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Headquarters gravity: How multinationals shape international trade☆

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ABSTRACT

Multinational firms, using their foreign affiliates as export platforms, are the largest players in international trade. The exporting behaviors of these multinationals differ systematically from those of local firms: Using the Chinese customs data, I find that the Chinese affiliates of foreign multinationals bias their exports towards the markets *close to* their headquarters. I incorporate this *headquarters gravity* into a general equilibrium model by, as in Head and Mayer (2019), allowing the export costs faced by multinational affiliates to depend on the proximity between headquarter and destination countries. To draw its aggregate implications, I calibrate my model to the Chinese customs data and perform counterfactual exercises, finding that (i) headquarters gravity accounts for about 20% of the Chinese exports in the early 2000s, and (ii) ignoring headquarters gravity would substantially bias our quantitative evaluation of trade shocks like the recent US-China trade war. I also consider the scenario in which the Chinese customs data on multinational sales is unavailable. I demonstrate the usefulness of my model in this scenario by constructing exact bounds on counterfactual results using only bilateral trade and multinational production (MP) data.

1. Introduction

Multinational firms, using their foreign affiliates as export platforms, are the largest players in international trade. Understanding their exporting behaviors is crucial for understanding the formation of international trade networks and for quantifying the consequences of trade shocks. In their recent seminal work, Head and Mayer (2019) have documented that in the car industry export platforms are prevalent and the exports of these export platforms are biased towards the markets close to their headquarters. If this pattern does not only hold in this single industry, it would have profound implications for our evaluation of the consequences of trade shocks.

For example, consider the recent US-China trade war. If the Chinese affiliates of Canadian multinationals concentrate their exports to the U.S. market, then they are likely to be heavily hurt by the Trump's protectionism tariffs on imports from China.[1] In

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[1] Recent news suggest that some Canadian firms are indeed heavily exposed to the US-China trade war because, as the CEO of a Canadian multinational said, "we do most of our business with the United States and our products are put together in China". See https://www.theglobeandmail.com/business/adv/article-canadian-companies-eye-new-supply-chains-amid-us-china-trade-war/

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this example, the detailed structure of the multinationals' export-platform networks is essential for quantifying the impacts of protectionism tariffs. However, we typically do not have such detailed data, which limits our capability for precise quantification.

This paper aims to improve our understanding of multinationals' export-platform networks and their implications for the aggregate economy. To this end, I utilize detailed export and multinational production (MP) data in China, a major exporter and FDI receiver in the world. In particular, I augment the Chinese customs data with the nationality of each exporter in 2001.[2] Using this augmented Chinese customs data, I find that the Chinese affiliates of foreign multinationals bias their exports towards the markets *close to* their headquarters. I name this market bias of multinational affiliates as *headquarters gravity*, distinctive from the standard gravity equation considering only bilateral relationships between exporting and importing countries. This paper is the first to document this market bias using trade data for *all industries*, showing that the empirical pattern documented by Head and Mayer (2019) does not only hold in the car industry.[3]

To understand the aggregate implications of headquarters gravity, I incorporate it into a quantifiable general equilibrium model. The model builds on the tractable framework developed by Arkolakis et al. (henceforth ARRY, Arkolakis et al., 2018), which allows firms to produce outside their home country and utilize their affiliates as export platforms. To capture headquarters gravity, I follow Head and Mayer (2019) by allowing the export costs of a multinational affiliate to depend on the location of its headquarters. Head and Mayer (2019) first introduce this “multinational sales (MS) friction” between *headquarters* and *destination markets* into an international trade-MP framework for the car industry. This paper follows this setting but focuses on the general equilibrium effects in the aggregate economy.

I then bring my model to data, pursuing two quantification exercises. First, I calibrate my model to the augmented Chinese customs data associated with the aggregate bilateral trade and MP data, resulting in point estimates of the model's counterfactual predictions. Second, I consider the scenario in which the detailed data on multinationals' export-platform sales is unavailable. I demonstrate the usefulness of my model in this scenario by constructing exact bounds on the model's counterfactual predictions using only bilateral trade and MP data.

In the first quantification exercise, I show that it is exactly the multinationals' export-platform sales documented in the augmented Chinese customs data that recover the MS frictions. The ARRY model does not include MS frictions and therefore cannot generate multinationals' export-platform networks consistent with the headquarters gravity observed in the data. Armed with the calibrated model, I investigate the implications of headquarters gravity by counterfactual exercises, finding that:

(i) Headquarters gravity accounts for a large fraction of international trade: eliminating headquarters gravity will reduce the Chinese exports by about 20%. Intuitively, in the presence of headquarters gravity, multinational affiliates provide host countries with access to foreign markets. Therefore, policies that induce inward MP are likely to promote exports.
(ii) Ignoring headquarters gravity would bias our quantification of the global consequences of trade shocks. For example, I simulate the recent US-China trade war by increasing the trade costs between the U.S. and China by 25%. My headquarters gravity (HG) model predicts that the welfare effect of the US-China trade war for Canada is −0.104%, whereas 0.095% is the prediction of the ARRY model. In the presence of headquarters gravity, the Chinese affiliates of Canadian multinationals bias their sales towards the US market. These Canadian multinationals therefore lose much more from the US-China trade war than implied by the ARRY model.

In the second quantification exercise, I ask what my model could predict if the augmented Chinese customs data is unavailable. This question is commonly asked in quantitative studies: in many cases, there is lack of data to point identify the model. For example, de Gortari (2019) builds a model that can generate many global value chains that are consistent with the world input-output data. In this case, instead of providing point estimates of the model's predictions, we can construct exact bounds on counterfactual predictions, using data as the constraints on changes in equilibrium outcomes.

In particular, I establish a framework of exact bounds on counterfactual predictions of my HG model using only bilateral trade and MP data. I then provide sufficient conditions under which the set of counterfactual predictions in interest is an interval. In this case, upper and lower bounds are sufficient to characterize the set of counterfactuals. I apply my framework to construct bounds on the welfare gains from openness and the welfare effects of the US-China trade war. The main message from these exercises is that bounds tend to be narrow for large countries but wide for small open economies. For example, the welfare effects of the US-China trade war on the U.S. lie between −0.42% and −0.02%, whereas the welfare effects on Canada lie between −1.5% and 0.36%. So the detailed data on the multinationals' export-platform networks is especially important to evaluating the impacts of global shocks on small open economies.

Finally, I ask what we can do if the bounds are too wide but the data for point identification is unavailable. In this case, I show that additional information on the multinationals' export-platform sales could exclude many model parameterizations and considerably narrow the bounds. For example, imposing the bridge MP shares of the U.S. multinationals in the BEA data as additional restrictions narrows the bounds for the welfare effects of the US-China trade war on Canada from [−1.5 % ,0.36%] to [−0.12 % ,0.36%].

[2] Unfortunately, I only observe the nationalities of firms operating in China in 2001. So all other micro datasets are restricted to this year.

[3] Head and Mayer (2019) have an advantage that they can observe a complete portrait of the multinationals' global production and sales for the car industry, whereas the firm-level data used in this paper is for all industries but only one production location, China.

1.1. Related literature

This paper is closely related to Head and Mayer (2019) which, as I have discussed, document headquarters gravity in a complete portrait of the multinationals' activity for the car industry and introduce MS frictions into a quantitative trade-MP framework. This paper complements their work by (i) documenting headquarters gravity in the data for all industries but in one production location, and (ii) incorporating their MS frictions into the ARRY model to quantify the implications of headquarters gravity for the aggregate economy.

This paper also contributes to the recent quantitative models of export platforms such as Ramondo and Rodriguez-Clare (2013), Tintelnot (2017), and Arkolakis et al. (2018). These models characterize multinationals' choices of production sites over a large number of potential locations and aggregate the firms' decisions elegantly under probabilistic specifications. But they cannot capture headquarters gravity since they assume that all firms producing in the same country face the same set of export costs.

Moreover, this paper relates to the discussion about the foreign multinationals' advantage in accessing export markets, especially markets close to their headquarters. Head and Mayer (2019) and Cosar et al. (2018) provide evidence for the global car industry. Bronnenberg et al. (2009) document that the U.S. consumer packaged goods firms have systematically higher market shares in the cities close to their origins, regardless of their production sites.[4] This market access advantage also relates to the discussion on what multinationals bring to host countries, complementing the conventional wisdom that foreign multinationals mainly bring jobs and advanced technologies to host countries.[5]

Finally, this paper relates to the literature on counterfactual analysis in partially (set) identified models.[6] Partial identification relaxes restrictive assumptions required for point identification and enables us to compare implications of various model specifications. It is widely used in structural models of labor economics and industrial organization, but receives little attention in general equilibrium analysis. A recent exception is de Gortari (2019). He proposes a multi-country general equilibrium model that can only be partially identified by the World Input-Output Database and constructs bounds on counterfactual predictions. This paper applies this methodology to construct counterfactual bounds in a completely different context.

The rest of the paper is organized as follows. Section 2 documents empirical regularities in the augmented Chinese customs data that motivate my quantitative framework. Section 3 builds and characterizes the model. Section 4 calibrates the model to the augmented Chinese custom data. Section 5 conducts counterfactual experiments. Section 6 constructs exact bounds on counterfactual predictions when the augmented Chinese customs data is unavailable. Section 7 concludes.

2. Data and motivational facts

2.1. The augmented Chinese customs data

To understand the export behaviors of multinational affiliates operating in China, I merge three sets of micro data. First, I use data on firm-level exports by destination from Chinese Customs Records (CCR). CCR documents transaction-level exports with destination country, the 6-digit HS code, export mode (ordinary or processing trade), and export value and quantity.

Second, I supplement CCR records with the Annual Survey of Chinese Manufacturing (ASCM), collected by the Chinese National Bureau of Statistics. It provides firm-level characteristics such as total sales, capital stock, employment, and expenditure on intermediates for all state-owned manufacturing firms and other manufacturing firms whose annual sales exceed 5 million RMB (about 0.6 million dollars).

Third, to understand the impact of headquarter locations on affiliates' sales, I need to know the nationalities of foreign affiliates operating in China. This information is rare for most of the commonly-used firm-level trade data sets. I collect this information from the Foreign-Invested Enterprise Survey in China (FIESC). It covers all foreign-invested firms in China in 2001, with names and nationalities of their foreign investors.

This augmented Chinese customs data for the year 2001 is ideal for studying export-platform MP. First, China is a major exporter and MP receiver in the world, with a large number of export destinations and countries of origin. Second, the data covers almost all Chinese manufacturing firms with their exports by destination and their nationalities. I am not aware of comparable data in other countries. Boehm and Pandalai-Nayar (2020) link the U.S. Census Bureau microdata to firms' international ownership structure. However, they focus on the imported inputs of the U.S. affiliates of multinationals instead of investigating their exports.

There is also a limitation for the augmented Chinese customs data: it has only one production location, China. Currently, the complete portrait of the multinationals' export-platform networks covering many source, host, and destination countries is only available for certain industries.

2.2. Descriptive statistics

The augmented Chinese customs data suggests that multinational affiliates are large producers and exporters in the host countries: Chinese firm-level data shows that in 2001 foreign multinationals affiliates accounted for 23% of Chinese manufacturing

[4] Bronnenberg et al. (2009) find that the main drivers of this advantage are marketing investments and the establishing brand identity in these markets.

[5] See Arnold and Javorcik (2009), Burstein and Monge-Naranjo (2009), McGrattan and Prescott (2009), and Antras and Yeaple (2014).

[6] Ho and Rosen (2016) provide a comprehensive summary on partial identification in applied research.

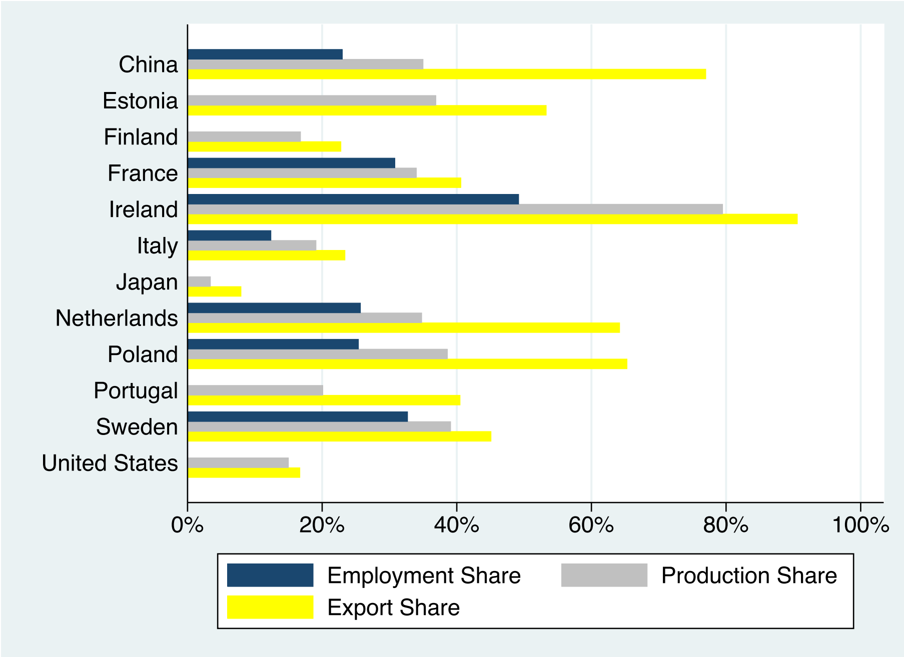


Fig. 1. Foreign multinational manufacturers in host countries. (Notes: Data for China is aggregated from the augmented Chinese customs data. Data for OECD countries is from the AMNE database. Observations for Estonia and Poland are for the year 2003. Others are for the year 2001. The employment share is unavailable for Estonia, Finland, United States, Japan, and Portugal.)

employment but 35% of manufacturing sales and 77% of manufacturing exports.[7] The multinationals' advantage in exporting is not unique in the Chinese data. In Fig. 1, I use the OECD AMNE data to show that even in developed countries, the foreign multinational manufacturers' export share tends to be larger than their production share.

The multinationals' advantage in exporting may come from their advantages on size or productivity. To address this concern, I regress the firms' extensive and intensive margins of exports on a dummy for foreign multinationals and several observed firm characteristics. The results, presented in Appendix A.3, suggest that after controlling for size, productivity, capital intensity, and industry fixed effects, the Chinese affiliates of foreign multinationals are still much more likely to export and export more than Chinese domestic firms. This could be because foreign firms have lower export costs or higher demand in destination markets than domestic firms. In either case, foreign multinational affiliates provide the host country with better access to foreign markets.

The augmented Chinese customs data suggests that the foreign multinationals' export advantage is not evenly distributed across destination markets. Instead, it is highly concentrated in their headquarter countries. Fig. 2 suggests that the Chinese affiliates of foreign multinationals have strong advantage in exporting to their headquarter countries, relative to the "average" firm operating in China. The Japanese multinationals in China exhibit very strong home bias: 60% of their exports went to Japan in 2001, while only 14% of the Chinese exports went to Japan. The U.S. multinationals in China also exhibit home bias in exports: 33% of their exports went to the U.S., while the U.S. only accounted for 23% of the Chinese exports.

This advantage in accessing headquarter countries is not unique in the Chinese data. In Appendix A.3, I use the BEA data on the U.S. multinational sales to show that the U.S. multinational affiliates have higher export shares to the U.S. than the "average" firm in most of the host countries.

2.3. Headquarters gravity

I proceed by investigating whether the multinationals' market access advantage can go beyond their headquarter countries, as documented by Head and Mayer (2019) for the car industry. The augmented Chinese customs data allows me to link a firm's export destinations to the location of its headquarters. I regress firms' export destination choices (both intensive and extensive margins) on the distance measures between headquarters and destination countries. I use affiliate fixed effects to control for size, productivity, and other affiliate-level characteristics. Since all affiliates produce in China, the standard gravity can be controlled by destination fixed effects. Following the literature of gravity equation, I measure the proximity between headquarters country

[7] Here foreign multinationals include firms from Hong Kong, Taiwan, and Macau. Among these foreign multinational affiliates in the manufacturing sector, the joint ventures accounted for 35% of the sales and 25% of the exports in 2001.

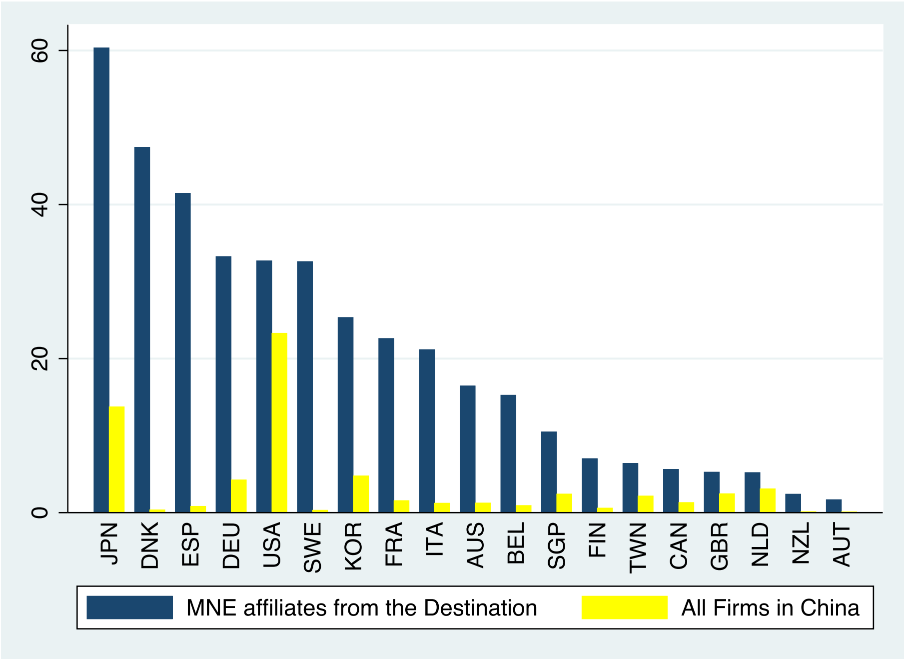


Fig. 2. Exports of the Chinese affiliates of multinationals to headquarter countries. (Notes: Data is aggregated from the augmented Chinese customs data. The blue bar reflects the export share of the Chinese affiliates of multinationals back to their headquarter countries. The yellow bar reflects the share of the Chinese total exports to that destination.)

i and destination n by their physical distance (dist_{in}), common language (lang_{in}), common legal origin (legal_{in}), OECD status (OECD_{in}),[8] and dummy for the headquarters country itself ($\mathbf{1}\{i = n\}$).

The results in Table 1 show that controlling for destination and affiliate fixed effects, the Chinese affiliates of foreign multinationals are more likely to export and export more to the destinations markets *closer to* their headquarters countries.

Column (1) and (2) in Table 1 suggest that *in addition to the headquarters country itself*, a Chinese affiliate of a foreign multinationals is more likely to export to countries that are physically closer to, use the same language as, share the same legal origin with, or have similar development levels to its headquarters country. Similar patterns hold for the intensive margin of firm export, reflected by the results in Column (3) and (4) of Table 1. Notice that in Column (2) and (4) of Table 1, I do not control for the destination fixed effects. Instead, I control for the distance between China and the destination, and the GDP of the destination. This specification enables me to compare the headquarters gravity with the standard gravity. The coefficients of distances show that the standard gravity is much stronger than headquarters gravity.

I also estimate headquarters gravity in the aggregate level. In particular, I regress the aggregate sales of Chinese affiliates of multinationals from country i to market n, $X_{i,\text{CHN},n}$, on destination fixed effects (controlling for the standard gravity), origin fixed effects (controlling for origin's productivity), and the proximity between headquarters countries and destination markets. I run similar regressions for the number of firms and the average firm sales associated with $X_{i,\text{CHN},n}$. Column (5) in Table 1 suggests that the headquarters gravity is sizable: doubling the physical distance between the headquarters country and the destination market will, ceteris paribus, lowering the aggregate trade value by about 20%.

Notably, all columns in Table 1 suggest that multinational affiliates have strongest advantage in exporting to their headquarter countries. Controlling for the standard gravity effects, the total export value of multinational affiliates back to their headquarter countries is 2.4 times more than that to other countries. This is consistent with the strong home bias of multinationals' exports shown in Fig. 2.

2.4. Robustness

An advantage of the augmented Chinese customs data, as I have discussed, is that it can estimate headquarters gravity in many industries. In this subsection, I split my sample into different industry groups and test how robust the results of headquarters gravity are across these groups. Using this detailed data in one production country, this paper complements previous studies on particular industries by examining how prevalent headquarters gravity is in all the manufacturing sectors.

[8] It is equal to 1 if both i and n are OCED countries or if neither of them is in OECD.

Table 1
Headquarters gravity.

	Affiliate-destination-level				Headquarter-destination-country-level					
	$\mathbf{1}\{x_{i,\mathrm{CHN},n}(\nu)>0\}$		$\log(X_{i,\mathrm{CHN},n}(\nu))$		$\log(X_{i,\mathrm{CHN},n})$		$\log(M_{i,\mathrm{CHN},n})$		$\log(\overline{X}_{i,\mathrm{CHN},n})$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\log(\mathrm{dist}_{in})$	-0.0067^{***}	0.0054	-0.085^{***}	-0.0506^{*}	-0.204^{***}	-0.05	-0.063^{***}	0.035^{*}	-0.14^{***}	-0.0841^{**}
	(0.0019)	(0.0044)	(0.034)	(0.028)	(0.056)	(0.047)	(0.022)	(0.019)	(0.048)	(0.040)
$\mathbf{1}\{i=n\}$	0.37^{***}	0.57^{***}	1.17^{***}	1.349^{***}	2.46^{***}	2.96^{***}	0.88^{***}	1.18^{***}	1.58^{***}	1.78^{***}
	(0.027)	(0.047)	(0.14)	(0.11)	(0.24)	(0.22)	(0.13)	(0.13)	(0.22)	(0.20)
lang_{in}	0.004	0.024^{***}	0.19^{***}	0.109^{**}	0.164	0.45^{***}	0.13^{**}	0.29^{***}	0.0320	0.16^{*}
	(0.003)	(0.0060)	(0.069)	(0.054)	(0.13)	(0.12)	(0.052)	(0.050)	(0.11)	(0.098)
legal_{in}	0.0055^{**}	0.0166^{**}	-0.0155	-0.0165	0.27^{***}	0.31^{***}	0.17^{***}	0.18^{***}	0.1	0.124
	(0.0028)	(0.0072)	(0.056)	(0.050)	(0.088)	(0.091)	(0.034)	(0.035)	(0.074)	(0.076)
OECD_{in}	0.001	0.020^{***}	0.0409	-0.0931^{*}	0.45^{***}	(0.091)	0.25^{***}	0.26^{***}	0.20^{***}	0.107
	(0.0022)	(0.0046)	(0.053)	(0.055)	(0.083)	(0.084)	(0.030)	(0.031)	(0.072)	(0.072)
$\log(\mathrm{dist}_{\mathrm{CHN},n})$		-0.030^{***}		-0.131^{***}		-0.48^{***}		-0.29^{***}		-0.19^{***}
		(0.005)		(0.038)		(0.072)		(0.029)		(0.061)
$\log(\mathrm{GDP}_n)$		0.0204^{***}		0.271^{***}		0.54^{***}		0.30^{***}		0.24^{***}
		(0.0012)		(0.014)		(0.022)		(0.0089)		(0.018)
Dest. FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Origin FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Affiliate FE	Yes	Yes	Yes	Yes	No	No	No	No	No	No
R-squared	0.25	0.204	0.56	0.55	0.516	0.414	0.741	0.659	0.325	0.208
# Obs.	366,300	361,350	17,270	17,266	2252	2248	2252	2248	2252	2248

(Notes: "i" refers to the country of origin and "n" refers to the destination country. ν refers to the affiliate. Column (1) and (2) present results of firms' extensive margins using the linear probability model. $X_{i,\mathrm{CHN},n}$ is the total sales of Chinese affiliates of country i's multinationals to destination n. $M_{i,\mathrm{CHN},n}$ is the number of affiliates associated with $X_{i,\mathrm{CHN},n}$. $\overline{X}_{i,\mathrm{CHN},n}=X_{i,\mathrm{CHN},n}/M_{i,\mathrm{CHN},n}$. Processing traders, firm located in exporting zones, Hong Kong, Macau, and Taiwanese firms, and Chinese domestic firms are excluded. The standard errors are clustered at the origin-destination level.)

First, I estimate headquarters gravity for homogeneous and differentiated goods, classified by Rauch (1999). In Column (1) and (2) in Table 2, I run similar regressions with Column (1) and (2) in Table 1, adding interactions between the dummy for differentiated goods and the distance measures. The results show that headquarters gravity is more pronounced in differentiated goods than in homogeneous goods. Intuitively, differentiated goods rely heavily on marketing and branding to penetrate markets. In contrast, the transactions of homogeneous goods are to large extent standardized and therefore do not rely much on marketing. This result is consistent with the industry evidence documented by Head and Mayer (2019) and Bronnenberg et al. (2009) that emphasize the role of marketing investments in accessing the markets.

Second, I estimate headquarters gravity for final and intermediate goods, classified by the Broad Economic Categories (Rev. 4). Column (3) and (4) in Table 2 suggest that headquarters gravity is stronger in final goods than in intermediate goods. Intuitively, consumers prefer goods developed by firms headquartered at home or nearby countries. This intuition is more relevant to final goods such as automobile than to intermediate goods. However, the interaction term between the dummy for final goods and $\mathbf{1}\{i=n\}$ suggests that the multinationals' advantage in accessing their headquarter country is almost identical between final and intermediate goods.

Third, I estimate headquarters gravity in 16 two-digit HS industries that vary substantially in factor intensity, comparative advantage across countries, and the prevalence of related-party trade.[9] Fig. 3 shows that headquarters gravity holds for 13 out of 16 industries.

I perform two additional robustness exercises: (i) I aggregate the augmented Chinese customs data at the origin-destination-sector level and estimate the aggregate headquarters gravity controlling for the origin-sector and destination-sector fixed effects; (ii) I exclude the firms from Japan and Korea and re-estimate the firm-level headquarters gravity. The main results of headquarters gravity hold in these two exercises. I report the results of these two specifications in Appendix A.4.

3. Model

I consider a world economy with N countries and build a model à la Arkolakis et al. (2018) which allows firms to produce outside of their countries of origin and utilize their foreign affiliates as export platforms. To the extent possible, I use index i to denote the firm's country of origin, index ℓ to denote the production location, and index n to denote the country where the firm sells its product. This model will characterize how a firm originated from country i chooses its production site to serve destination market n, and how the firms' individual sales are aggregated into total sales of firms originated from country i to

[9] The sectoral shares of related-party trade in the U.S. are documented by Antras (2003).

Table 2
Headquarters gravity: sectoral heterogeneity.

	$\mathbf{1}\{x^j_{i,\mathrm{CHN},n}(\nu) > 0\}$	$\log(x^j_{i,\mathrm{CHN},n}(\nu))$	$\mathbf{1}\{x^k_{i,\mathrm{CHN},n}(\nu) > 0\}$	$\log(x^k_{i,\mathrm{CHN},n}(\nu))$
	(1)	(2)	(3)	(4)
$\log(\mathrm{dist}_{in})$	0.000771	0.00531	0.000807	−0.0664
	(0.00081)	(0.074)	(0.0013)	(0.044)
$\log(\mathrm{dist}_{in}) \times$ Diff	−0.00631***	−0.122		
	(0.0020)	(0.082)		
$\log(\mathrm{dist}_{in}) \times$ Final			−0.00650***	0.00207
			(0.0023)	(0.058)
$\mathbf{1}\{i = n\}$	0.175***	0.977***	0.336***	1.269***
	(0.033)	(0.29)	(0.028)	(0.19)
$\mathbf{1}\{i = n\} \times$ Diff	0.199***	0.0709		
	(0.045)	(0.32)		
$\mathbf{1}\{i = n\} \times$ Final			−0.0427	−0.156
			(0.047)	(0.22)
lang_{in}	0.00499**	0.228	0.00615***	0.206**
	(0.0021)	(0.16)	(0.0023)	(0.092)
$\mathrm{lang}_{in} \times$ Diff	0.000427	−0.116		
	(0.0037)	(0.17)		
$\mathrm{lang}_{in} \times$ Final			−0.00179	−0.0930
			(0.0040)	(0.13)
legal_{in}	0.000486	−0.333**	0.00121	−0.110
	(0.0011)	(0.14)	(0.0021)	(0.076)
$\mathrm{legal}_{in} \times$ Diff	0.00469	0.387***		
	(0.0030)	(0.15)		
$\mathrm{legal}_{in} \times$ Final			0.00412	0.167*
			(0.0033)	(0.098)
OECD_{in}	−0.00287***	0.0456	−0.000375	0.0220
	(0.0010)	(0.12)	(0.0016)	(0.076)
$\mathrm{OECD}_{in} \times$ Diff	0.00471**	−0.0345	–	–
	(0.0024)	(0.14)	–	–
$\mathrm{OECD}_{in} \times$ Final			0.00229	−0.0393
			(0.0025)	(0.10)
Destination FE	Yes	Yes	Yes	Yes
Affiliate FE	Yes	Yes	Yes	Yes
R-squared	0.224	0.502	0.201	0.522
# Obs.	654,579	15,424	754,600	17,190

(Notes: "i" refers to the country of origin and "n" refers to the destination country. $j \in \{\text{Diff.}, \text{Homo.}\}$ is the indicator for differentiated/homogeneous goods. $k \in \{\text{Final}, \text{Int.}\}$ is the indicator for final/intermediate goods. Differentiated goods are goods coded by "n" in Rauch (1999). Final goods are consumption and capital goods in BEC (Rev. 4). The firms' extensive margin in Column (1) and (3) is estimated using the linear probability model. Processing traders, firm located in exporting zones, Hong Kong, Macau, and Taiwanese firms, and Chinese domestic firms are excluded. The standard errors are clustered at the origin-destination level.)

destination country n from their affiliates in country ℓ, $X_{i\ell n}$. The collection of aggregate flows $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$ is called *the multinationals' export-platform networks*, which will be shown as crucial statistics in quantifying the global consequences of trade and MP shocks.

3.1. Preferences and firm's optimization

Country i is endowed with labor L_i, which is the only primary factor of production. In each country, the representative consumer has a CES preference over a continuum of varieties, with the elasticity of substitution $\sigma > 1$.

Each differentiated variety is produced by a single firm under monopolistic competition. Firms can produce anywhere in the world with varying productivities. Formally, a firm is characterized by a vector of productivities, $(z_{i\ell}(\omega))_{\ell=1}^N$, where $z_{i\ell}(\omega)$ is the productivity of firm ω originated from country i producing in country ℓ.

There is free entry for firms: before drawing productivities, a firm has to pay a fixed cost f^e in units of labor. Following Melitz (2003) and Arkolakis et al. (2018), I regard the creation of firms as innovation. In the presence of MP, a country tends to specialize in innovation if its multinationals offshore a large fraction of production, whereas a country tends to specialize in production if it receives a large volume of inward MP.

There are various frictions that impede firms to operate outside of their home countries and make sales across borders. To serve destination n, firm ω pays a fixed marketing cost F_n in terms of country n's labor. There are three sets of iceberg frictions for global production and sales: (i) Firms that export from country ℓ to market n incur an iceberg trade cost $\tau_{\ell n} \geq 1$ with $\tau_{nn} = 1$, which captures the standard barriers of international trade such as transportation costs, tariffs, and administrative costs. (ii) Firms originated in country i that produce in country ℓ incur an iceberg MP cost $\gamma_{i\ell} \geq 1$ with $\gamma_{\ell\ell} = 1$, which captures the barriers that multinationals face when operating in an environment different from their home countries and the

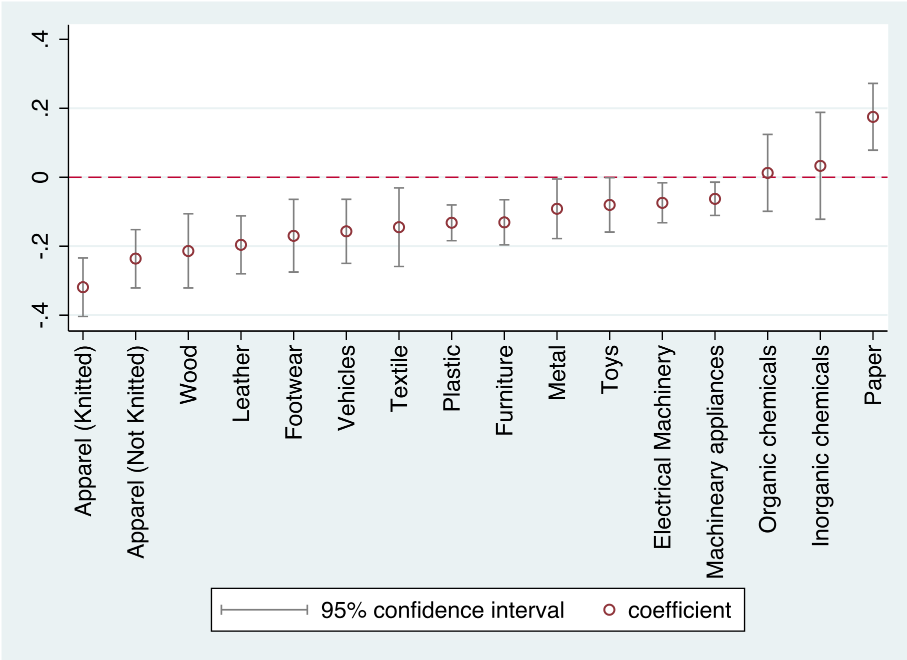


Fig. 3. Headquarters gravity in 2-digit HS industries. (Note: In each sector, I estimate the headquarters gravity for the firms' extensive margin of exports, controlling for affiliate and destination fixed effects, using the Probit model. Each red circle refers to the coefficient of the distance between headquarter and destination countries.)

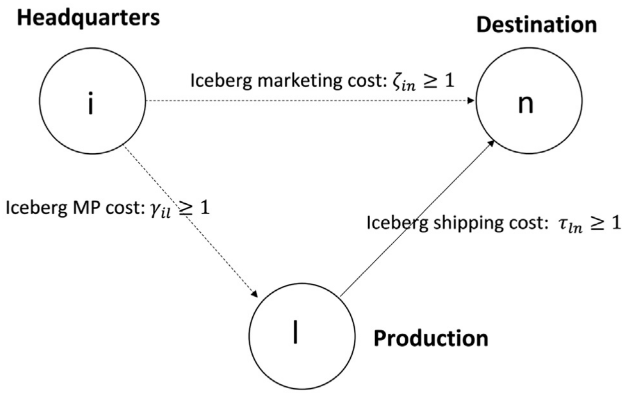


Fig. 4. Spatial frictions shaping global production and sales. (Note: A similar set of frictions is introduced by Head and Mayer (2019) for the car industry.)

communication and coordination costs between headquarters and affiliates. (iii) Firms originated in country i incur an iceberg marketing cost $\zeta_{in} \geq 1$ for selling in country n. I follow Head and Mayer (2019) to name $\{\zeta_{in}\}$ as "*Multinational Sales (MS) friction*". Fig. 4 illustrates the structure of trade and MP frictions in the model.

The MS friction, $\{\zeta_{in}\}$, is the key element that enables my model to capture headquarters gravity observed in the data. My model is identical to the ARRY model if $\zeta_{in} = 1$ for all (i,n). First introduced by Head and Mayer (2019), $\{\zeta_{in}\}$ captures various impediments multinationals incur when making sales to destinations far away from their country of origin, which include the costs on advertising, hiring marketing experts, and learning the consumers' preferences. In this paper, I set this trade friction in the form of iceberg costs for four reasons. First, it simplifies the model aggregation and delivers tractable solutions. Second, it is consistent with the results in Table 1 that the average firm sales strongly decreases with respect to the distance between

[10] Cosar et al. (2018) separate the supply- and demand-driven sources of home market advantage by estimating a structural model with variable markups. I stay with the constant markup to preserve tractability of my general equilibrium framework. Therefore, the supply- and demand-driven factors are inseparable in my model.

headquarter and destination countries. Third, it resembles the thought that making larger sales incurs higher marketing costs. Fourth, under the CES preference, the iceberg cost is equivalent to a headquarters-destination-specific demand shifter.[10]

Due to the CES preference and monopolistic competition, the firm charges a markup $\tilde{\sigma} = \sigma/(\sigma - 1)$ over its marginal costs. Conditional on serving market n, the firm originated from country i chooses the production location that minimizes the effective serving costs:

$$\ell = \arg\min_k \tilde{\sigma} c_{ikn}(\omega) = \arg\min_k \frac{\xi_{ikn}}{z_{i\ell}(\omega)}, \quad \xi_{i\ell n} := \gamma_{i\ell}\tau_{\ell n}\zeta_{in}w_\ell, \tag{1}$$

where w_ℓ is the wage in country ℓ.

If the operating profit of serving market n is higher than the fixed marketing cost $w_n F_n$, then the firm chooses to serve the market. Let X_n be the total expenditure in country n. Then the maximum unit cost under which the firm will enter into market n is

$$c_n^* = \left(\frac{\sigma w_n F_n}{X_n}\right)^{\frac{1}{1-\sigma}} \frac{P_n}{\tilde{\sigma}}. \tag{2}$$

3.2. Aggregation

I proceed by aggregating firms' global sales into the multinationals' export-platform networks, $\{X_{i\ell n}\}$, focusing on how the MS frictions shape these networks. Following Arkolakis et al. (2018), I assume that $(z_{i\ell}(\omega))_{\ell=1}^N$ are drawn from a multi-variate Pareto distribution:

$$Prob[z_{i1}(\omega) \le z_1, \ldots, z_{iN}(\omega) \le z_N] = 1 - T_i\left[\sum_{\ell=1}^N A_\ell z_\ell^{-\frac{\theta}{1-\rho}}\right]^{1-\rho}, \quad z_\ell \ge \tilde{T}_i := T_i^{\frac{1}{\theta}}\left[\sum_{\ell=1}^N A_\ell^{\frac{1}{1-\rho}}\right]^{\frac{1-\rho}{\theta}}, \tag{3}$$

where $\rho \in [0,1)$ and $\theta > \max\{1, \sigma - 1\}$.

Let M_i be the mass of firms in country i. Arkolakis et al. (2018) have shown that if $\xi_{i\ell n} > \tilde{T}_i c_n^*$ for all (i, ℓ, n), then the multinationals' export-platform networks, $\{X_{i\ell n}\}$, can be characterized by:

$$\pi_{i\ell n} := \frac{X_{i\ell n}}{X_n} = \psi_{i\ell n}\lambda_{in}, \tag{4}$$

where

$$\psi_{i\ell n} = \frac{A_\ell \xi_{i\ell n}^{-\frac{\theta}{1-\rho}}}{\Psi_{in}^{\frac{1}{1-\rho}}}, \quad \Psi_{in} = \left[\sum_{\ell=1}^N A_\ell \xi_{i\ell n}^{-\frac{\theta}{1-\rho}}\right]^{1-\rho}, \quad \lambda_{in} = \frac{M_i T_i \Psi_{in}}{\sum_k M_k T_k \Psi_{kn}}.$$

Eq. (4) expresses the multinationals' export-platform networks, $\{X_{i\ell n}\}$, in terms of technologies, factor prices, destination market size, and bilateral MP, trade, and marketing frictions. To link this structural equation with the observed bilateral trade data, I let $X_{\ell n}^{TR} := \sum_{i=1}^N X_{i\ell n}$ and then have

$$\log\left(X_{\ell n}^{TR}\right) = \underbrace{\log A_\ell - \frac{\theta}{1-\rho}\log(w_\ell)}_{\text{Exporter Fixed Effect}} + \underbrace{\log\left(\sum_{i=1}^N \frac{\lambda_{in}}{\Psi_{in}} X_n\right)}_{\text{Importer Fixed Effect}} \underbrace{- \frac{\theta}{1-\rho}\log\tau_{\ell n}}_{\text{Bilateral trade barrier}} + \underbrace{\log\sum_{i=1}^N (\gamma_{i\ell}\zeta_{in})^{-\frac{\theta}{1-\rho}}}_{\text{Third-country effect via MP}}. \tag{5}$$

Eq. (5) resembles the standard gravity equation by expressing bilateral trade flows in terms of an exporter fixed effect (here technologies and factor prices in exporting countries), an importer fixed effect (here the total expenditure and a multilateral resistance term), and the bilateral trade cost between exporting and importing countries.

However, due to headquarters gravity, there is an additional term entering into Eq. (5), representing a third-country effect via MP. This term can be understood through a simple example. Suppose that the exporting country ℓ is China and the importing country n is Canada. Then a large fraction of Chinese exports to Canada is contributed by the Chinese affiliates of the U.S. multinationals who have advantage in serving the Canadian market. The standard gravity equation of trade flows does not capture this third-country effect.

Take an analogy from physics. The standard gravity equation suggests that the center of gravity for exporters lies in their production locations. The new third-country effect in Eq. (5) suggests that, for multinationals, the center of gravity lies somewhere in between their production locations and their headquarters. The sales of multinational affiliates are then biased by the center of gravity towards their headquarters.

Notice the new third-country effect via MP does not exist without headquarters gravity. If $\zeta_{in} = 1$ for all (i,n) as in Arkolakis et al. (2018), then the new third-country effect in Eq. (5) will be absorbed by the exporter fixed effect and Eq. (5) will degenerate to the standard gravity equation.

In sum, Eqs. (4) and (5) shows that in the presence of MP and headquarters gravity, it is important to understand the structure of the multinationals' export-platform networks even if we only care about the aggregate bilateral trade flows.

3.3. Equilibrium

I close the model by market clearing conditions. Based on the property of multi-variate Pareto distribution, it is straightforward to show that (i) the fixed marketing cost has a share $s := \frac{\theta-(\sigma-1)}{\theta\sigma}$ in the sales; and (ii) the firms' net profits have a share $s^f := \frac{1}{\sigma} - s = \frac{\sigma-1}{\theta\sigma}$ in the sales. Then the general equilibrium consists of (w_i, M_i) such that:

(i) The equilibrium wage is determined by the labor market clearing:

$$w_\ell L_\ell = \underbrace{\left(1 - \frac{1}{\sigma}\right)\sum_{i,n} X_{i\ell n}}_{\text{Production Wage}} + \underbrace{s\sum_{i,k} X_{ik\ell}}_{\text{Marketing Wage}} + \underbrace{s^f \sum_{k,n} X_{\ell kn}}_{\text{Profit}}, \tag{6}$$

where the total expenditure is equal to the wage income, $X_i = w_i L_i$.

(ii) The equilibrium firm mass M_i is determined by the free entry condition:

$$M_i w_i f^e = s^f \sum_{\ell,n} X_{i\ell n}. \tag{7}$$

In this model with CES preference, the welfare in country n can be measured by its real wage, $W_n := \frac{w_n}{P_n}$, where the final price index can be expressed as

$$P_n^{-\theta} = \left(\frac{w_n F_n}{X_n}\right)^{-\frac{\theta-(\sigma-1)}{\sigma-1}} \left[\sum_k M_k T_k \Psi_{kn}\right]. \tag{8}$$

3.4. Equilibrium in relative changes

The model in this paper is primarily used to compute changes in equilibrium outcomes with respect to exogenous shocks. Following Arkolakis et al. (2018), I express the relative changes in equilibrium outcomes in terms of exogenous shocks, parameters (θ, ρ, σ), and the multinationals' export-platform networks $\{X_{i\ell n}\}$.

Proposition 1 ("Exact-hat" Algebra) *For any variable y, I denote y' as the level of y after changes and $\hat{y} = y'/y$. Consider exogenous shocks $(\hat{\gamma}_{i\ell}, \hat{\tau}_{\ell n}, \hat{\zeta}_{in})$. Then $(\hat{w}_i, \hat{M}_i)$ can be solved by the following system of equations:*

1. Labor market clearing conditions in relative changes

$$w_\ell L_\ell \hat{w}_\ell = \left(1 - \frac{1}{\sigma}\right)\sum_{i,n} X_{i\ell n}\hat{\pi}_{i\ell n}\hat{w}_n + s\sum_{i,k} X_{ik\ell}\hat{\pi}_{ik\ell}\hat{w}_\ell + s^f \sum_{k,n} X_{\ell kn}\hat{\pi}_{\ell kn}\hat{w}_n, \tag{9}$$

where

$$\hat{\pi}_{i\ell n} = \hat{\psi}_{i\ell n}\hat{\lambda}_{in}, \quad \hat{\psi}_{i\ell n} = \frac{\hat{\xi}_{i\ell n}^{-\frac{\theta}{1-\rho}}}{\hat{\Psi}_{in}^{\frac{1}{1-\rho}}}, \quad \hat{\Psi}_{in} = \left[\sum_{\ell=1}^{N} \psi_{i\ell n}\hat{\xi}_{i\ell n}^{-\frac{\theta}{1-\rho}}\right]^{1-\rho}, \quad \hat{\lambda}_{in} = \hat{M}_i\hat{\Psi}_{in}\hat{P}_n^{\theta}$$

and where

$$\hat{P}_n = \left[\sum_k \lambda_{kn}\hat{M}_k\hat{\Psi}_{kn}\right]^{-\frac{1}{\theta}}, \quad \hat{\xi}_{i\ell n} = \hat{\gamma}_{i\ell}\hat{\tau}_{\ell n}\hat{\zeta}_{in}\hat{w}_\ell.$$

2. Free entry conditions in relative changes

$$\hat{M}_i \hat{w}_i M_i w_i f^e = s^f \sum_{\ell,n} X_{i\ell n} \hat{\pi}_{i\ell n} \hat{w}_n. \tag{10}$$

Proposition 1 requires $\{X_{i\ell n}\}_{i,\ell,n=1,\ldots,N}$ for counterfactual predictions. Since typically we do not have detailed data on the multinationals' export-platform sales across many countries, what lies at the center of my quantification exercises is to impute them based on my model from available datasets.

In many cases, we are interested in welfare changes with respect to exogenous shocks. Based on Proposition 1, the welfare changes can be expressed as

$$\hat{W}_i = \left[\underbrace{\hat{\lambda}_{ii}^{-\frac{1}{\theta}}}_{\text{Foreign Technology}} \underbrace{\hat{\psi}_{iii}^{-\frac{1-\rho}{\theta}}}_{\text{Offshoring}} \right] \underbrace{\left(\frac{\hat{Y}_i^f}{\hat{X}_i} \right)^{\frac{1}{\theta}}}_{\text{Specialization in Innovation}}, \tag{11}$$

where $Y_i^f := \sum_{n,\ell} X_{i\ell n}$.

Eq. (11) decomposes welfare changes into three parts: the impacts of accessing the foreign technologies, the impacts of offshoring, and the impacts of specialization in innovation. Notice that innovation is an increasing-returns-to-scale activity, whereas production is of constant-returns-to-scale. Therefore, a country can gain from specializing in innovation.

4. Model's calibration

In this section, I calibrate my model to the augmented Chinese customs data associated with the aggregate bilateral trade and MP data. I will show that using these data sets my model generates point estimates of the multinationals' export-platform network, $\{X_{i\ell n}\}_{i,\ell,n=1,\ldots,N}$, which leads to point estimates of the counterfactual predictions.

Proposition 1 suggests that in addition to $\{X_{i\ell n}\}_{i,\ell,n=1,\ldots,N}$, counterfactual analysis requires the values on (θ,ρ,σ). I calibrate (θ,ρ,σ) from Arkolakis et al. (2018), making the counterfactual results in my model comparable to theirs. Therefore, I set $\sigma = 4$, $\theta = 4.5$, and $\rho = 0.55$.

4.1. Data and procedures for imputing $\{X_{i\ell n}\}_{i,\ell,n=1,\ldots,N}$

I restrict the quantification exercises in this paper to 13 major economies plus the rest of the world (so $N = 14$).[11] I aggregate the augmented Chinese customs data in 2001 to get the $N \times N$ matrix of the sales of the Chinese affiliates of multinationals originated from any country i to any destination country n, $\{X_{i,\mathrm{CHN},n}\}_{i,n=1,\ldots,N}$.[12]

The bilateral manufacturing MP flows come from the OECD AMNE database for the year 2005, which is the earliest year this database covers.[13] Using this information, I construct the $N \times N$ matrix of MP flows, $\{X_{i\ell}^{MP}\}$.

For trade, the World Input-Output Database (WIOD) contains bilateral manufacturing flows from any country ℓ to country n, including home sales.[14] Using this information, I construct the $N \times N$ matrix of trade flows, $\{X_{\ell n}^{TR}\}$, and the $N \times 1$ vector of aggregate manufacturing expenditure, $\{X_n\}$. To accommodate the MP data, I use the WIOD in 2005. To combine these three datasets for calibration, I assume that the patterns of headquarters gravity in the augmented Chinese customs data remain unchanged between 2001 and 2005.

I proceed by discussing how to impute $\{X_{i\ell n}\}_{i,\ell,n=1,\ldots,N}$ based on my model using these three datasets. Let $\widetilde{T}_{i\ell} = (M_i T_i)^{-\frac{1}{\theta}} \gamma_{i\ell}$ and $\widetilde{\tau}_{\ell n} = A_\ell^{-\frac{1-\rho}{\theta}} \tau_{\ell n} w_\ell$. Eq. (4) implies that

$$X_{i\ell n}\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right) := \frac{\widetilde{T}_{i\ell}^{-\frac{\theta}{1-\rho}} \widetilde{\tau}_{\ell n}^{-\frac{\theta}{1-\rho}} \zeta_{in}^{-\frac{\theta}{1-\rho}} \left[\sum_k \widetilde{T}_{ik}^{-\frac{\theta}{1-\rho}} \widetilde{\tau}_{kn}^{-\frac{\theta}{1-\rho}} \zeta_{in}^{-\frac{\theta}{1-\rho}} \right]^{-\rho}}{\sum_h \sum_r \widetilde{T}_{hr}^{-\frac{\theta}{1-\rho}} \widetilde{\tau}_{rn}^{-\frac{\theta}{1-\rho}} \zeta_{hn}^{-\frac{\theta}{1-\rho}} \left[\sum_k \widetilde{T}_{hk}^{-\frac{\theta}{1-\rho}} \widetilde{\tau}_{kn}^{-\frac{\theta}{1-\rho}} \zeta_{hn}^{-\frac{\theta}{1-\rho}} \right]^{-\rho}} X_n. \tag{12}$$

[11] These economies include Benelux (Belgium + Luxembourg + the Netherlands), Canada, China, Germany, France, the United Kingdom, India, Ireland, Japan, Korea, Mexico, Taiwan, the United States.

[12] Notice that the imputation based on my model does not accommodate well with observations in which $X_{i,\mathrm{CHN},n} = 0$. To address this issue, I run the reduced-form headquarter gravity for $\{X_{i,\mathrm{CHN},n}\}_{i,n=1,\ldots,N}$ as in Table 1 and replace $X_{i,\mathrm{CHN},n} = 0$ by its predicted value.

[13] The details of this database can be found in https://www.oecd.org/sti/ind/amne.htm

[14] The details of this database can be found in http://www.wiod.org/home. Please also see Timmer et al. (2015) for the detailed description.

Eq. (12) suggests that $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$ can be expressed in terms of three matrices $\widetilde{\mathbf{T}} \coloneqq [\widetilde{T}_{i\ell}]$, $\widetilde{\boldsymbol{\tau}} \coloneqq [\widetilde{\tau}_{\ell n}]$, and $\boldsymbol{\zeta} \coloneqq [\zeta_{in}]$. The bilateral trade and MP flows provide the following $2 \times N^2$ moments:

$$\frac{\sum_i X_{i\ell n}\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)}{X_n} = \frac{X_{\ell n}^{TR}}{X_n}, \quad \frac{\sum_n X_{i\ell n}\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)}{\sum_{k,n} X_{k\ell n}\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)} = \frac{X_{i\ell}^{MP}}{\sum_k X_{k\ell}^{MP}}. \tag{13}$$

To recover the MS friction, $\{\zeta_{in}\}$, I impose the additional N^2 moments:

$$\frac{X_{i,\mathrm{CHN},n}\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)}{\sum_k X_{k,\mathrm{CHN},n}\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)} = \frac{X_{i,\mathrm{CHN},n}}{\sum_k X_{k,\mathrm{CHN},n}}. \tag{14}$$

Combining Eqs. (13) and (14) provides $3 \times N^2$ moments that can exactly recover $\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)$ and thereby deliver point estimates on $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$.

Arkolakis et al. (2018) obtain point estimates on $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$ because they assume that $\zeta_{in} = 1$ for all (i,n). Under this assumption, the $2 \times N^2$ moments in Eq. (13) are sufficient to recover $\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}\right)$ and impute $\{X_{i\ell n}\}_{i\ \ell,n=1,\dots,N}$.

4.2. Calibration results

4.2.1. Sensitivity of moments to parameters

Which moments are most important in recovering the MS friction $\{\zeta_{in}\}$? Notice that I select $\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)$ to exactly match three sets of moments in Eqs. (13) and (14). Therefore, a moment tends to be more important in recovering $\{\zeta_{in}\}$ if its model-generating value is very sensitive to $\{\zeta_{in}\}$. In contrast, a moment contains little information about $\{\zeta_{in}\}$ if its value does not change much with $\{\zeta_{in}\}$.

Fig. 5 illustrates the sensitivity of moments to $\{\zeta_{in}\}$ at the solution point of $\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)$. It shows that the sales distribution of the Chinese affiliates of multinationals in Eq. (14) is very sensitive $\{\zeta_{in}\}$, whereas bilateral trade and MP shares in Eq. (13) are insensitive to $\{\zeta_{in}\}$. Therefore, $\{\zeta_{in}\}$ are mainly recovered from the sales distribution of the Chinese affiliates of multinationals.

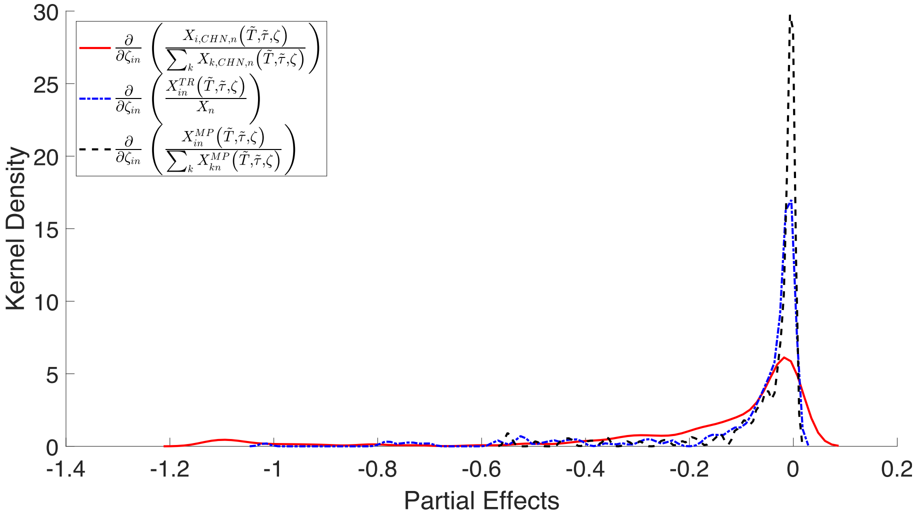


Fig. 5. Sensitivity of moments in Eqs. (13) and (14) to $\{\zeta_{in}\}$. (Notes: The sensitivity of moments to $\{\zeta_{in}\}$ is measured by the numerical partial derivatives at the solution point of $\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)$. The density estimate is based on a normal kernel function, and is evaluated at equally-spaced points that cover the range of the data.)

Table 3
Imputed $(\boldsymbol{\zeta},\boldsymbol{\gamma},\boldsymbol{\tau})$ and bilateral distances.

	$\log(\zeta_{in})$	$\log(\gamma_{in})$	$\log(\tau_{in})$
$\log(\text{dist}_{in})$	0.0380*	0.0492***	0.0559***
	(0.021)	(0.0080)	(0.0071)
$\mathbf{1}\{i=n\}$	−0.395***	−0.149***	−0.134***
	(0.12)	(0.043)	(0.030)
lang_{in}	−0.00145	−0.0419	0.0369*
	(0.038)	(0.027)	(0.020)
legal_{in}	−0.0327	−0.0400	−0.0364*
	(0.048)	(0.036)	(0.019)
OECD_{in}	0.0142	−0.0711***	−0.00614
	(0.048)	(0.022)	(0.019)
R-squared	0.373	0.576	0.719
N. of Obs.	100	100	100

(Notes: $(\boldsymbol{\zeta},\boldsymbol{\gamma},\boldsymbol{\tau})$ are imputed by matching the model to the moments in Eqs. (13) and (14). In all regressions, I exclude observations for Taiwan, Mexico, India, and the rest of the world. The results for the full sample are presented in Appendix C.1.)

Analogously, I show in Appendix C.1, that $\left\{\widetilde{T}_{i\ell}\right\}$ are mainly recovered from bilateral MP shares, and $\{\widetilde{\tau}_{\ell n}\}$ are mainly recovered from bilateral trade shares.

Assuming trade and MP costs are all symmetric, I can solve $\{\gamma_{i\ell},\tau_{\ell n}\}$ from $\left(\widetilde{\mathbf{T}},\widetilde{\boldsymbol{\tau}}\right)$:

$$\gamma_{i\ell}=\sqrt{\frac{\widetilde{T}_{i\ell}\widetilde{T}_{\ell i}}{\widetilde{T}_{ii}\widetilde{T}_{\ell\ell}}},\quad \tau_{\ell n}=\sqrt{\frac{\widetilde{\tau}_{\ell n}\widetilde{\tau}_{n\ell}}{\widetilde{\tau}_{\ell\ell}\widetilde{\tau}_{nn}}}. \tag{15}$$

4.2.2. Frictions and gravity

I then correlate the imputed $(\boldsymbol{\zeta},\boldsymbol{\gamma},\boldsymbol{\tau})$ with gravity controls, comparing the magnitudes of iceberg trade, MP, and MS frictions recovered from the data. Table 3 suggests that all three fictions increase with the distance. As the bilateral distance increases, trade costs τ raises faster than MP costs γ. This is consistent with the fact documented by Antras and Yeaple (2014) that the gravity effect on trade volumes is stronger than on affiliate sales. The distance elasticity of the MS friction is 0.038. Head and Mayer (2019) report a larger value of this elasticity being 0.088 for the car industry. It might be because headquarters gravity is stronger in differentiated and final goods, as shown in Table 2.

4.2.3. Model-implied export-platform networks

Notice that the imputation procedures described in Section 4.1 lead to two point estimates on $\{X_{i\ell n}\}$, $\{X_{i\ell n}^{HG}\}$ and $\{X_{i\ell n}^{ARRY}\}$. The former utilizes the sales distribution of the Chinese affiliates of multinationals to identify MS frictions $\{\zeta_{in}\}$, whereas the latter simply assumes that $\zeta_{in}=1$ for all (i,n).

I compare $\{X_{i\ell n}^{HG}\}$ with $\{X_{i\ell n}^{ARRY}\}$ to understand how headquarters gravity revealed by the augmented Chinese customs data affects the calibration results. First, I regress the simulated $\{X_{i,\text{CHN},n}^{ARRY}\}$ on measures of the distance between country i and n, comparing the regression results with their data counterparts.[15] The idea is to see whether the ARRY model can capture headquarters gravity without MS frictions. Column (1) to (4) in Table 4 suggest that it cannot: the ARRY model predicts that multinational affiliates tend to export *less* to the markets close to their headquarters, which is opposite to the headquarters gravity in the data. As a result, the MS friction is essential for my model to capture headquarters gravity in the data.

Second, I regress the simulated $\{X_{i\ell n}^{HG}\}$ and $\{X_{i\ell n}^{ARRY}\}$ and measures of distance between country i and n, controlling for the origin-production-site and production-site-destination fixed effects. Column (5) and (6) in Table 4 show that the HG model and the ARRY model have very different implications for multinationals' export-platform networks: after controlling for the standard gravity effects, the HG model suggests that multinationals' have advantage in accessing the markets close to their headquarters, whereas the ARRY model suggests the opposite. This is because under $\rho=0.55$, trade and MP are largely substitutes in the ARRY model and thereby multinational affiliates tend to concentrate their sales to the host countries.

Finally, I perform an out-of-sample check by looking at the bridge MP (BMP) share, defined as the ratio of BMP to total MP flows, $\sum_{n\neq\ell}X_{i\ell n}/\sum_n X_{i\ell n}$. The Bureau of Economic Analysis (BEA) reports the U.S. multinational sales in each host country, splitting the total sales into sales in the local market, back to the U.S., and to third countries. I compute the BMP shares implied by the HG model and the ARRY model, comparing them to the BEA data in 2005. The BMP shares of the U.S. multinationals predicted by the ARRY model (average 19.7%) are much lower than the BEA data (average 35.7%), whereas the ones predicted by the HG model (average 46%) are higher than but closer to the BEA data.[16] It is not surprising that the HG model achieves a better fit since it has much more degrees of freedom and is calibrated to richer data.

[15] I re-run the regression using the Chinese augmented data for firms from 14 countries used in imputation. Notice that $\{X_{i,\text{CHN},n}^{HG}\}$ is imputed to exactly match the Chinese data on $\{X_{i,\text{CHN},n}\}$.

[16] I present the details of BMP shares in Appendix C.1.

Table 4
Headquarters gravity: data vs. model simulations.

Dependent variables:	$\log(X_{i,\text{CHN},n})$				$\log(X_{i\not n})$	
	Data	ARRY	Data	ARRY	ARRY	HG
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{dist}_{in})$	−0.315***	0.678***	−0.215**	0.560***	0.637***	−0.226***
	(0.11)	(0.056)	(0.093)	(0.066)	(0.044)	(0.063)
$\mathbf{1}\{i=n\}$	1.118***	−1.594***	1.331***	−1.962***	−1.278***	0.687**
	(0.41)	(0.46)	(0.41)	(0.59)	(0.29)	(0.30)
lang_{in}	−0.380	−0.361**	−0.334	−0.237	−0.414***	−0.174
	(0.32)	(0.15)	(0.25)	(0.15)	(0.11)	(0.18)
legal_{in}	0.478**	0.0196	0.356	−0.00627	−0.121	−0.0621
	(0.23)	(0.100)	(0.22)	(0.12)	(0.094)	(0.12)
OECD_{in}	0.722	−0.0413	0.280	0.174	0.0269	0.234
	(0.56)	(0.12)	(0.22)	(0.12)	(0.17)	(0.26)
$\log(\text{dist}_{CHN,n})$			0.469***	−1.229***		
			(0.15)	(0.079)		
$\log(\text{GDP}_n)$			−0.158*	0.844***		
			(0.091)	(0.075)		
FE_n	Yes	Yes	No	No	No	No
FE_i	Yes	Yes	Yes	Yes	No	No
$\text{FE}_{i\not}$	No	No	No	No	Yes	Yes
$\text{FE}_{\not n}$	No	No	No	No	Yes	Yes
R-squared	0.841	0.974	0.788	0.960	0.989	0.972
# Obs.	131	144	131	144	1000	1000

(Notes: "i" refers to the country of origin and "n" refers to the destination country. In Column (1)–(4), I exclude observations for China and the rest of the world. In Column (5) and (6), I exclude observations for Mexico, India, Taiwan, and the rest of the world. The dependent variable in Column (1) and (3) is aggregated from the augmented Chinese customs data. The dependent variables in Column (2), (4), and (5) are simulated using the ARRY model. The dependent variable in Column (6) is simulated using the HG model.)

I further split the BMP share into the share of sales back to the U.S. and the share of sales to third countries, finding that the ARRY model substantially underestimates the share of sales back to the U.S. (average 2.3% comparing to 10.3% in the BEA data and 15.8% in the HG model). This result shows that the HG model predicts a much larger fraction of the vertical MP than the ARRY model.

Moreover, Arkolakis et al. (2018) find that their model achieve a much better fit of the BMP shares for the U.S. multinationals when $\rho=0$. My calibration confirms this finding: the ARRY model with $\rho=0$ outperforms the ARRY model with $\rho=0.55$ and the HG model in fitting the BMP shares of the U.S. multinationals. This result suggests that what the HG model achieves is keeping $\rho=0.55$ but having a reasonably good fit of the BMP shares.[17]

In sum, the HG model yields a multinationals' export-platform network that is very different from the one predicted by the ARRY model: it has a large volume of bridge MP, a large fraction of which go back to the headquarter countries and nearby. As a result, the offshored imports are much more prevalent in the HG model than in the ARRY model. In the next section, I will show that these features of the HG model have profound implications for my counterfactual analysis.

5. Counterfactual experiments

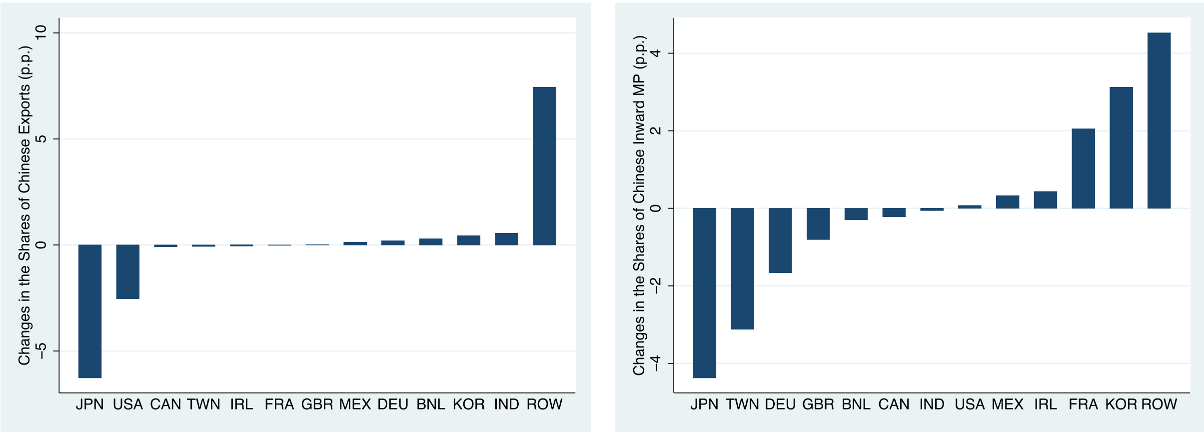
What are the implications of headquarters gravity for my models' counterfactual predictions? Armed with the calibrated model, I answer this question by three sets of counterfactual exercises. First, I eliminate the headquarters gravity of foreign multinationals operating in China. Second, I examine the welfare gains from openness, trade, and MP. Third, I quantify the welfare effects of the recent US-China trade war.

5.1. The implications of headquarters gravity for the Chinese exports

To understand the effects of headquarters gravity on the Chinese exports, I eliminate headquarters gravity in China by forcing all Chinese affiliates of foreign multinationals to incur the same set of export costs as the one of the Chinese domestic firms, i.e. $\xi_{i,\text{CHN},n}=\gamma_{i,\text{CHN}}\times\tau_{\text{CHN},n}\times\zeta_{\text{CHN},n}\times w_{\text{CHN}}$ for all $n\neq\text{CHN}$ and $i\neq\text{CHN}$. This reduces Chinese exports by 18.6%. Therefore, the export advantage of foreign multinational affiliates accounted for about 20% of the Chinese exports in the early 2000s.

Headquarters gravity also shapes the destination composition of the Chinese exports as well as the portfolio of headquarter countries of the Chinese inward MP. Fig. 6 suggests that if I eliminate headquarters gravity in China, then (i) the Chinese exports will shift from Japan and United States to Korea, India, and the rest of the world (mainly developing countries), and (ii) the

[17] Notably, the ARRY model with $\rho=0$ cannot capture headquarters gravity since it predicts that controlling for standard gravity the affiliate sales is independent with the proximity between headquarter and destination countries.



(a) Export Share by Destination (b) Inward MP Share by Source

Fig. 6. Changes in the Chinese exports and inward MP after eliminating headquarters gravity. (Notes: I eliminate headquarters gravity in China by letting $\xi_{i,\mathrm{CHN},n} = \gamma_{i,\mathrm{CHN}} \times \tau_{\mathrm{CHN},n} \times \zeta_{\mathrm{CHN},n} \times w_{\mathrm{CHN}}$ for all $n \neq \mathrm{CHN}$ and $i \neq \mathrm{CHN}$. Panel (a) shows the percentage-point changes in $X^{TR}_{\mathrm{CHN},n}/(\sum_k X^{TR}_{\mathrm{CHN},k})$. Panel (b) shows the percentage-point changes in $X^{MP}_{i,\mathrm{CHN}}/(\sum_k X^{MP}_{k,\mathrm{CHN}})$.)

Chinese inward MP will shift from Japan, Taiwan, and Germany to France, Korea, and the rest of the world. These results suggest that headquarters gravity accounted for a large fraction of the Chinese inward MP from and exports to developed countries.

5.2. Gains from openness, trade, and MP

To understand the welfare implications of headquarters gravity, I compute welfare changes from autarky to the current equilibrium, or in short, gains from openness (GO). According to Eq. (11), GO in country i can be expressed as

$$\mathrm{GO}_i := \frac{W_i}{W_i^{\mathrm{autarky}}} = \left[\lambda_{ii}^{-\frac{1}{\theta}} \psi_{iii}^{-\frac{1-\rho}{\theta}}\right] \left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}. \tag{16}$$

Table 5 shows that the HG model predicts lower gains from openness than the ARRY model. This is mainly because the HG model predicts lower gains from accessing foreign technologies, $\left\{\lambda_{ii}^{-\frac{1}{\theta}}\right\}$. In the presence of headquarters gravity, a large fraction of, for example, the U.S. imports such as iPhone and iPad are actually created by the U.S. multinationals. The U.S. would retain

Table 5
Gains from openness, MP, and trade: ARRY vs HG.

	Gains from openness						Gains from MP		Gains from trade	
	ARRY			HG			ARRY	HG	ARRY	HG
%Δ in:	W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	W_i	W_i	W_i	W_i
Benelux	51.65	45.72	0.28	38.79	32.26	0.88	10.83	12.89	12.47	14.12
Canada	41.50	46.25	0.07	38.11	42.82	0.11	5.63	6.27	8.87	8.75
China	5.66	7.86	0.00	3.27	5.38	0.08	−0.13	−0.35	0.56	0.56
Germany	25.20	24.59	0.05	14.38	12.58	1.24	4.89	4.57	7.08	7.62
France	31.07	29.72	0.04	18.19	15.70	1.18	6.87	6.47	7.32	8.02
Britain	32.83	30.58	0.09	18.51	14.80	1.56	7.73	7.33	8.21	9.30
India	5.91	6.88	0.00	5.80	6.77	0.00	0.51	0.89	1.42	1.42
Ireland	85.04	80.07	26.39	85.04	80.07	26.39	24.94	28.15	12.88	13.14
Japan	7.88	5.14	0.00	6.61	3.40	0.47	2.60	3.04	5.01	5.13
Korea	10.92	10.49	0.00	7.81	7.12	0.26	1.65	1.72	4.75	5.20
Mexico	16.96	20.05	0.00	12.64	15.72	0.01	1.83	1.52	3.44	3.36
R.O.W.	7.96	9.49	0.01	5.43	6.57	0.40	0.83	0.81	2.02	1.71
Taiwan	19.40	20.57	0.00	10.49	11.16	0.49	1.80	1.18	6.34	9.58
United States	10.85	8.93	0.12	8.70	6.32	0.57	3.51	3.83	4.06	4.10

(Notes: Gains from openness refer to welfare changes from autarky to the current equilibrium. Gains from trade refer to welfare changes from the MP-only equilibrium to the current equilibrium. Gains from MP refer to welfare changes from the trade-only equilibrium to the current equilibrium.)

Table 6
Welfare effects of the US-China trade conflicts.

%Δ in:	ARRY W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	$\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$	HG W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	$\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$
Benelux	0.062	−0.144	0.002	0.204	−0.430	0.258	−0.068	−0.620
Canada	0.095	0.045	0.000	0.050	−0.104	0.130	0.015	−0.249
China	−0.180	−0.098	0.000	−0.082	−0.070	−0.130	−0.003	0.062
Germany	0.044	−0.004	0.000	0.049	−0.068	0.055	−0.002	−0.121
France	0.025	−0.038	0.000	0.063	−0.023	−0.016	0.002	−0.010
Britain	0.063	−0.058	0.001	0.120	0.118	−0.068	0.020	0.166
India	0.012	−0.018	0.000	0.029	0.002	−0.020	0.000	0.022
Ireland	−0.666	0.348	−0.095	−0.919	−0.286	−0.233	0.171	−0.224
Japan	0.053	−0.002	0.000	0.055	−0.038	−0.013	0.012	−0.037
Korea	0.021	−0.031	0.000	0.052	−0.064	−0.030	0.011	−0.045
Mexico	0.109	−0.014	0.000	0.124	−0.033	0.112	0.000	−0.145
R.O.W.	0.029	0.027	0.000	0.003	−0.031	0.036	0.000	−0.067
Taiwan	−0.021	−0.129	0.000	0.108	−0.528	0.097	0.002	−0.628
United States	−0.404	−0.470	0.000	0.066	−0.212	−0.360	−0.069	0.217

(Notes: The US-China trade war refers to a 25 percent increase in bilateral trade costs between the U.S. and China, i.e. $\hat{\tau}_{\text{CHN,USA}} = \hat{\tau}_{\text{USA,CHN}} = 1.25$. Here I use bilateral trade and MP data in 2014.)

an access to these technologies even if it moves to autarky. This counterfactual result suggests that the ARRY model in which MP is overwhelmingly horizontal tends to overestimate welfare gains from openness.

Besides the gains from openness, I also investigate welfare changes from the trade-only equilibrium to the current equilibrium (gains from MP) and welfare changes from the MP-only equilibrium to the current equilibrium (gains from trade). Table 5 shows that in the ARRY model the gains from MP and trade are much smaller than the gains from openness. This is because trade and MP are substitutes in the ARRY model: having access to either trade or MP, adding the other does not result in substantial additional welfare gains. In contrast, the HG model predicts larger gains from MP and trade relative to the gains from openness. Headquarters gravity creates complementarity between trade and MP: multinational affiliates can boost the host country's exports by their advantage in accessing destination markets close to their headquarters.

5.3. Implications of the US-China trade conflicts

The US-China trade war starting from 2018 is one of the most influential shocks to the current world economy. I analyze how its welfare implications rely on headquarters gravity. To achieve this, I calibrate my model to bilateral trade and MP data in 2014, associated with the augmented Chinese customs data.[18] Motivated by Trump's protectionism tariffs on imports from China and China's retaliation tariffs, I consider a 25 percent increase in bilateral trade costs between the U.S. and China, i.e. $\hat{\tau}_{\text{CHN,USA}} = \hat{\tau}_{\text{USA,CHN}} = 1.25$. I perform this exercise using the HG model as well as the ARRY model.

Table 6 shows that the U.S. and China both lose from the increase in bilateral trade costs. In the HG model, a considerable fraction of the U.S. imports from China are conducted by the Chinese affiliates of the U.S. multinationals. Therefore, the HG model implies that the trade war tends to hurt the U.S. offshored imports, reflected by the decrease in $\psi_{\text{USA,USA,USA}}^{-\frac{1-\rho}{\theta}}$. Moreover, the ARRY model suggests that the US-China trade war tends to make China further specialize in production, whereas the HG model predicts the opposite. Intuitively, trade and MP are largely substitutes in the ARRY model. Therefore, an increase in trade costs spurs inward MP to China, making China further specialize in production. In the presence of headquarters gravity, however, the trade war disproportionately hurts foreign multinationals in China and thus promotes the innovation of the Chinese domestic firms.

The counterfactual results also highlight the role of multinationals' export-platform networks in transmitting trade shocks between the U.S. and China to other countries. For example, the ARRY model suggests that Canada gains from the US-China trade war, whereas the HG model predicts the opposite. This is because in the ARRY model Canadian MP to China and the U.S. are mostly horizontal. In this case, the increase in bilateral trade costs between the U.S. and China effectively protects these Canadian multinationals from import competition, making Canada specialize in innovation. In contrast, the HG model suggests that the Chinese affiliates of Canadian multinationals concentrate their exports to Canada and the U.S. In this case, these Canadian multinationals are likely to be heavily exposed to Trump's protectionism tariffs, leading to the decline in $\left(\frac{Y_{\text{CAN}}^f}{X_{\text{CAN}}}\right)^{\frac{1}{\theta}}$.

A lesson from this counterfactual exercise is that the impacts of bilateral trade shocks do not only rely on *how much* these two countries trade, but also *who* conduct these transactions. The HG model, consistent with the data, emphasizes that a large fraction

[18] The last year covered by the WIOD is 2014. Due to the data limitation, I assume that headquarters gravity remains unchanged between 2001 and 2014.

of international trade is conducted by multinationals via export platforms. The losses of multinationals from the increase in trade frictions have to be taken into account in evaluating the impacts of trade conflicts.

6. Bounding counterfactuals

I have shown that the point estimates of my model's counterfactual predictions require either (i) detailed data on multinationals' export-platform networks, such as the augmented Chinese customs data, or (ii) restrictive assumptions such as $\zeta_{in} = 1$ for all (i,n) made by Arkolakis et al. (2018) and Ramondo and Rodriguez-Clare (2013). In the scenario where the detailed data on multinationals' export-platform networks are unavailable and we are unwilling to make restrictive assumptions such as $\zeta_{in} = 1$ for all (i,n), is the my model still useful in quantifying the consequences of trade and MP shocks?

In this section, I establish a framework to construct exact bounds on the model's counterfactual predictions when there is no sufficient data to point-identify the model. I first state and characterize this framework. Then I apply it to characterize one particular counterfactual result, welfare gains from openness, the bounds of which are easy to compute. Finally, I compute the bounds on welfare effects of the recent US-China trade war.

6.1. Exact bounds on counterfactuals

Suppose that we only have data on bilateral trade and MP flows. Eq. (13) provides $2N^2$ constraints for $3N^2$ parameters, $\left(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta}\right)$. In other words, there are many model parameterizations that are consistent with the observed bilateral trade and MP flows. Eqs. (12) and (13) imply that these model parameterizations are covered by the following set:

$$\mathcal{A} = \left\{ \left(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}\right) \in [0, \overline{a}]^{3*N^2} : X_{i\ell n} = a^1_{i\ell} a^2_{\ell n} a^3_{in} X_n; \sum_i X_{i\ell n} = X^{TR}_{\ell n}; \sum_n X_{i\ell n} = X^{MP}_{i\ell} \right\}, \tag{17}$$

where $\overline{a}>1$ is the upper bound of the parameters and $(X_n, X^{TR}_{\ell n}, X^{MP}_{i\ell})$ are all data observations. Accordingly, I define

$$\mathcal{X} = \left\{ \{X_{i\ell n}\}_{i,\ell,n=1,\dots,N} : X_{i\ell n} = a^1_{i\ell} a^2_{\ell n} a^3_{in} X_n, \quad \left(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}\right) \in \mathcal{A} \right\}. \tag{18}$$

It is straightforward to show that $\left\{X^{ARRY}_{i\ell n}\right\} \in \mathcal{X}$ and $\left\{X^{HG}_{i\ell n}\right\} \in \mathcal{X}$. Admittedly, set $\mathcal{X}$ does not cover all possible export-platform networks $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$. I intentionally restrict $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$ to be multiplicative as in Eq. (17). As shown in Section 4, under this specification, my model is (i) flexible enough to capture key features of export-platform networks observed in the data, and (ii) restrictive enough to be point-identified by the augmented Chinese customs data.

Proposition 1 shows that changes in equilibrium outcomes can be expressed in terms of (θ, ρ, σ), $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$, and exogenous shocks $\left\{\hat{\gamma}_{i\ell}, \hat{\tau}_{\ell n}, \hat{\zeta}_{in}\right\}$. Therefore, I define a function $H : \mathcal{A} \to \mathrm{R}$ that maps model parameterizations to a particular counterfactual prediction in interest, for example, the welfare gain from MP for country 1.

The exact bounds on counterfactuals are then

$$\overline{H} \coloneqq \arg \max_{\left(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}\right) \in \mathcal{A}} H\left(\left\{X_{i\ell n}\left(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}\right)\right\}\right). \tag{19}$$

The lower bound $\underline{H}$ can be defined analogously.

Notably, the framework of Problem (19) focuses on bounding the counterfactuals, not parameters. In many cases, what we are interested in is counterfactuals, not parameters. It could be the case that the bounds on parameters are wide and high-dimensional, while the bounds on counterfactuals are narrow and simple. As I have discussed, de Gortari (2019) considers a similar problem in a completely different context. He builds a model that can generate many global value chains consistent with the observed world input-output data and focuses on the bounds on the model's counterfactuals.

The characteristics of counterfactual bounds defined in Problem (19) rely on the properties of set $\mathcal{A}$ in Eq. (17). Notably, this set is not convex. But it has the following properties:

Lemma 2. *The set $\mathcal{A}$ defined in Eq. (17) is compact and path-connected.*

Given $\mathcal{A}$ and $H : \mathcal{A} \to \mathbb{R}$, I define the set of feasible counterfactuals as

$$H(\mathcal{A}) = \left\{ H\left(\left(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}\right)_{i,\ell,n=1,\dots,N} \right) \in \mathbb{R} : \left(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}\right) \in \mathcal{A} \right\}. \tag{20}$$

Then I provide sufficient conditions in which $H(\mathcal{A})$ is an interval:

Proposition 3. *Suppose that $H : \mathcal{A} \to \mathbb{R}$ is continuous. Then $\overline{H}$ and $\underline{H}$ exist and $H(\mathcal{A}) = \left[\underline{H}, \overline{H}\right]$.*

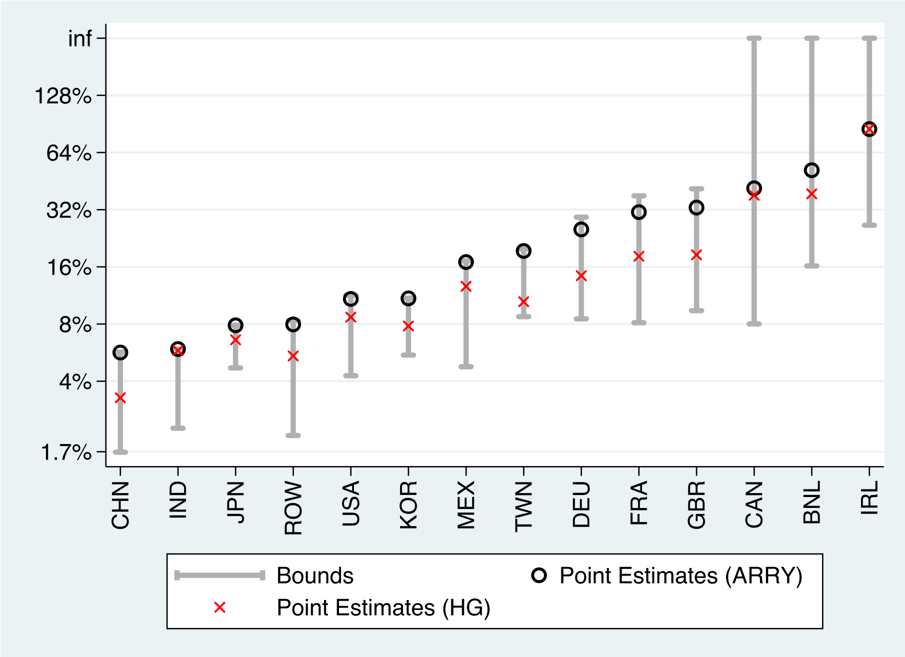


Fig. 7. Bounds on the welfare gains from openness.

Solving the bounds on counterfactuals by Eq. (19) is generally computationally intensive. I use the mathematical program with equilibrium constraints (MPEC) approach developed by Judd and Su (2012). Using their method, I do not need to compute counterfactual predictions for each $(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}) \in A$. Instead, the constrained optimization algorithms used in the MPEC approach do not enforce constraints to be satisfied until the final iteration in the search process. This feature reduces the computational burden of solving Eq. (19). However, due to high dimensionality and nonlinearity of the constraints, computing the bounds on counterfactual predictions is still much more difficult than computing the point-identified counterfactual estimates. I solve the problem using the optimization solver, KNITRO. Notably, no solver of the nonlinear optimization can guarantee achieving the global optimum. To make the bounds as exact as possible, I start from multiple randomly-assigned initial guesses and use multiple optimization algorithms in KNITRO.

6.2. Bounds on gains from openness

There is one special case in which the computation of counterfactual bounds can be greatly simplified: welfare gains from openness. Based on Eq. (16), the bounds on the gains from openness in country 1 can be computed by

$$\max(\min)_{(a^1_{i\ell}, a^2_{\ell n}, a^3_{in}) \in \mathcal{A}} \mathrm{GO}_1^{-1} := \left[\left(a^1_{11} a^2_{11} a^3_{11} \right)^{\frac{1-\rho}{\theta}} \left(\sum_k a^1_{1k} a^2_{k1} a^3_{11} \right)^{\frac{\rho}{\theta}} \right] \left(\frac{Y^f_1}{X_1} \right)^{-\frac{1}{\theta}}. \tag{21}$$

I set the objective to be GO_1^{-1} because it is bounded and continuous at $\mathcal{A}$.

Fig. 7 shows that the bounds on gains from openness vary substantially across countries. For large countries like the U.S., the range of welfare gains from openness lies between 4.3 − 11.3%. In contrast, bounds for small open economies tend to be wide. The upper bounds of gains from openness for Canada, Benelux, and Ireland go to infinity. This is because for these countries $X^{MP}_{ii} \le \sum_{n \ne i} X^{TR}_{in}$. In this case, it is consistent with the observed bilateral trade and MP flows that all varieties consumed by these countries are created by foreign multinationals. In a nutshell, without detailed data on multinationals' export-platform networks, my model is not so useful in quantifying gains from openness for small open economies.

I proceed by characterizing the MS frictions (ζ_{in}) and export-platform networks $\{X_{i\ell n}\}$ that correspond to the bounds. These extremes are informative about how multinationals' export-platform networks matter for my model's counterfactual predictions. I take (ζ_{in}) that correspond to bounds on gains from openness for China, Germany, Japan, and the U.S. and regress them on gravity controls. The results in Table 7 show that to achieve the upper bounds of gains from openness, MP must be overwhelmingly horizontal so that (ζ_{in}) has very low correlation with the distance between country i and n. This is consistent with the results in Fig. 7 indicating that in most countries welfare gains from openness implied by the ARRY model are close to the upper bounds.

Table 7
$\{\zeta_{in}\}$ Corresponding to the bounds of gains from openness.

	Dependent variable: $\log(\zeta_{in})$							
	Lower bounds				Upper bounds			
	CHN	DEU	JPN	USA	CHN	DEU	JPN	USA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\text{dist}_{in})$	0.107**	−0.00416	0.0456	0.129*	0.00752	−0.0174	0.0122	0.0677**
	(0.052)	(0.050)	(0.043)	(0.069)	(0.014)	(0.028)	(0.023)	(0.031)
$\mathbf{1}\{i=n\}$	−0.0705	−0.842***	−0.810***	−0.867**	0.0333	0.000612	0.137	0.401*
	(0.18)	(0.23)	(0.21)	(0.41)	(0.11)	(0.18)	(0.14)	(0.21)
lang_{in}	−0.340***	−0.306*	−0.508***	−0.219	0.0278	0.0596	−0.0169	−0.0229
	(0.11)	(0.15)	(0.13)	(0.29)	(0.044)	(0.060)	(0.044)	(0.055)
legal_{in}	0.0203	0.368*	0.324*	0.592	−0.00277	0.121	0.0516	−0.00967
	(0.098)	(0.22)	(0.18)	(0.43)	(0.050)	(0.092)	(0.066)	(0.048)
OECD_{in}	−0.480**	0.119	0.0898	0.111	0.0868***	−0.0436	−0.0391	−0.0983
	(0.20)	(0.13)	(0.12)	(0.14)	(0.033)	(0.079)	(0.054)	(0.090)
R-squared	0.169	0.119	0.195	0.135	0.0624	0.0727	0.0347	0.0924
N. of Obs.	100	100	100	100	100	100	100	100

(Notes: The dependent variable for Column (1) is $\log(\zeta_{in})$ that minimizes gains from openness in China. In all regressions, I exclude Taiwan, Mexico, India, and the rest of the world. The results for the full sample are presented in the Appendix C.3.)

Table 8
$\{X_{i,\text{CHN},n}\}$ Corresponding to the bounds of gains from openness.

	Dependent variable: $\log(X_{i,\text{CHN},n})$							
	Lower bounds				Upper bounds			
	CHN	DEU	JPN	USA	CHN	DEU	JPN	USA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\text{dist}_{in})$	0.148	−0.0350	0.0395	0.133	−0.113*	−0.0652	−0.0495	−0.258***
	(0.19)	(0.20)	(0.16)	(0.35)	(0.061)	(0.13)	(0.12)	(0.092)
$\mathbf{1}\{i=n\}$	1.073	2.300*	2.602**	3.739**	0.0703	−0.499	−0.679	−1.508**
	(0.77)	(1.39)	(1.25)	(1.46)	(0.23)	(0.90)	(0.57)	(0.67)
lang_{in}	0.0873	0.737	0.675	0.215	−0.164	−0.316	−0.401	0.262
	(0.28)	(0.48)	(0.50)	(0.64)	(0.13)	(0.40)	(0.33)	(0.28)
legal_{in}	−0.572	−0.681	−0.394	−1.081	−0.131	−0.160	−0.116	−0.0605
	(0.39)	(0.48)	(0.34)	(0.94)	(0.13)	(0.24)	(0.26)	(0.17)
OECD_{in}	0.636**	−0.0195	−0.0201	−0.388	−0.0223	0.199	0.351	0.267*
	(0.26)	(0.32)	(0.27)	(0.48)	(0.11)	(0.19)	(0.21)	(0.15)
R-squared	0.865	0.756	0.797	0.472	0.953	0.883	0.851	0.864
N. of Obs.	144	144	144	144	144	144	144	144

(Notes: The dependent variable for Column (1) is $\log(X_{i,\text{CHN},n})$ that minimizes gains from openness in China. In all regressions, I exclude China and the rest of the world.)

In contrast, the lower bounds of gains from openness correspond to multinationals' export-platform networks with a substantial fraction of bridge MP and offshored imports, reflected by the strong headquarters gravity in Table 7. Since all $\{X_{i\ell n}\}\in\mathcal{X}$ are set to be consistent with the same bilateral trade and MP flows, it must be that domestic firms concentrate their sales to the domestic markets, implying low gains from openness.

I also regress the simulated $\{X_{i,\text{CHN},n}\}$ corresponding to lower and upper bounds on gravity controls. Comparing the results in Table 8 to data results in Table 4, I find that the bias towards headquarter countries, reflected by the coefficient of $\mathbf{1}\{i=n\}$, is much stronger in the simulated $\{X_{i,\text{CHN},n}\}$ corresponding to lower bounds than in the augmented Chinese customs data. Moreover, there is no home bias in the simulated $\{X_{i,\text{CHN},n}\}$ corresponding to upper bounds, which is very different from the data results.

6.3. Narrowing the bounds on gains from openness

My model has provided bounds on gains from openness using only bilateral trade and MP data. As shown in Fig. 7, the bounds are wide for small open economies. Intuitively, inserting more information about the multinationals' export-platform sales as restrictions on $\mathcal{A}$ could narrow the bounds. The question is which restrictions are relevant and how they would change the bounds.

In this subsection, I still consider the scenario in which there is no sufficient data to point-identify $\{X_{i\ell n}\}_{i,\ell,n=1,\dots,N}$. In addition to bilateral trade and MP data, I consider the following two *alternative* sets of restrictions on $\mathcal{A}$:

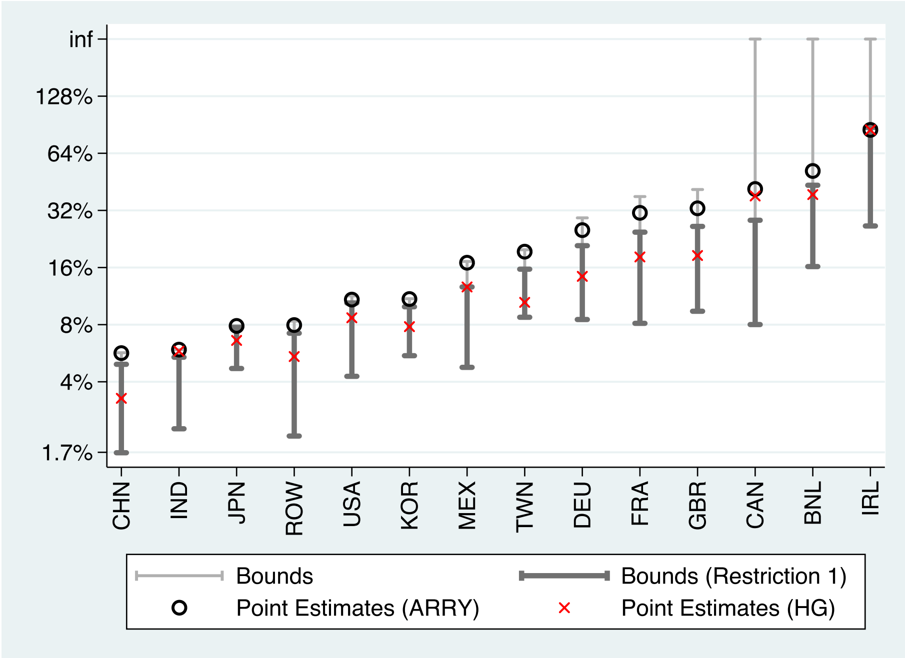


Fig. 8. Bounds on the welfare gains from openness: restriction 1.

– **Restriction 1:** The foreign multinationals' export share is greater than or equal to their *production* share in the host country:

$$\frac{\sum_{i\neq\ell}\sum_{n}X_{i\ell n}\left(a^1,a^2,a^3\right)}{\sum_{i}\sum_{n}X_{i\ell n}\left(a^1,a^2,a^3\right)} \leq \frac{\sum_{i\neq\ell}\sum_{n\neq\ell}X_{i\ell n}\left(a^1,a^2,a^3\right)}{\sum_{i}\sum_{n\neq\ell}X_{i\ell n}\left(a^1,a^2,a^3\right)}, \quad \forall\ell, \tag{22}$$

– **Restriction 2:** The model-generated BMP shares of the U.S. multinationals are equal to their *counterparts* in the BEA data:

$$\frac{\sum_{n\neq\ell}X_{\mathrm{USA},\ell n}\left(a^1,a^2,a^3\right)}{\sum_{n}X_{\mathrm{USA},\ell n}\left(a^1,a^2,a^3\right)} = \frac{\sum_{n\neq\ell}X_{\mathrm{USA},\ell n}}{\sum_{n}X_{\mathrm{USA},\ell n}}. \tag{23}$$

Restriction 1 is consistent with the patterns shown in Fig. 1 for OECD countries and China. Restriction 2 utilizes the publicly available BEA data on the U.S. multinationals to narrow the bounds. The bound framework allows us to see exactly to what extent each additional restriction narrows the bounds and leads to more precise counterfactual predictions.[19]

Fig. 8 illustrates the exact bounds on gains from openness with additional restriction 1. It shows that even this very simple additional restriction can substantially narrows the bounds. For small open economies such as Canada and Ireland, restriction 1 rules out the multinationals' export-platform networks in which all goods consumed in these countries are created by foreign multinational affiliates, and thereby dramatically lowers the upper bound of their gains from openness.

Moreover, restriction 1 has no impacts on the lower bounds of gains from openness. As I have discussed, the lower bounds correspond to the export-platform networks that have substantial bridge MP and thereby satisfy restriction 1.

Finally, for most countries, restriction 1 rules out the gains from openness implied by the ARRY model. In contrast, the HG model is within the bounds under restriction 1 for all economies but Canada and Taiwan.

Fig. 9 illustrates the exact bounds on gains from openness with additional restriction 2. It shows that restriction 2 dramatically narrow the bounds for Canada, Mexico, and Benelux where the U.S. multinationals account for a large fraction of manufacturing production and exports. Ireland is an exception. Although the U.S. multinationals are big in Ireland, the Irish domestic manufacturing firms are too small relative to foreign multinationals. Therefore, restriction 2 on the U.S. multinationals does not rule out the extreme export-platform networks corresponding to lower and upper bounds for Ireland.

[19] If all restrictions cannot be satisfied simultaneously, we can minimize their distance to 0, following the spirit of the general method of moments.

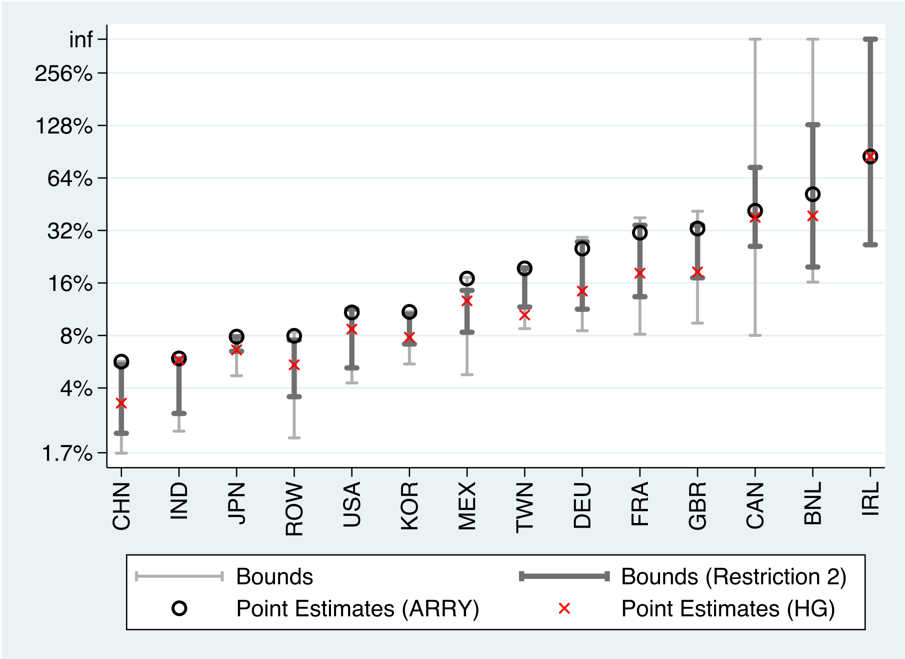


Fig. 9. Bounds on the welfare gains from openness: restriction 2.

In sum, I have shown that two simple restrictions can dramatically narrow bounds on gains from openness. Therefore, my model is useful in quantification even if the detailed data on multinational sales such as the augmented Chinese customs data is non-available.

6.4. Bounds on the effects of the US-China trade conflicts

In this section, I construct exact bounds on the counterfactual predictions for the US-China trade war. Unlike welfare gains from openness, the predictions of these general counterfactuals cannot be expressed analytically in terms of $(\lambda_{ii},\psi_{iii})$. Instead, I have to solve nonlinear system of Equations in Proposition 1. This is computationally challenging and the codes take a long time to converge.

As in Section 5.3, I consider a 25% increase in the trade costs between China and the U.S., $\hat{\tau}_{\text{CHN,USA}} = \hat{\tau}_{\text{USA,CHN}} = 1.25$. Fig. 10 shows that the bounds on welfare effects of the US-China trade war are narrow for the U.S. and China but wide for small economies such as Canada and Taiwan. Canada would lose considerably from the US-China trade war if the sales of its affiliates in China (the U.S.) are concentrated to the U.S. (China). In contrast, Canada would gain from the US-China trade war if its MP in the U.S. and China are completely horizontal.

I also impose restriction 2 to see how it can narrow bounds on welfare effects of the US-China trade war. Restriction 2 rules out the extreme export-platform networks for Canada in which the U.S. affiliates of Canadian multinationals concentrate their sales to China. So the bounds on welfare effects of the US-China trade war on Canada are narrowed from from $[-1.5\,\%\,,0.36\%]$ to $[-0.12\,\%\,,0.36\%]$.

7. Conclusion

This paper makes three contributions. First, using the augmented Chinese customs data, I find that multinational affiliates tend to bias their sales towards their headquarter countries. This headquarters gravity is first documented in this paper for all industries. Second, I incorporate this headquarters gravity into a general equilibrium model to quantify its aggregate implications. Counterfactual analysis suggests that ignoring headquarters gravity could substantially bias our estimates of the consequences of trade shocks such as the US-China trade war. Third, I consider the scenario in which the augmented Chinese customs data is unavailable. I demonstrate the usefulness of my model in this scenario by constructing exact bounds on counterfactual results using only bilateral trade and multinational production (MP) data.

Multinational firms are largest players and main organizers of global production, sales, and supply chains. How these giant multinationals respond to various shocks are therefore crucial for the global consequences of these shocks. Currently there is still lack of detailed data on multinationals' activities, in particular export-platform networks, across many countries in many

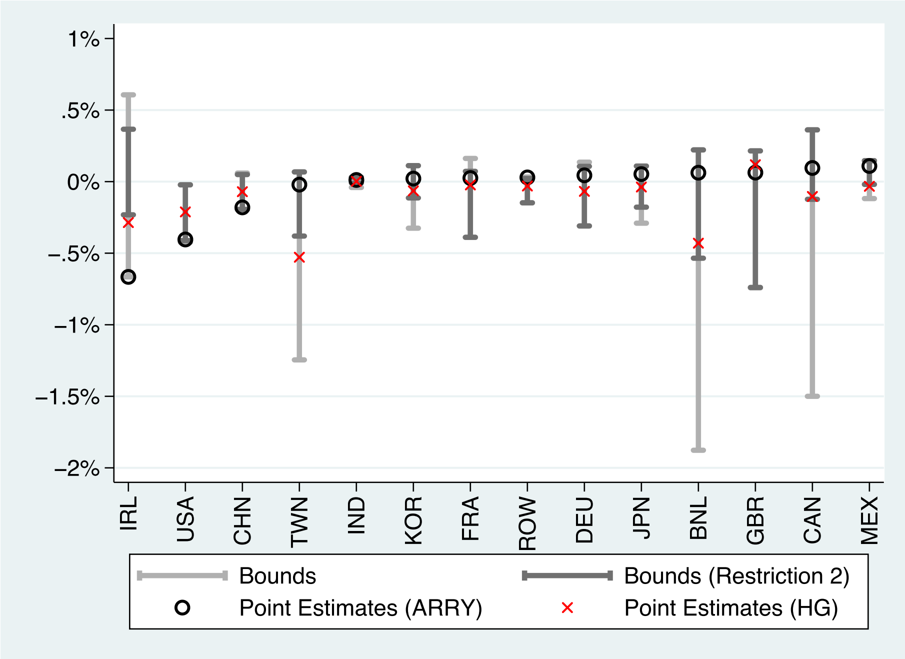


Fig. 10. Bounds on the welfare effects of the US-China trade war. (Note: The US-China trade war refers to a 25 percent increase in bilateral trade costs between the U.S. and China, i.e. $\hat{\tau}_{CHN,USA} = \hat{\tau}_{USA,CHN} = 1.25$. Here I use bilateral trade and MP data in 2014.)

industries. This paper incorporates detailed data on multinationals' global sales into a unified quantitative framework, serving as a first step towards more precise policy evaluation.

The potential avenue for future research is rich. First, I have shown that incorporating detailed data on multinationals' activities can narrow bounds on counterfactuals. Incorporating other sources of micro data, e.g. the Orbis data and the BEA micro data on multinationals, would lead to more accurate counterfactual predictions. If we have more data moments than parameters, we can either put weights on these moments and estimate the model under over-identification, or develop a more flexible model to accommodate richer data. Second, multinationals also account for a large fraction of imports. The global sourcing strategies of a multinational affiliate depend crucially on where its headquarters and sibling affiliates locate. Understanding the role of multinationals in shaping global value chain would be a fascinating direction of future research to deepen our understanding of globalization.

Data availability

Replication files for "Headquarters Gravity: How Multinationals Shape International Trade" (Original data) (Mendeley Data)

Appendix A. Data and empirical regularities

A.1. Construction of the augmented Chinese customs data

The balance sheet data in manufacturing survey contains a numerical firm identifier which is consistent over time. The customs records also includes a numerical identifier for exports. Unfortunately, two numerical identifiers coming from different systems have no way to be connected directly. As in the literature (see, for example, Wang and Yu (2012)), a fuzzy matching algorithm is required. I use the standardized firm name, the manager name, phone number, and zip code as fuzzy identifiers. Exports are restricted within manufacturing goods whose 2-digit HS code is above 15 and below 98 (excluding 25, 26, 27).

One complication is the exports through intermediaries. My theory cannot rationalize the exports of intermediaries since they do not export what they produce. So I exclude them in the data by dropping exporters whose names contain key words such as “import”, “export”, “foreign trade”, “service trade”, and so on. This step excludes about 48% of the export transactions which account for about one third of Chinese manufacture exports in 2001. This result is in line with Manova and Zhang (2012).

Table A.1
FIESC firms matched with ASCM.

	Employment	#Firm
Unmatched	10,504,859	115,311
Matched	8,524,621	29,924
Matching rate (%)	45	21

Table A.2
Summary statistics for CCR exports in 2001.

2-digit HS code	CCR exports	UN comtrade	Destination	CCR Exports	UN comtrade
85	51,357	51,299	United States	54,375	54,355
84	33,698	33,579	Hong Kong	46,518	46,541
62	18,982	18,952	Japan	45,163	44,941
61	13,477	13,456	Korea	12,576	12,519
64	10,096	10,096	Germany	9777	9751
95	9087	9082	Netherlands	7323	7278
94	7569	7559	United Kingdom	6795	6781
42	6995	6988	Singapore	5804	5791
39	6702	6697	Taiwan	5009	–
90	6472	6446	Italy	4014	3992
Total	267,066	266,098	–	–	–

(Note: all values are in million dollars in 2001.)

Another complication is that the same exporter in the customs records may correspond to different names and phone numbers. The same occurs in the manufacturing survey. To address this problem, I first collect all names and other identifiers used by each exporter over 2000–2006 (the period covered by data), given it exports in 2001. I then do similar work in manufacturing survey for each firm operating in 2001. Then I merge two sets of fuzzy identifiers by a matching algorithm based on the weighted average of string distance. I allow multiple exporters to correspond to the same firm in manufacturing survey, but I do not allow multiple firms in manufacturing survey to correspond to the same exporter. For the latter case, I merge two datasets manually. This algorithm matches exporters which account for about 85% of Chinese manufacturing direct exports.

Foreign-invested-enterprise survey shares a unique numerical firm identifier with manufacturing survey. So merging this two datasets is straightforward. Table A.1 summarizes the total matching rate. It shows that only 20% of foreign firms in China are manufacturers. But these manufacturers are larger than non-manufacturing foreign firms: they account for 45% of employees hired by foreign firms in China.

A.2. Data quality

Chinese Customs Records (CCR) provide transaction-level information on Chinese imports and exports. I compare Chinese aggregate exports in 2001 recorded by CCR with the one in UN COMTRADE. They turn out to be very close. In CCR, China exported \$267065578080 in 2001, while in UN COMTRADE, Chinese exported \$266098208590 in 2001. The difference is less than 0.5%. Table A.2 shows that these two datasets are close in each 2-digit HS code.

To examine the quality of Chinese firm database I constructed in the previous section, I compare the aggregate sales of the U.S. affiliates in China in Chinese firm data with the records in the BEA database. I take the BEA database "Data on activities of multinational enterprises" in 2001 which contains information on, for each host country, the total sales of the U.S. affiliates, the sales to the host country, the sales to the U.S., and the sales to other countries. Table A.3 shows the comparison result. The aggregate statistics of the U.S. affiliates in China recorded in Chinese firm data is reasonably close to the records in BEA database. This result suggests that the quality of Chinese firm data is good for my purpose.

Table A.3
The U.S. affiliates in China: Chinese data vs BEA data.

	The U.S. affiliates in China in 2001	
	Chinese data	BEA data
Total Sales	32,255	29,578
Sales in China	21,808	20,419
Sales to the U.S.	3418	3066
Sales to other	7029	6094

(Note: All values are in million dollars.)

Table A.4
Summary statistics for manufacturers in China by origin.

Origin	#Firms	#Exporters	#Exp to Origin	Sales	Value-added	Employment	Export	Exp. to origin
AUS	268	161	67	1260	353	45	328	54
AUT	49	35	13	383	100	17	59	1
BEL	40	26	13	1414	359	11	118	18
CAN	243	140	47	1828	387	41	320	18
DEU	429	299	206	14,094	3815	131	1837	611
DNK	25	17	10	571	160	7	312	148
ESP	42	20	10	243	65	9	41	17
FIN	27	21	13	5759	740	8	2449	172
FRA	191	130	62	2651	707	42	442	100
GBR	495	330	122	7378	2070	196	2676	141
ITA	138	81	47	956	253	30	170	36
JPN	3088	2531	2319	37,738	9375	927	20,928	12,631
KOR	1247	1049	889	14,713	3136	456	10,090	2558
NLD	163	122	45	5279	1045	55	2377	124
NZL	33	17	2	243	48	9	83	2
SGP	933	617	336	12,155	3189	294	4387	460
SWE	67	43	21	2815	584	13	414	135
TWN	3400	2374	1117	14,312	3578	743	6598	422
USA	2341	1515	1028	33,415	9394	630	11,607	3797
CHN	96,804	15,251	–	588,496	147,952	33,185	37,981	–

(Note: Sales, value-added, exports, exports to origin are in million dollars. Employment is in thousands. Firms from Hong Kong and Macau are excludEd.)

Table A.5
The export advantage of foreign affiliates of multinationals in China.

	$\mathbf{1}\{\exp(\nu) > 0\}$	$\exp(\nu)/\text{sales}(\nu)$	$\log(\exp(\nu)/\text{sales}(\nu))$
	(1)	(2)	(3)
Foreign	1.434***	0.195***	0.132**
	(0.044)	(0.022)	(0.054)
Employment (in log)	0.200***	0.0178***	0.295***
	(0.015)	(0.0033)	(0.053)
Capital (in log)	0.0449***	−0.00767***	−0.399***
	(0.013)	(0.0020)	(0.035)
Material (in log)	0.0984***	−0.000270	−0.331***
	(0.020)	(0.0013)	(0.041)
TFP (in log)	−0.0537	−0.0203***	−0.997***
	(0.043)	(0.0043)	(0.31)
2-digit CIC Industry *f.e.*	Yes	Yes	Yes
R-square		0.17	0.26
N. of Obs.	106,482	101,529	7964

(Note: In Column (1), I regress the firm's export status on its foreign ownership and other performances, using the Probit model. In Column (2) and (3), I regress the firm's export intensity on its foreign ownership and other performances. Notably, in Column (3) I take log on the firm's export intensity and therefore exclude the non-exporting firms. The state-owned firms, the processing traders, and the firms in exporting zones are excluded in all regressions. The TFP is estimated using the method developed by Levinsohn and Petrin (2003). The standard errors are clustered at the 2-digit CIC industry level.)

A.3. Summary statistics

Table A.4 provides summary statistics for multinational affiliates operating in China documented by the augmented Chinese customs data for 2001. It shows that (i) Comparing to Chinese firms a larger fraction of foreign affiliates are exporters. (ii) A large fraction of foreign affiliates in China export to their headquarters countries. (iii) Foreign affiliates in China are larger than Chinese firms either in terms of total sales, number of employees, or value-added. (iv) The value-added share of foreign affiliates in China is not significantly lower than the value-added share of Chinese firms.

To examine the foreign multinational affiliates' advantage in exports, I regress the firms' extensive and intensive margins of exports on a dummy for foreign multinationals, controlling for employment, capital, expenditure on intermediates, and productivity. The results are presented in Table A.5. I find that controlling for these observed characteristics, foreign multinational affiliates are still more likely to export and export more than Chinese domestic firms.

The U.S. Bureau of Economic Analysis (BEA) collects aggregate sales of the U.S. multinationals in each host country, dividing the total sales into the sales to the local market, to the U.S., and to third countries. It is straightforward to compute the exports to the U.S. as a share of total exports for the U.S. multinationals in each host country. The export share to the U.S. for all firms comes from WIOD. Fig. A.1 shows that for most of the host countries, the U.S. multinational affiliates have higher export shares to the U.S. than other firms.

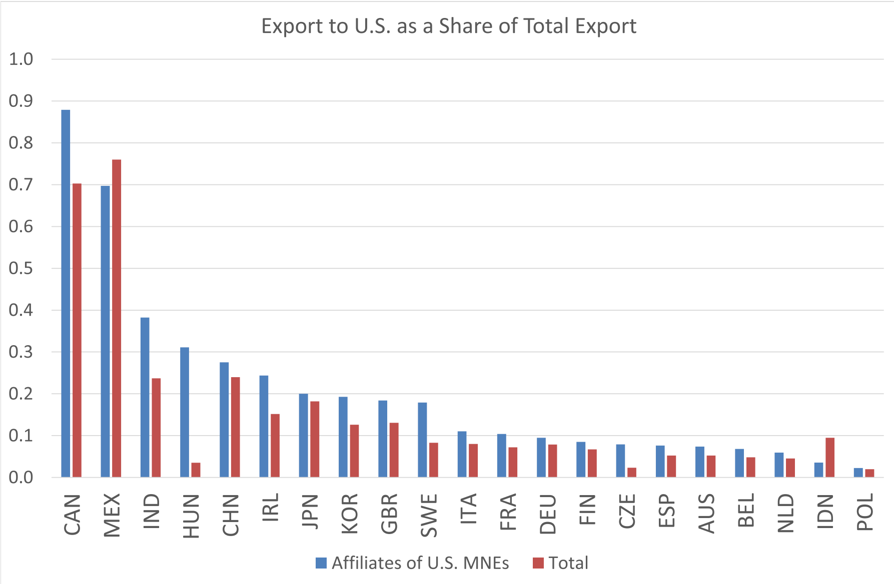


Fig. A.1. Exports to the U.S. as a share of total exports. (Notes: the export share to the U.S. for the U.S. multinational affiliates comes from the BEA data for multinational operation. The export share to the U.S. for all firms comes from WIOD data. All shares are for the year 2001.)

A.4. Reduced-form results

In this subsection, I perform two robustness exercises for headquarters gravity. First, I aggregate the augmented Chinese customs data into origin-destination-sector level and estimate the headquarters gravity, controlling for origin-sector and destination-sector fixed effects. The results are presented in Table A.6.

Second, I exclude affiliates from Japan and Korea and re-estimate headquarters gravity in order to address the concern that headquarters gravity is specific to"Factory Asia" in which multinationals from Japan and Korea assemble their products in China and make sales in the U.S. and Europe. Headquarters gravity still holds, as suggested by Table A.7.

Table A.6
Headquarters gravity in the origin-destination-sector level.

	$\log(X^j_{i,\mathrm{CHN},n})$	$\log(M^j_{i,\mathrm{CHN},n})$	$\log(\overline{X}^j_{i,\mathrm{CHN},n})$
$\log(\mathrm{dist}_{in})$	-0.206^{***}	-0.0621^{***}	-0.144^{***}
	(0.045)	(0.013)	(0.040)
$\mathbf{1}\{i=n\}$	1.337^{***}	0.624^{***}	0.714^{***}
	(0.21)	(0.068)	(0.19)
lang_{in}	-0.00280	-0.0331	0.0303
	(0.11)	(0.031)	(0.10)
legal_{in}	0.185^{**}	0.135^{***}	0.0504
	(0.083)	(0.022)	(0.076)
OECD_{in}	0.106	0.0775^{***}	0.0288
	(0.087)	(0.021)	(0.081)
Origin-Sector FE	Yes	Yes	Yes
Destination-Sector FE	Yes	Yes	Yes
R-squared	0.501	0.652	0.454
# Obs.	4971	4971	4971

Table A.7
Headquarters gravity: excluding Japanese and Korean firms.

	$\mathbf{1}\{x_{i,\mathrm{CHN},n}(\nu)>0\}$		$\log(x_{i,\mathrm{CHN},n}(\nu))$	
$\log(\mathrm{dist}_{in})$	−0.00422***	−0.00605***	−0.0850***	−0.148***
	(0.0014)	(0.0012)	(0.032)	(0.040)
$\mathbf{1}\{i=n\}$	0.321***		0.939***	
	(0.023)		(0.14)	
lang_{in}	0.00748***	0.00456**	0.0601	−0.0194
	(0.0023)	(0.0021)	(0.069)	(0.079)
legal_{in}	0.00665***	0.00600***	0.0712	0.0660
	(0.0017)	(0.0017)	(0.055)	(0.056)
OECD_{in}	0.0112***	0.0106***	0.0995*	0.0842
	(0.0022)	(0.0021)	(0.052)	(0.053)
Destination FE	Yes	Yes	Yes	Yes
Affiliate FE	Yes	Yes	Yes	Yes
R-squared	0.226	0.186	0.438	0.422
# Obs.	198,998	197,635	9824	8750

(Notes: The extensive margin is estimated using the Probit model. Processing traders are excluded. Firm located in exporting zones, Japanese, Korean, Hong Kong, Macau, and Taiwanese firms, and Chinese domestic firms are excluded. In the last column, I exclude all export transactions back to the headquarters countries. The standard errors are clustered at the origin-destination level.)

Appendix B. Theory

B.1. Proof to Lemma 2

Proof. By construction, set $\mathcal{A}$ is bounded. For any sequence $(a^{(1)},a^{(2)},\ldots)$ where $a^k\in\mathcal{A}$ for all k, we have $X_{i\ell n}=(a^1_{i\ell})^{(k)}(a^2_{\ell n})^{(k)}(a^3_{in})^{(k)}X_n$ satisfying $\sum_i X_{i\ell n}=X^{TR}_{\ell n}$ and $\sum_n X_{i\ell n}=X^{MP}_{i\ell}$. Suppose that $\lim_{k\to\infty}a^k=a^*$. Then $X_{i\ell n}=(a^1_{i\ell})^*(a^2_{\ell n})^*(a^3_{in})^*X_n$ satisfy $\sum_i X_{i\ell n}=X^{TR}_{\ell n}$ and $\sum_n X_{i\ell n}=X^{MP}_{i\ell}$. Therefore, $a^*\in\mathcal{A}$ and $\mathcal{A}$ is closed. A bounded and closed set in the Euclidean space is compact.

To show the path-connectedness of set $\mathcal{A}$, I want to show the path-connectedness of the following set:

$$\mathcal{B}=\left\{(a,b,c)\in\left[0,\overline{\mathrm{a}}\right]^3:ab+\mathrm{c}=\mathrm{D}\right\}, \tag{B.1}$$

where $D>0$ is a constant.

Consider two points in $\mathcal{B}$, (a_1,b_1,c_1) and (a_2,b_2,c_2). Without loss of generality, assume that $c_1>c_2$. Then there exists $b_3\in[0,\overline{a}]$ such that $a_1b_3+c_2=D$ and $(a_1,b_3,c_2)\in\mathcal{B}$. Notice that $(a_1,b_1,c_1)\in\mathcal{B}$ and $(a_1,b_3,c_2)\in\mathcal{B}$ are path-connected since the set $\{(b,c)\in[0,\overline{\mathrm{a}}]^2:\mathrm{a_1b+c=D}\}$ is convex.

Notice that the set $\{(a,b)\in[0,\overline{\mathrm{a}}]^2:ab=\mathrm{C}\}$ where $C>0$ is a constant is path-connected since it is a continuous transformation of the following convex set

$$\left\{\left(\log(\mathrm{a}),\log(\mathrm{b})\right)\in\left[0,\log(\overline{\mathrm{a}})\right]^2:\log(\mathrm{a})+\log(\mathrm{b})=\log(\mathrm{C})\right\}. \tag{B.2}$$

Therefore, $(a_2,b_2,c_2)\in\mathcal{B}$ and $(a_1,b_3,c_2)\in\mathcal{B}$ are path-connected. Since $(a_1,b_1,c_1)\in\mathcal{B}$ and $(a_1,b_3,c_2)\in\mathcal{B}$ are path-connected and $(a_2,b_2,c_2)\in\mathcal{B}$ and $(a_1,b_3,c_2)\in\mathcal{B}$ are path-connected, (a_1,b_1,c_1) and (a_2,b_2,c_2) are path-connected. Therefore, $\mathcal{B}$ is path-connected.

With analogous but tedious algebra, $\mathcal{A}$ is also path-connected. □

B.2. Proof to Proposition 3

Proof. By Lemma 2, set $\mathcal{A}$ is compact. Then since $H:\mathcal{A}\to\mathbb{R}$ is continuous, $\overline{H}$ and $\underline{H}$ exist due to the Extreme Value Theorem. Moreover, since set $\mathcal{A}$ is path-connected, $H(\mathcal{A})$ is also path-connected. In the one-dimension Euclidean space, a path-connected set is an interval. Therefore, $H(\mathcal{A})=[\underline{H},\overline{H}]$. □

Appendix C. Calibration and counterfactuals

C.1. Calibration results

Fig. C.2 illustrates the sensitivity of moments in Eqs. (13) and (14) to $\left\{\widetilde{T}_{i\ell}\right\}$. It shows that $\left\{\widetilde{T}_{i\ell}\right\}$ are mainly recovered from bilateral MP shares.

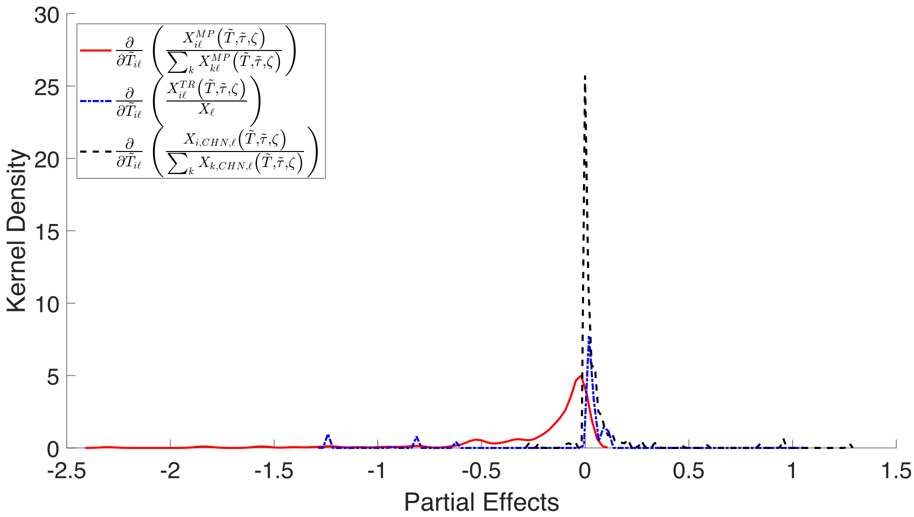


Fig. C.2. Sensitivity of moments in Eqs. (13) and (14) to $\{\widetilde{T}_{i\ell}\}$. (Notes: The sensitivity of moments to $\{\widetilde{T}_{i\ell}\}$ is measured by the numerical partial derivatives at the solution point of $(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta})$. The density estimate is based on a normal kernel function, and is evaluated at equally-spaced points that cover the range of the data.)

Fig. C.3 illustrates the sensitivity of moments in Eqs. (13) and (14) to $\{\widetilde{\tau}_{\ell n}\}$. It shows that $\{\widetilde{\tau}_{\ell n}\}$ are mainly recovered from bilateral trade shares.

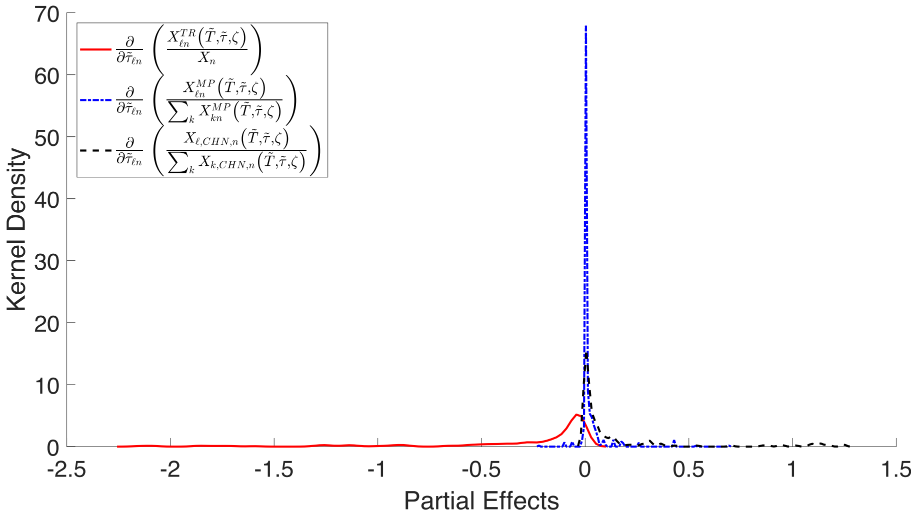


Fig. C.3. Sensitivity of moments in Eqs. (13) and (14) to $\{\widetilde{\tau}_{\ell n}\}$. (Notes: The sensitivity of moments to $\{\widetilde{\tau}_{\ell n}\}$ is measured by the numerical partial derivatives at the solution point of $(\widetilde{\mathbf{T}}, \widetilde{\boldsymbol{\tau}}, \boldsymbol{\zeta})$. The density estimate is based on a normal kernel function, and is evaluated at equally-spaced points that cover the range of the data.)

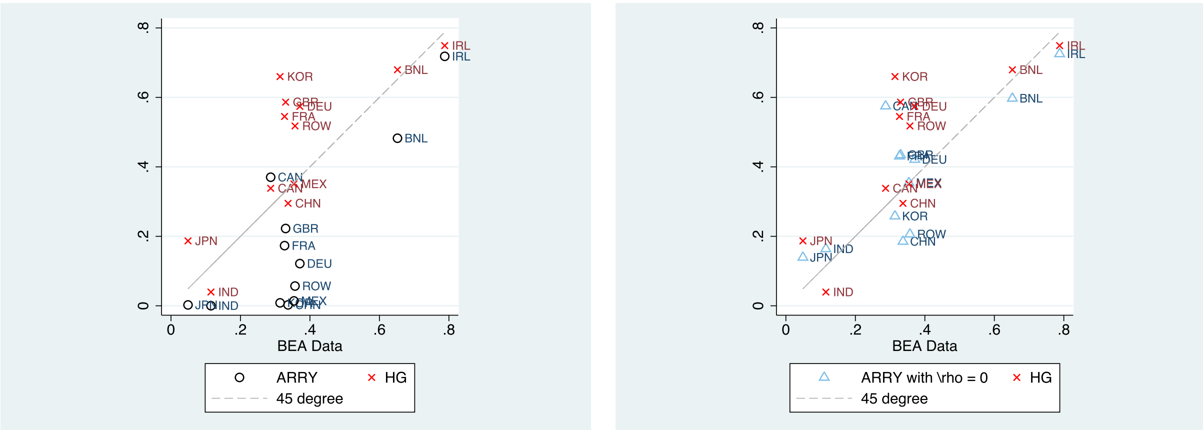
Table C.8 shows the regression results as in Table 3 but includes all observations except the rest of the world. Including observations for Taiwan, India, and Mexico, the coefficient of distance is not significant in the regression of ζ_{in}. But the coefficients of $\mathbf{1}\{i = n\}$ are still highly significant in all regressions.

Fig. C.4 plots the BMP shares of the U.S. multinationals predicted by the HG model and the ARRY model against the ones in the BEA data. It shows that the ARRY model substantially underestimates the BMP shares while the HG model overestimates the BMP shares. The ARRY model with $\rho = 0$ fits the BMP shares in the BEA data very well.

Table C.8
Imputed $(\boldsymbol{\zeta}, \boldsymbol{\gamma}, \boldsymbol{\tau})$ and bilateral distances.

	$\log(\zeta_{in})$	$\log(\gamma_{in})$	$\log(\tau_{in})$
$\log(\text{dist}_{in})$	0.0203	0.0797***	0.104***
	(0.017)	(0.010)	(0.011)
$\mathbf{1}\{i = n\}$	−0.430***	−0.219***	−0.118**
	(0.089)	(0.041)	(0.048)
lang_{in}	0.00658	−0.0845***	0.00123
	(0.030)	(0.028)	(0.031)
legal_{in}	−0.0245	0.0141	0.0168
	(0.029)	(0.030)	(0.035)
OECD_{in}	0.00741	−0.0677**	−0.0230
	(0.028)	(0.027)	(0.026)
R-squared	0.352	0.475	0.488
N. of Obs.	169	169	169

(Notes: $(\boldsymbol{\zeta}, \boldsymbol{\gamma}, \boldsymbol{\tau})$ are imputed by matching the model to the moments in Eqs. (13) and (14). In all regressions, I exclude samples for the rest of the world.)

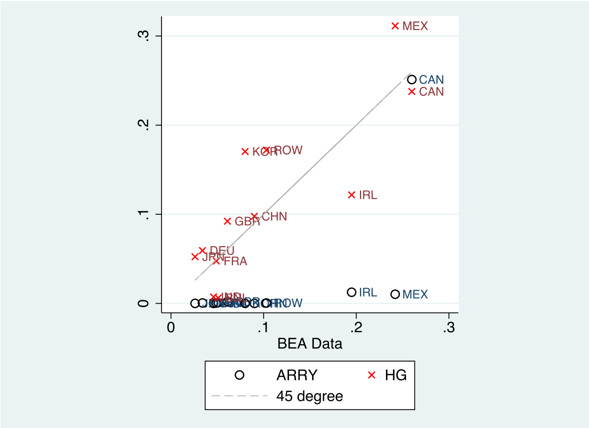


(a) ARRY vs HG

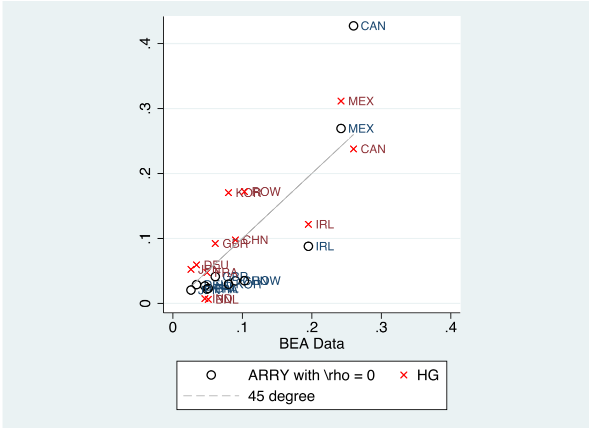
(b) ARRY with $\rho = 0$ vs HG

Fig. C.4. BMP shares of the U.S. multinationals: model vs. data. (Note: BEA data is for 2005.)

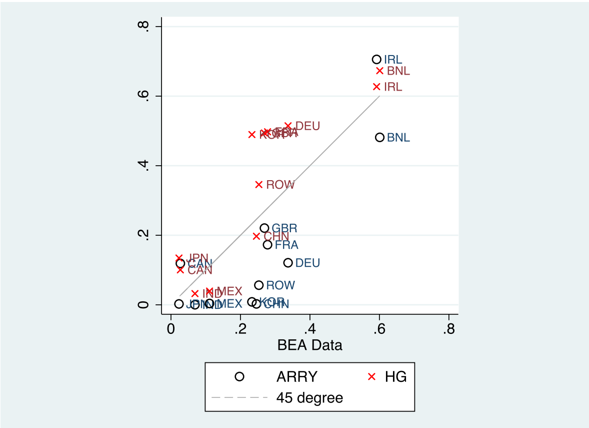
I then split the BMP sales of the U.S. multinationals into sales back to the U.S. and to third countries. Fig. C.5 compares the model predictions with the BEA data. It shows that the ARRY model substantially underestimates the sales back to the U.S., while the HG model fits the data well in this dimension.



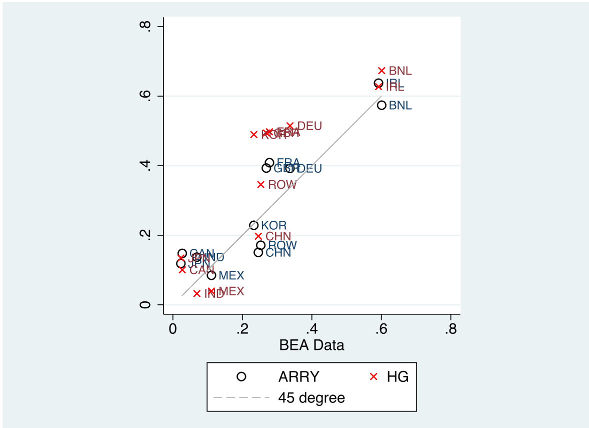
(a) Sales to the US: ARRY vs HG



(b) Sales to the US: ARRY with $\rho = 0$ vs HG



(c) Sales to Others: ARRY vs HG



(d) Sales to Others: ARRY with $\rho = 0$ vs HG

Fig. C.5. Sales distribution of the U.S. multinationals: model vs. data. (Note: BEA data is for 2005.)

C.2. Counterfactuals under point identification

In this subsection, I perform two counterfactual exercises. First, I consider a unilateral MP liberalization in China. I start from the 2005 economy and let $\hat{\gamma}_{i,\mathrm{CHN}} = 0.9$ for $i \neq \mathrm{CHN}$. Table C.9 shows that this unilateral MP liberalization makes China further specialize in production. Moreover, China gains from this unilateral MP liberalization in the ARRY model but loses in the HG model. Intuitively, in the HG model foreign multinationals conduct a large volume bridge MP in China. In this case, China gains less from accessing foreign technologies.

Second, I consider the Trump's protectionism tariffs on imports from China. I start from the 2014 economy and let $\hat{\tau}_{\mathrm{CHN,USA}} = 1.25$. Similar to the results in Table 6, Table C.10 shows that economies like Canada, Taiwan, and Germany loses from the Trump's protectionism tariffs in the HG model. The HG model suggests that the Chinese affiliates of multinationals from these economies export a considerable fraction of their products to the U.S. Therefore, the Trump's protectionism tariffs decrease $\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$ in these countries.

C.3. Bounds on counterfactuals

Table C.11 presents the regression results similar to ones in Table 7 but including all economies except the rest of the world. The coefficients of distance become insignificant but the coefficients of $\mathbf{1}\{i = n\}$ remain largely unchanged.

Table C.12 presents numbers for GO bounds illustrated by Figs. 7, 8, and 9.

Table C.13 presents numbers for welfare bounds of the US-China trade war illustrated by Fig. 10.

Table C.9
Welfare effects of China's inward MP liberalization.

	ARRY				HG			
%Δ in:	W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	$\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$	W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	$\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$
Benelux	0.168	1.097	−0.011	−0.917	0.140	0.608	−0.012	−0.456
Canada	0.306	0.806	−0.001	−0.499	0.270	0.826	−0.001	−0.555
China	0.022	3.364	0.000	−3.342	−0.560	2.313	0.032	−2.905
Germany	0.116	0.064	0.000	0.052	−0.006	0.148	0.014	−0.168
France	0.474	−0.155	0.001	0.628	0.762	−0.183	0.059	0.886
Britain	−0.019	0.634	−0.022	−0.632	−0.243	0.532	−0.062	−0.713
India	0.168	0.279	0.000	−0.111	0.159	0.196	0.000	−0.038
Ireland	4.360	−0.552	4.555	0.358	3.507	−0.066	3.271	0.301
Japan	0.404	−0.054	0.000	0.458	0.518	−0.014	0.151	0.381
Korea	1.140	−0.208	0.000	1.348	1.346	−0.098	0.152	1.292
Mexico	0.260	0.498	0.000	−0.239	0.243	0.385	0.000	−0.143
R.O.W.	0.240	−0.147	0.000	0.386	0.391	−0.105	0.060	0.436
Taiwan	1.166	−0.238	0.000	1.403	0.663	0.376	0.172	0.114
United States	0.118	−0.054	0.001	0.170	0.215	−0.059	0.048	0.226

(Notes: China's Inward MP Liberalization refers to a 10 percent decrease in China's inward MP costs, i.e. $\hat{\gamma}_{i,\mathrm{CHN}} = 0.9$ for $i \neq \mathrm{CHN}$. Here I use bilateral trade and MP data in 2005.)

Table C.10
Welfare effects of the trump's protectionism tariffs.

	ARRY				HG			
%Δ in:	W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	$\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$	W_i	$\lambda_{ii}^{-\frac{1}{\theta}}$	$\psi_{iii}^{-\frac{1-\rho}{\theta}}$	$\left(\frac{Y_i^f}{X_i}\right)^{\frac{1}{\theta}}$
Benelux	0.065	−0.150	0.002	0.213	−0.252	0.184	−0.064	−0.373
Canada	0.081	−0.010	−0.001	0.092	−0.139	0.140	0.000	−0.280
China	−0.116	−0.075	0.000	−0.041	−0.039	−0.092	−0.002	0.056
Germany	0.037	−0.010	0.000	0.048	−0.046	0.048	−0.008	−0.087
France	0.014	−0.038	0.000	0.052	0.004	−0.019	0.000	0.024
Britain	0.052	−0.057	0.000	0.109	0.186	−0.111	0.025	0.272
India	0.020	−0.009	0.000	0.029	0.008	−0.010	0.000	0.018
Ireland	−0.516	−0.168	0.029	−0.377	−0.217	−0.224	0.216	−0.209
Japan	0.046	0.006	0.000	0.040	−0.010	−0.014	0.017	−0.013
Korea	0.000	−0.036	0.000	0.036	−0.054	−0.039	0.015	−0.030
Mexico	0.120	−0.025	0.000	0.145	−0.014	0.106	0.000	−0.120
R.O.W.	0.025	0.026	0.000	−0.001	−0.028	0.035	−0.003	−0.060
Taiwan	−0.061	−0.143	0.000	0.082	−0.387	0.005	0.011	−0.403
United States	−0.377	−0.353	0.002	−0.026	−0.209	−0.276	−0.039	0.106

(Notes: I approximate the Trump's protectionism tariffs by a 25 percent increase in $\tau_{\mathrm{CHN,USA}}$. Here I use bilateral trade and MP data in 2014.)

Table C.11
$\{\zeta_{in}\}$ on the bounds of gains from openness.

	Dependent variable: $\log(\zeta_{in})$							
	Lower bounds				Upper bounds			
	CHN	DEU	JPN	USA	CHN	DEU	JPN	USA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(\mathrm{dist}_{in})$	−0.000543	−0.0184	−0.00875	0.0594	0.0148	−0.0148	0.00370	0.0510**
	(0.038)	(0.036)	(0.034)	(0.045)	(0.013)	(0.027)	(0.020)	(0.021)
$\mathbf{1}\{i = n\}$	−0.337*	−0.639***	−0.714***	−0.637**	0.0103	−0.00406	0.0860	0.317*
	(0.19)	(0.17)	(0.17)	(0.27)	(0.086)	(0.15)	(0.12)	(0.17)
lang_{in}	−0.238**	−0.207**	−0.357***	−0.00704	0.0469	0.0273	0.0612	0.0162
	(0.095)	(0.10)	(0.083)	(0.17)	(0.043)	(0.040)	(0.060)	(0.038)
legal_{in}	−0.0258	0.207	0.181	0.267	0.0469	0.0367	0.0535	−0.00995
	(0.12)	(0.14)	(0.11)	(0.23)	(0.042)	(0.043)	(0.058)	(0.036)
OECD_{in}	−0.161	0.0494	0.0711	0.160	0.0305	−0.0185	−0.0650	−0.0493
	(0.11)	(0.091)	(0.082)	(0.12)	(0.033)	(0.040)	(0.047)	(0.040)
R-squared	0.0600	0.0604	0.123	0.0735	0.0377	0.0150	0.0333	0.0569
N. of Obs.	169	169	169	169	169	169	169	169

(Notes: The dependent variable for Column (1) is $\log(\zeta_{in})$ that minimizes gains from openness in China. In all regressions, I exclude the rest of the world.)

Table C.12
Bounds on gains from openness.

%Δ in *W*:	Baseline		Restriction 1		Restriction 2	
	LB	UB	LB	UB	LB	UB
BNL	16.19	∞	16.19	43.42	19.74	129.25
CAN	8.01	∞	8.01	28.40	25.94	73.53
CHN	1.69	5.69	1.69	4.95	2.20	5.43
DEU	8.52	29.23	8.52	20.85	11.31	27.55
FRA	8.13	37.85	8.13	24.58	13.34	34.28
GBR	9.41	41.24	9.41	26.35	17.13	34.33
IND	2.26	5.91	2.26	5.39	2.86	5.86
IRL	26.50	∞	26.50	87.59	26.50	∞
JPN	4.70	7.88	4.70	7.72	6.49	7.87
KOR	5.49	10.95	5.49	9.94	7.14	10.58
MEX	4.77	17.23	4.77	12.64	8.35	14.50
ROW	2.07	8.36	2.07	7.21	3.57	7.53
TWN	8.75	19.85	8.75	15.69	11.65	19.45
USA	4.27	11.34	4.27	10.41	5.21	11.34

Table C.13
Bounds on the welfare effects of the US-China trade war.

%Δ in *W*:	Baseline		Restriction 2	
	LB	UB	LB	UB
BNL	−1.877	0.222	−0.535	0.222
CAN	−1.500	0.362	−0.123	0.362
CHN	−0.195	0.060	−0.194	0.049
DEU	−0.310	0.136	−0.310	0.106
FRA	−0.390	0.162	−0.389	0.072
GBR	−0.742	0.215	−0.739	0.215
IND	−0.041	0.031	−0.009	0.031
IRL	−0.666	0.606	−0.232	0.366
JPN	−0.290	0.108	−0.178	0.108
KOR	−0.325	0.112	−0.114	0.112
MEX	−0.118	0.146	−0.019	0.146
ROW	−0.148	0.032	−0.148	0.021
TWN	−1.245	0.068	−0.380	0.068
USA	−0.424	−0.022	−0.412	−0.022

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