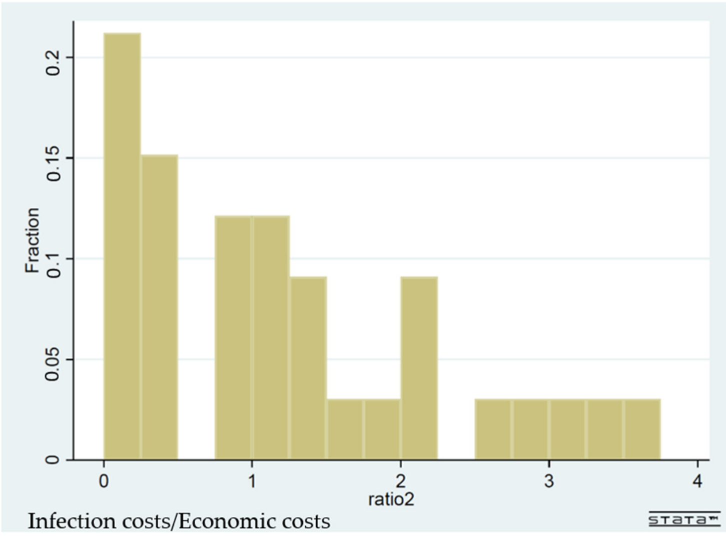

Figure 4. The frequency distribution of the ratio infection costs/economic costs: high-income countries (with per capita GDP over USD 20,000; 34 countries).

See Table 3 for detailed results from the one-sample *t*-tests. At conventional levels of significance of either 5% or 1%, we strongly reject the null hypothesis. As a matter of fact, the *p*-value from the test is less than 0.0001. The results from the one-sample *t*-test for the high-income subsample are also presented in Table 3, and do not reject the null hypothesis that the mean ratio is one at conventional levels of significance.

Table 3. Results from one-sample *t*-tests against the null hypothesis of parity between two costs.

Sample	Obs.	Mean	Std. Err.	Std. Dev.	*T*	Lower B. (95% CI)	Upper B. (95% CI)
Whole sample	158	0.4661	0.0680	0.8549	−7.8495	0.3317	0.6004
High-income	34	1.1785	0.1816	1.0591	0.9828	0.8089	1.5480

4. Discussion and Concluding Remarks

We have applied a simple framework with fairly light data requirements and assessed efficiency in the global practice of social distancing, and found that the intensity in social distancing was overly strict in a majority of countries during the first year of the pandemic. We used the annual timeframe to compare infection and economic costs. In countries where GDP estimates are expediently made available at a higher frequency, it might be possible to put the paper's framework to a practical, "ballpark"-style assessment of the social distancing practice, for instance on a quarterly basis.

An ideal and more rigorous assessment of efficiency in social distancing as a response to the COVID-19 pandemic would require a set of elaborate models and a range of reliable data. For instance, Thunström and others [19] used the SIR (Susceptible Infectious Recovered) epidemiological model to estimate expected numbers of deaths and used macroeconomic forecasts from the global consulting firm McKinsey under different scenarios of social distancing to "flatten out" the curve in the initial phase of the pandemic. An obvious drawback of rigorous approaches for a practical global assessment is the unavailability of parameter estimates and other data required for a large number of countries. Striking the appropriate balance between saving lives and keeping the economy afloat is an urgent challenge across the world. Our hope is that the simple conceptual framework and the economy in data requirements in our "ballpark" efficiency assessment might provide a practically useful data point for desperate policymakers in the developing world.

For the whole sample, it was obvious that the vast majority of countries in the world were erring on the overly strict side of the balance, that is, on the right-hand side of the optimal distancing level, D^*, in Figure 1. We have already noted that both infection costs and economic costs are likely to be underestimated in our approximations. In the ratio of infection costs over economic costs, the extent of underestimation is most probably larger for the denominator, that is, the economic costs. This implies that in the absence of measurement errors, the distribution of the values of the ratio of infection costs over economic costs should tilt further to the left, rendering the ratios for countries even further away from unity and closer to zero.

Assuming no measurement error, parity between infection costs and economic costs should be desired in the normative sense, as a society struggles to cope with the pandemic at the lowest possible costs. We surmise at the same time that there might also be a positive tendency for the ratio to converge to one over time. This would be the case, for instance, if the political processes in a given society are successful in incorporating diverse interests and voices among the public in an efficient manner. This observation suggests two natural extensions to the study that this paper reports: When the GDP data become available for 2021, we should be able to check whether countries do migrate closer to the 45-degree line in a chart as in Figure 2. Additionally, we could investigate what political, social, or cultural factors correlate with the distance between their infection costs/economic costs ratios and unity.

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Data Availability Statement: We have used the publicly archived datasets for our analysis. The link to the data sources are included in the references.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. International Comparison of Efficiency in Social Distancing.

Country	Code	IC	EC	IC/EC	Country	Code	IC	EC	IC/EC
Egypt, Arab Rep.	EGY	38	8	4.54	**Costa Rica**	CRI	907	1643	0.55
Switzerland	CHE	11,673	3303	3.53	**Ecuador**	ECU	614	1156	0.53
Belgium	BEL	13,151	3947	3.33	**Latvia**	LVA	1156	2190	0.53
Sweden	SWE	8390	2609	3.22	**Jordan**	JOR	206	392	0.53
Brazil	BRA	2126	702	3.03	**South Africa**	ZAF	542	1033	0.52
Luxembourg	LUX	12,986	4692	2.77	**Paraguay**	PRY	274	557	0.49
United States	USA	9720	3556	2.73	**Sao Tome and Principe**	STP	17	35	0.48
Slovenia	SVN	6495	2922	2.22	**Finland**	FIN	847	1823	0.46
Ireland	IRL	5930	2711	2.19	**Ukraine**	UKR	228	493	0.46
Netherlands	NLD	6240	2957	2.11	**Albania**	ALB	353	786	0.45
Italy	ITA	7421	3780	1.96	**Belarus**	BLR	172	391	0.44
France	FRA	6976	4301	1.62	**Armenia**	ARM	711	1673	0.42
Czech Republic	CZE	4829	3242	1.49	**Malta**	MLT	2168	5404	0.40
Lithuania	LTU	2571	1791	1.44	**Eswatini**	SWZ	139	347	0.40
United Kingdom	GBR	7544	5270	1.43	**Montenegro**	MNE	1344	3845	0.35
Peru	PER	2689	1905	1.41	**Guatemala**	GTM	136	402	0.34
Bosnia and Herzegovina	BIH	1300	979	1.33	**Belize**	BLZ	370	1127	0.33
Hungary	HUN	3442	2619	1.31	**Azerbaijan**	AZE	245	785	0.31
Austria	AUT	5626	4445	1.27	**Bahamas, The**	BHS	1984	6370	0.31
Poland	POL	2635	2104	1.25	**Georgia**	GEO	471	1522	0.31
Spain	ESP	6141	4925	1.25	**Moldova**	MDA	291	941	0.31
Chile	CHL	2552	2159	1.18	**Cyprus**	CYP	765	2501	0.31
Croatia	HRV	3023	2761	1.09	**Bolivia**	BOL	307	1063	0.29
Bulgaria	BGR	1654	1572	1.05	**Estonia**	EST	699	2500	0.28
Portugal	PRT	3070	2925	1.05	**Panama**	PAN	1945	7353	0.26
Greece	GRC	2048	1980	1.03	**Equatorial Guinea**	GNQ	83	341	0.24
Serbia	SRB	574	558	1.03	**Tunisia**	TUN	265	1091	0.24
Israel	ISR	2463	2456	1.00	**Australia**	AUS	339	1428	0.24
Mexico	MEX	2003	2054	0.98	**Saudi Arabia**	SAU	678	3347	0.20
Canada	CAN	3521	3640	0.97	**Kazakhstan**	KAZ	347	1731	0.20
North Macedonia	MKD	1107	1162	0.95	**Bahrain**	BHR	755	3844	0.20
Germany	DEU	3194	3492	0.91	**Iraq**	IRQ	257	1583	0.16
Romania	ROU	2101	2336	0.90	**Honduras**	HND	106	701	0.15
Denmark	DNK	2404	2699	0.89	**Trinidad and Tobago**	TTO	262	1833	0.14
Norway	NOR	1141	1462	0.78	**Morocco**	MAR	107	789	0.14
Russian Federation	RUS	988	1281	0.77	**Gambia, The**	GMB	7	51	0.13
Turkey	TUR	774	1046	0.74	**Dominican Republic**	DOM	277	2175	0.13
Colombia	COL	1037	1500	0.69	**El Salvador**	SLV	114	912	0.12
Slovak Republic	SVK	1566	2366	0.66	**Qatar**	QAT	838	6736	0.12
Argentina	ARG	1406	2233	0.63	**West Bank and Gaza**	PSE	108	868	0.12
Country	**Code**	**IC**	**EC**	**IC/EC**	**Country**	**Code**	**IC**	**EC**	**IC/EC**
Iceland	ISL	747	6049	0.12	**Uganda**	UGA	1	52	0.02
Cabo Verde	CPV	112	1240	0.09	**Angola**	AGO	6	370	0.02
Suriname	SUR	248	2930	0.08	**Myanmar**	MMR	12	817	0.02
Uruguay	URY	148	1873	0.08	**Lesotho**	LSO	4	327	0.01
Mauritania	MRT	20	266	0.08	**Mali**	MLI	2	129	0.01
Jamaica	JAM	76	1079	0.07	**Zimbabwe**	ZWE	4	352	0.01
Namibia	NAM	71	1025	0.07	**Malaysia**	MYS	36	2955	0.01
Indonesia	IDN	59	855	0.07	**Togo**	TGO	1	79	0.01
Korea, Rep.	KOR	97	1671	0.06	**Maldives**	MDV	85	7310	0.01
Gabon	GAB	42	717	0.06	**Botswana**	BWA	22	2081	0.01
Lebanon	LBN	174	3045	0.06	**St. Lucia**	LCA	34	3334	0.01
Sudan	SDN	11	186	0.06	**Ghana**	GHA	3	320	0.01
Pakistan	PAK	9	166	0.05	**Nigeria**	NGA	2	241	0.01

Table A1. *Cont.*

Country	Code	IC	EC	IC/EC	Country	Code	IC	EC	IC/EC
Kyrgyz Republic	KGZ	35	679	0.05	**Congo, Dem. Rep.**	COD	0	55	0.01
Algeria	DZA	45	893	0.05	**Niger**	NER	0	50	0.01
Libya	LBY	198	4131	0.05	**Burkina Faso**	BFA	1	77	0.01
Bangladesh	BGD	10	210	0.05	**Sierra Leone**	SLE	1	109	0.01
Afghanistan	AFG	5	109	0.05	**Madagascar**	MDG	1	114	0.01
Senegal	SEN	6	130	0.05	**Cote d'Ivoire**	CIV	1	239	0.01
New Zealand	NZL	37	881	0.04	**Mozambique**	MOZ	0	81	0.01
India	IND	36	949	0.04	**China**	CHN	4	786	0.01
Antigua and Barbuda	ATG	138	4024	0.03	**Sri Lanka**	LKA	6	1126	0.01
Nepal	NPL	9	269	0.03	**Singapore**	SGP	46	8853	0.01
Cameroon	CMR	4	135	0.03	**Rwanda**	RWA	1	222	0.00
Philippines	PHL	42	1378	0.03	**Mauritius**	MUS	16	4204	0.00
Haiti	HTI	4	154	0.03	**Papua New Guinea**	PNG	0	366	0.00
Nicaragua	NIC	7	276	0.03	**Thailand**	THA	1	1706	0.00
Kenya	KEN	6	243	0.03	**Tanzania**	TZA	0	105	0.00
Hong Kong SAR, China	HKG	127	5034	0.03	**Burundi**	BDI	0	11	0.00
Congo, Rep.	COG	7	263	0.02	**Vietnam**	VNM	0	268	0.00
Barbados	BRB	69	2781	0.02	**Fiji**	FJI	1	3018	0.00
Ethiopia	ETH	2	72	0.02	**Mongolia**	MNG	0	1558	0.00
Uzbekistan	UZB	8	342	0.02	**Comoros**	COM	3	-54	−0.05
Zambia	ZMB	5	239	0.02	**Central African Republic**	CAF	1	−16	−0.05
Benin	BEN	1	38	0.02	**Guinea**	GIN	1	−19	−0.05
Tajikistan	TJK	2	89	0.02	**Guyana**	GUY	310	−5145	−0.06
Guinea-Bissau	GNB	2	115	0.02	**Brunei Darussalam**	BRN	41	−587	−0.07
Malawi	MWI	1	48	0.02	**Iran, Islamic Rep.**	IRN	654	−189	−3.46
Chad	TCD	1	46	0.02					
Liberia	LBR	1	76	0.02					

IC = Infection cost per capita, EC = Economic cost per capita, IC/EC = Infection cost per capita/Economic cost per capita.

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