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 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 multi-country general equilibrium model à la Arkolakis et al. (2018) by allowing the export costs of a multinational affiliate to depend on the location of its headquarters. I show that my model can generate many export-platform networks of multinationals that replicate the observed bilateral trade and multinational production (MP) flows, and the model’s counterfactual predictions depend crucially on the structure of these networks. I then construct bounds on counterfactual predictions using this partially identified model and explore to what extent incorporating information on multinationals’ exports can narrow these bounds. The counterfactual results suggest that (i) headquarters gravity accounts for 23% of the Chinese exports, and (ii) ignoring headquarters gravity could substantially bias our quantification of the welfare consequences of trade and MP shocks such as the recent US-China trade war.

Keywords: Multinational Firm; Export Platform; Welfare

JEL classification: F12, F23, O19.

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1 Introduction

Multinational firms, using their foreign affiliates as export platforms, are the largest players in international trade. Figure [1] shows that foreign multinational affiliates account for a large fraction of production in the host countries; their export share is even larger than their production share. How would these giant multinationals adjust their production sites and sales destinations in response to various shocks on international trade and investment? Due to the sheer scale of these multinationals, their responses is important to understanding the consequences of the recent disruption of regional integration: For example, will Trump’s tariff increase against Chinese imports drive foreign multinational affiliates out of China and, if so, which countries’ multinationals will be mostly affected? To what extent will Brexit shift the British affiliates of U.S. multinationals towards Ireland? What are the aggregate implications of multinationals’ adjustments in response to these shocks?

Answering these questions requires a full picture of multinationals’ complex networks of export-platform sales, which we usually do not have. For example, if the Chinese affiliates of Canadian multinationals concentrate their exports to the U.S. market, then they are likely to be heavily exposed to the US-China trade war. However, typically we can only observe the aggregate multinational production (MP) sales of Canadian firms in China (bilateral MP flow) and the total value of Chinese exports to the U.S. (bilateral trade flow). Facing this data limitation, few existing quantitative studies either (i) impute multinationals’ export-platform networks from bilateral trade and MP flows, resulting in implications inconsistent with micro data\(^1\) or (ii) utilize data on specific industries, the results of which are not directly applicable to the aggregate economy\(^2\).

This paper aims to overcome this challenge and improve our understanding of multinationals’ export-platform networks and their implications for the aggregate economy. To this end, I utilize detailed export and 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. Using this augmented 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 that considers only bilateral relationships between exporting and importing countries. To the best of my knowledge, this paper is the first to document this empirical

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1 See Ramondo and Rodriguez-Clare (2013), Tintelot (2017), and Arkolakis et al. (2018). The advantages and limitations of these models will be discussed in detail below.

2 Head and Mayer (2019) and Cosar et al. (2018) utilize detailed global production and sales data of the car industry to estimate quantitative models with trade and MP.
I incorporate this salient feature of multinationals’ export-platform networks, headquarters gravity, into a quantifiable multi-country general equilibrium framework. The model builds on the general equilibrium framework developed by Arkolakis et al. (ARRY, 2018), which allows firms to produce outside their home country and utilize their affiliates as export platforms. The ARRY model is highly tractable and transparent to estimate using the bilateral trade and MP data. However, the ARRY model cannot capture the headquarters gravity documented in the Chinese customs data since it assumes that all firms producing in the same country incur the same export cost to a given destination. With the goal of taking into account features of multinationals’ exports, I extend the ARRY model by allowing the export costs of a multinational affiliate to depend on the location of its headquarters. This friction between headquarters and destination markets is first introduced in the model developed by Head and Mayer (2019), which is designed to study the car industry. This paper, instead, incorporates this friction into a tractable general equilibrium framework and focuses on general equilibrium counterfactuals.

I then bring my model to data. I show that without restrictions on multinationals’ ex-

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3Head and Mayer (2019) document similar bias of multinationals’ sales in the car industry. Moreover, using data on 34 consumer packaged goods industries in 50 largest U.S. cities, Bronnenberg, Dhar, and Dube (2009) find that a brand’s market shares are systematically higher in markets closer to its city of origin, regardless of production locations.

4This assumption has been made in several recent quantitative models of export platform, including Ramondo and Rodriguez-Clare (2013) and Tintelot (2017).
ports, my model can generate many export-platform networks of multinationals that exactly replicate the observed bilateral trade and MP flows. Moreover, I show that different export-platform networks of multinationals lead to different quantitative counterfactual predictions following any economic shock. In other words, my model and its counterfactual predictions are partially identified by bilateral trade and MP flows. The ARRY model, in contrast, is pointly identified by bilateral trade and MP flows because it imposes the assumption that all firms producing in the same country incur the same set of export costs.

What counterfactual predictions can be made without imposing restrictive assumptions on multinationals’ exports? I construct bounds on counterfactual predictions based on all model-generated export-platform networks that exactly replicate the observed bilateral trade and MP flows. I find that the U.S. welfare gain from a 10-percent decline in the MP costs into China lie between 0.04 – 0.25%, whereas the point estimate of the ARRY model is 0.12%. The upper bound corresponds to the export-platform network in which the Chinese affiliates of US multinationals concentrate their exports to the United States. In this case, MP liberalization into China would considerably reduce the price index faced by the U.S. consumers. This result suggests that by assuming that foreign multinational affiliates face the same set of export costs with domestic firms, the ARRY model may under-estimate the U.S. welfare gains from MP liberalization into China.

Sometimes the bounds on counterfactual predictions are wide and uninformative. I therefore incorporate additional information on multinationals’ exports to narrow the bounds. I do it in two approaches. In a first approach, motivated by Figure 1, I assume that the export share of foreign multinational affiliates is larger than their production share in each host country. The results show that even this very simple restriction can substantially narrow the counterfactual bounds. For example, the bounds on welfare gains from openness in the United Kingdom are narrowed from 15 – 35.7% to 17.7 – 25%.

In a second approach, I combine the Chinese customs data with bilateral trade and MP flows. I show that the Chinese customs data identifies the frictions between headquarters and destinations and therefore leads to point identification of my model. This point-identified model (henceforth, the HG model) generates a multinationals’ export-platform network that is consistent with headquarters gravity. It also suggests that:

(i) Headquarters gravity accounts for a large fraction of international trade: eliminating headquarters gravity will reduce the Chinese exports by 23%. 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) The bridge MP (BMP), MP sales sold outside of the host country, are much more important in the global economy than implied by the ARRY model. Comparing to the ARRY model, the average BMP share of US multinationals predicted by the HG model rises from 8.6% to 23.3%, bringing it much closer to the 31.3% observed in the BEA data.

Finally, I perform a policy-motivated counterfactual exercise using the HG model. Motivated by Trump’s tariff increase against Chinese imports, I increase the trade cost from China to the U.S. by 25%. The counterfactual results show that headquarters gravity leads to an interesting third-country effect: the HG model predicts that the welfare effect of the US-China trade war for Canada is $-0.074\%$, whereas 0.014% 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 Trump’s tariffs than implied by the ARRY model. In fact, recent news suggest that Canadian firms are 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.” Ignoring this third-country effect could bias our quantification of the global consequences of the US-China trade disputes.

This paper contributes to recent efforts in quantifying the impacts of MP by incorporating salient features of multinationals’ export-platform networks into a general equilibrium framework. Recent general equilibrium models of export platforms such as Ramondo and Rodriguez-Clare (2013), Tintelot (2017), and ARRY (2018) 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 observed in the Chinese customs data since they assume that all firms producing in the same country face the same set of export costs. I depart from these models by developing a tractable general equilibrium model that is flexible to capture headquarters gravity. My model is also closely related to recent quantitative MP models that take into account the micro-structure of multinational production. In particular, Head and Mayer (2019) introduce a marketing friction between headquarters and the destination market into a quantitative model and estimate the model using data from the car industry. However, as mentioned

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5 The BMP shares are defined as the ratio of BMP to total MP flows. Then I average the BMP shares of the US multinationals over all production locations.

6 The BEA data shows that for most of the host countries, the affiliates of US multinationals have higher export shares to the U.S. than other firms. Therefore, the sales bias towards the U.S. market can explain at least part of the BMP of US multinationals. Details of the BEA data are presented in the appendix.

above, their model is designed to characterize a single industry and cannot be directly used to study general equilibrium and welfare effects.\(^8\)

This paper also relates to the literature on estimation and counterfactual analysis in partially (set) identified models.\(^9\) Partial identification relaxes restrictive assumptions required for point identification and enables us to compare implications of various model specifications. It is used widely in estimating 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. In this paper, I apply the methodology of de Gortari (2019) to construct counterfactual bounds in a general equilibrium model with both trade and MP.

This paper is related to the empirical assessments on how foreign multinational affiliates differ from local firms. Antras and Yeaple (2014) provide a comprehensive summary of the differences documented in the literature. In this paper, I document a novel feature of multinationals’ export-platform networks, headquarters gravity, using Chinese customs data for all industries and show its quantitative importance. Also relevant is the discussion on what multinationals bring to the host countries. The conventional wisdom is that these firms bring jobs and advanced production technologies.\(^{10}\) My work complements this literature by suggesting that multinationals also provide host countries with access to foreign markets.

By exploring the impacts of headquarters locations on affiliate exports, this paper sheds light on informational and marketing frictions in international trade documented in Arkolakis (2010) and Allen (2014). Unlike domestic firms whose production sites and headquarters are located in the same country, multinationals produce outside home countries, enabling us to disentangle the standard gravity from headquarters gravity. Structural estimates suggest these informational and marketing costs of international trade are quantitatively important.

The rest of the paper is organized as follows. Section 2 documents empirical regularities in the Chinese customs data that motivate my quantitative framework. Section 3 incorporates headquarters gravity into a general equilibrium model and discusses its implications for counterfactual predictions. Section 4 calibrates the model to aggregate trade and MP data and studies its counterfactual predictions. Section 5 concludes.

\(^8\)Cosar et al. (2018) also document the home market advantage in the automobile industry and estimate a quantitative model of this industry.

\(^9\)Ho and Rosen (2017) provide a comprehensive summary on partial identification in applied research.

\(^{10}\)See Arnold and Javorcik (2009), Burstein and Monge-Naranjo (2009), and McGrattan and Prescott (2009).
2 Empirical Regularities

2.1 Micro Data

To understand the export behaviors of multinational affiliates operating in China, I merge three sets of micro data. First, the Annual Survey of Chinese Manufacturing (ASCM), collected by the Chinese National Bureau of Statistics, provides firm-level operation characteristics such as sales, capital, 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). The manufacturers excluded from ASCM are small and unlikely to be engaged in international trade. Therefore, ASCM covers the majority of Chinese manufacturing exporters.

Second, I supplement ASCM with firm-level exports by destination from Chinese Customs Records (CCR). CCR documents transaction-level exports with destination country, the 8-digit HS code, export mode (ordinary or processing trade), export value and quantity. CCR is merged with ASCM by firms’ contact information such as name, address, zip code, and phone number.

Finally, 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 (not only for manufacturing firms), with names and nationalities of their foreign investors. Moreover, FIESC can be merged with ASCM by numeric firm identifiers.

The combined Chinese firm data is ideal for studying export-platform FDI. First, China is a major exporter and FDI 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 et al. (2015) links restricted U.S. Census Bureau microdata to firms’ international ownership structure. However, they focus on the imported inputs of the U.S. affiliates of foreign multinationals instead of exploring their export behaviors.

Now I turn to describing two empirical regularities in the combined Chinese firm data. The first documents the multinationals’ advantage in exporting, and the second motivates a novel ingredient that I argue should be included in the quantitative MP models.
1 \{\exp(\nu) > 0\} & \exp(\nu) / \text{sales}(\nu) & \log(\exp(\nu) / \text{sales}(\nu)) \\
\hline
\text{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. & ✓ & ✓ & ✓ \\

R-square & .17 & .26 \\
N. of Obs. & 106482 & 101529 & 7964 \\
\hline

Table 1: The export advantage of foreign affiliates of multinationals in China

(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.)

2.2 Export advantage of Chinese affiliates of foreign multinationals

Multinational affiliates are large producers and exporters in host countries. As illustrated in Figure [1], Chinese firm-level data shows that in 2001 foreign multinationals affiliates accounted for 23% of Chinese manufacturing plants but 35% of manufacturing sales and 77% of manufacturing exports.

The multinationals’ export advantage in aggregate data may come from their advantages on size or productivity. To control for these effects, I regress firms’ export decision (both in intensive and extensive margins) on a dummy for foreign multinationals and several observed firm characteristics. To make firms comparable, I restrict the sample as follows: (i) I exclude processing traders; (ii) I exclude firms located in exporting zones; (iii) I exclude state-owned firms; and (iv) I exclude Hong Kong, Macau, and Taiwanese firms. The results are shown in Table [1].

Fact 1: Controlling for observed firm characteristics, the Chinese affiliates of foreign multinationals are more much likely to export and export more than Chinese domestic firms.

The results in Table [1] show that after controlling for size, productivity, and industry fixed effects, foreign firms are still more likely to export and export more than 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.

### 2.3 Headquarters Gravity

The combined Chinese firm data allows me to link a firm’s export destinations to the location of its headquarters. In this subsection, I test whether the proximity of headquarters and destination countries facilitates the affiliates’ exports. In particular, 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 \(i\) and destination \(n\) by their physical distance (\(\text{dist}_{in}\)), common language (\(\text{lang}_{in}\)), common legal origin (\(\text{legal}_{in}\)), OECD status (\(\text{OECD}_{in}\))[11] and dummy for the headquarters country itself (\(1\{i = n\}\)). The results are shown in Table 2.

**Fact 2:** 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) in Table 2 suggests 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 (Column (2) in Table 2). Notice that for Chinese domestic firms, the headquarters gravity cannot be separated from the standard gravity. So I exclude Chinese domestic firms in these regressions.

I also estimate aggregate headquarters gravity by regressing the aggregate sales of Chinese affiliates of multinationals from country \(i\) to market \(n\) 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. The results are reported in Column (3) of Table 2. The aggregate 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%.

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[11]It is equal to 1 if both \(i\) and \(n\) are OECD countries or if neither of them is in OECD.
<table>
<thead>
<tr>
<th></th>
<th>Column (1)</th>
<th>Column (2)</th>
<th>Column (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1{x_{i,CHN,n}(\nu) &gt; 0}$</td>
<td>-.082***</td>
<td>-.085***</td>
<td>-.204***</td>
</tr>
<tr>
<td>log(dist$_{in}$)</td>
<td>(.018)</td>
<td>(.03)</td>
<td>(.056)</td>
</tr>
<tr>
<td>lang$_{in}$</td>
<td>.075*</td>
<td>.19***</td>
<td>.16</td>
</tr>
<tr>
<td></td>
<td>(.038)</td>
<td>(.07)</td>
<td>(.13)</td>
</tr>
<tr>
<td>legal$_{in}$</td>
<td>.10***</td>
<td>-.016</td>
<td>.27***</td>
</tr>
<tr>
<td></td>
<td>(.026)</td>
<td>(.06)</td>
<td>(.09)</td>
</tr>
<tr>
<td>OECD$_{in}$</td>
<td>.1***</td>
<td>.041</td>
<td>.45***</td>
</tr>
<tr>
<td></td>
<td>(.02)</td>
<td>(.05)</td>
<td>(.08)</td>
</tr>
<tr>
<td>$1{i = n}$</td>
<td>.95***</td>
<td>1.17***</td>
<td>2.46***</td>
</tr>
<tr>
<td></td>
<td>(.13)</td>
<td>(.14)</td>
<td>(.24)</td>
</tr>
<tr>
<td>Destination FE</td>
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<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Origin FE</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Affiliate FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>R-squared</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Obs.</td>
<td>366300</td>
<td>17270</td>
<td>2252</td>
</tr>
</tbody>
</table>

(Notes: “$i$” refers to the country of origin and “$n$” refers to the destination country. In column (1), I regress the dummy for a Chinese affiliate of country $i$’s multinational to export to country $n$ on measures of distance between country $i$ and $n$, using the Probit model. In column (2), I conduct the similar regression for the intensive margin of exports. In column (3), I regress the total exports of Chinese affiliates of country $i$’s multinationals to country $n$ on distance between country $i$ and $n$. 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.)
2.4 Discussion

Headquarters gravity suggests that a firm’s capability of making sales is destination-specific and depends on its country of origin. It is consistent with empirical evidence from data on specific industries (Head and Mayer (2019) and Cosar et al. (2018) on car industry, Bronnenberg, Dhar, and Dube (2009) on consumer packaged goods). These studies suggest that firms tend to bias their sales towards markets close to their headquarters, regardless of their production locations. They argue that this bias may be due to the firms’ advantage in marketing costs, consumers’ perceived quality of brands, or knowledge about the consumers’ tastes in these markets. No matter if this bias is driven by demand- or supply-side factors, it implies that multinational affiliates effectively create foreign demand for labor in the host countries.

Table 3: Headquarters Gravity: Differentiated vs Homogeneous Goods

<table>
<thead>
<tr>
<th>Dependent Variable: $1{x_{i,\text{CHN,n}(\nu)}&gt;0}$</th>
<th>Diff.</th>
<th>Homo.</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(dist$_{in}$)</td>
<td>-.0954***</td>
<td>.0378*</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>lang$_{in}$</td>
<td>.0719*</td>
<td>.116**</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>legal$_{in}$</td>
<td>.114***</td>
<td>.0172</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.037)</td>
</tr>
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<td>OECD$_{in}$</td>
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<td>.0521*</td>
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<td>(0.021)</td>
<td>(0.031)</td>
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<td>$1{i=n}$</td>
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<td>1.148***</td>
</tr>
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<td>(0.13)</td>
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<td>✓</td>
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<tr>
<td>Affiliate FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td># Obs.</td>
<td>294866</td>
<td>52884</td>
</tr>
</tbody>
</table>

(Notes: Differentiated goods are goods coded by “n” in Rauch (1999), while all other products are regarded as homogeneous goods. The extensive margin is estimated using the Probit 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.)

Using the augmented Chinese customs data, I can estimate headquarters gravity in a large variety of industries. Doing this, I test whether headquarters gravity merely reflects features of global value chains for specific industries such as car and consumer electronics. First, I estimate headquarters gravity for homogeneous and differentiated goods, classified by Rauch (1999). Table 3 shows 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 far away from headquarters. In contrast, the transactions of
homogeneous goods are to large extent standardized and therefore rely little on marketing.

Second, 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. As shown in Figure 2, headquarters gravity is quite robust, holding for 13 out of 16 industries.

![Figure 2: Headquarters Gravity in 2-digit HS Industries](image)

(Note: Each red circle refers to the coefficient of physical distance between headquarters and destination in the regression a la column (1) of Table 2.)

Another concern is 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. To address this concern, I exclude affiliates from Japan and Korea and re-estimate headquarters gravity. Headquarters gravity still holds, as suggested by Table 4.

It is also interesting to compare the magnitudes of headquarters gravity with the standard gravity. To achieve this, I replace the destination fixed effects in the firm-destination-level regression by the distance between the destination country and China and the GDP of the destination country. The result suggests that the standard gravity is much stronger than headquarters gravity; but headquarters gravity is not negligible. The details are presented in the appendix.

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12 The sectoral shares of related-party trade in the U.S. are documented by Antras (2003).
log\( (x_i, \text{CHN}, n(\nu)) \) 

<table>
<thead>
<tr>
<th></th>
<th>( \log(\text{dist}_{in}) )</th>
<th>( 1{x_i, \text{CHN}, n(\nu) &gt; 0} )</th>
</tr>
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<tr>
<td></td>
<td>(-0.0850^{**})</td>
<td>(-0.0304^{**})</td>
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<td></td>
<td>(0.033)</td>
<td>(0.014)</td>
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<tr>
<td>lang(_{in})</td>
<td>0.0601</td>
<td>0.131^{***}</td>
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<td>(0.071)</td>
<td>(0.028)</td>
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<tr>
<td>legal(_{in})</td>
<td>0.0712</td>
<td>0.109^{***}</td>
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<td>(0.021)</td>
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<td>OECD(_{in})</td>
<td>0.0995*</td>
<td>0.135^{***}</td>
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</table>

**Table 4:** Headquarters Gravity: Excluding Japanese and Korean Firms

(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.)

### 3 Model

I consider a world economy with \( N \) countries and build a model a la ARRY (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 \( \ell \) 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 the total sales of firms originated from country \( i \) to destination country \( n \) from their affiliates in country \( \ell \), \( X_{i\ell n} \). The collection \( \{X_{i\ell n}\}_{i,\ell,n=1,...,N} \) is called the *multinationals’ export-platform networks*, which I argue are crucial in shaping the welfare consequences of trade and MP shocks in this model.

#### 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 \(\omega\) originated from country \(i\) producing in country \(\ell\).

Following Melitz (2003) and ARRY (2018), I call the process of creating differentiated varieties “innovation”. I assume that creating a new variety in country \(i\) requires \(f^e\) units of country \(i\)’s labor. In the presence of MP, a country tends to specialize in innovation if its firms offshore a large fraction of their 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 \(\omega\) 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 \(\ell\) 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 \(\ell\) 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 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 \(n\). Figure 3 summarizes trade and MP frictions in the model.

The headquarters-destination-specific marketing cost, \(\zeta_{in}\), is the new element that enables my model to capture headquarters gravity observed in the data. It captures various impediments that multinational firms face 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. This new margin of trade friction is set in the form of iceberg costs for three reasons. First, it simplifies the model aggregation and delivers tractable solutions. Second, it resembles the thought that making larger sales incurs higher marketing costs. Third, under the CES preference, the iceberg cost is equivalent to a headquarters-destination-specific demand shifter.\(^{13}\)

Subject to frictions of international production and sales, firm \(\omega\) originated from \(i\) has a unit cost \(c_{i\ell n}(\omega)\) to serve market \(n\) from its plant in country \(\ell\):

\[
c_{i\ell n}(\omega) = \frac{\gamma_{i\ell} T_{\ell n} \zeta_{in} w_{\ell}}{z_{i\ell}(\omega)},
\]

\(^{13}\)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.
where $w_{\ell}$ is the wage in country $\ell$.

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

$$\ell = \arg\min_k \bar{\sigma} c_{ikn}(\omega) = \arg\min_k \frac{\xi_{ikn}}{z_{ik}(\omega)}, \quad \xi_{i\ell n} := \gamma_{i\ell} \tau_{\ell n} \zeta_{in} w_{\ell}.$$  \hfill (2)

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

$$c^*_n = \left( \frac{\sigma w_n F_n}{X_n} \right)^{\frac{1}{\bar{\sigma}}} \frac{P_n}{\bar{\sigma}}.$$  \hfill (3)

### 3.2 Aggregation and Theory-Based Gravity Equation

In this subsection, I aggregate the firms’ choices and deliver theory-based gravity equations that shape multinationals’ export-platform networks, preparing my model to match with the aggregate bilateral trade and MP data. Following Arkolakis et al. (2018), I assume
that \((z_{i\ell}(\omega))_{\ell=1}^N\) are drawn from a multi-variate Pareto distribution:

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

(4)

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

Let \(M_i\) be the mass of firms in country \(i\). Following ARRY (2018), if \(\xi_{i\ell n} \geq \tilde{T}_i c^{*}_{in}\) for all \((i, \ell, n)\), then the multinationals’ export-platform networks, \(\{X_{i\ell n}\}\), can be characterized by:

\[
\pi_{i\ell n} := \frac{X_{i\ell n}}{X_n} = \psi_{i\ell n} \lambda_{in},
\]

(5)

where

\[
\psi_{i\ell n} = \frac{A_\ell \xi_{i\ell n}^{-\frac{\theta}{1-\rho}}}{\Psi_{in}^{-\frac{1-\rho}{\theta}}}, \quad \Psi_{in} = \left[ \sum_{\ell=1}^N A_\ell \xi_{i\ell n}^{-\frac{\theta}{1-\rho}} \right]^{1-\rho},
\]

(6)

and

\[
\lambda_{in} = \frac{M_i T_i \Psi_{in}}{\sum_k M_k T_k \Psi_{kn}}.
\]

(7)

Equation (5) is a theory-based gravity equation that expresses the multinationals’ export-platform networks, \(\{X_{i\ell n}\}\), in terms of technologies in innovation and production countries, factor prices in production countries, market size and prices in destination countries, and bilateral MP, trade, and marketing frictions. As discussed in ARRY (2018), Equation (5) is a strict extension on the gravity equation for bilateral trade flows based on pure trade models such as Eaton and Kortum (2002) and Melitz (2003).

How should we understand the observed bilateral trade flows using my model with MP and headquarters gravity? Letting \(X_{TRn} := \sum_{i=1}^N X_{i\ell n}\), I have:

\[
\log (X_{TRn}) = \log A_\ell - \frac{\theta}{1-\rho} \log (w_\ell) + \log \left( \sum_{i=1}^N \lambda_{in} \Psi_{in} \right) X_n \tag{8}
\]

\[
- \frac{\theta}{1-\rho} \log \tau_{in} + \sum_{i=1}^N (\gamma_{i\ell} \xi_{i\ell n})^{-\frac{\theta}{1-\rho}}.
\]

Bilateral trade barrier

Third-country effect via MP

Equation (8) 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 Equation (8), representing a third-country effect via MP. This term can be understood through a simple example. Suppose that the exporting country \( \ell \) 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 for 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 Equation (8) suggests that, for multinationals, the center of gravity lies somewhere in between their production locations and their headquarters. The sales of multinationals 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 ARRY (2018), then the new third-country effect in Equation (8) will be absorbed by the exporter fixed effect and Equation (8) will degenerate to the standard gravity equation.

In sum, in the presence of MP and headquarters gravity, the standard gravity equation is not sufficient to characterize bilateral trade flows across countries. The third-country effect via MP has to be considered.

### 3.3 Equilibrium

I then close the model by market clearing conditions. Based on the property of multivariate 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 \( s^f := \frac{1}{\sigma} - s = \frac{2-1}{\theta \sigma} \) in the sales. Then the equilibrium wage is determined by the labor market clearing:

\[
W_\ell L_\ell = \left(1 - \frac{1}{\sigma}\right) \sum_{i,n} X_{i\ell n} + s \sum_{i,k} X_{ik\ell} + s^f \sum_{k,n} X_{\ell kn}.
\]  

(9)

The total expenditure is equal to the wage income:

\[
X_i = w_i L_i.
\]  

(10)
The price index can be expressed as

\[ P_n^{-\delta} = \left( \frac{w_nF_n}{X_n} \right)^{-\frac{\theta-(\sigma-1)}{\sigma-1}} \left[ \sum_k M_k T_k \Psi_{kn} \right]. \]  \hspace{1cm} (11)

Finally, free entry implies that

\[ M_i w_i f^e = s^f \sum_{\ell,n} X_{i\ell n}. \] \hspace{1cm} (12)

**Definition 1** The equilibrium consists of \((w_i, M_i)\) such that

1. Wage satisfies labor market clearing in Equation (9).
2. Firm mass satisfies the free entry condition in Equation (12).

### 3.4 Welfare

In this subsection, I explore how multinationals’ export-platform networks, \{\(X_{i\ell n}\)\}, shape the welfare implications of my model. I first show that the sufficient statistics of welfare changes based on my model is identical to the one developed by ARRY (2008). Consider shocks on technologies or trade/MP frictions. For any variable \(y\), I denote \(y'\) as the level of \(y\) after shocks and \(\hat{y} = y' / y\). Let \(W_i := w_i / P_i\) be the real wage in country \(i\) and \(Y_i f := \sum_{n,\ell} X_{i\ell n}\). Then welfare changes led by shocks can be expressed by

\[ \hat{W}_i = \left[ \pi_{iii}^{-\frac{1-\sigma}{\sigma}} \lambda_{ii}^{-\frac{\theta}{\sigma}} \right] \left( \frac{\dot{Y}_i f}{\dot{X}_i} \right)^{\frac{1}{\theta}}. \] \hspace{1cm} (13)

Equation (13) requires \((\pi_{iii})\) and \((\lambda_{ii})\) before and after shocks. There is one special case: welfare changes from autarky to the current equilibrium. In autarky, \(\pi_{iii} = \lambda_{ii} = 1\) for all \(i\). Then I have

\[ \text{GO}_i := \frac{W_i}{W_i^{\text{Aut}}} = \left[ \pi_{iii}^{-\frac{1-\sigma}{\sigma}} \lambda_{ii}^{-\frac{\theta}{\sigma}} \right] \left( \frac{Y_i f}{X_i} \right)^{\frac{1}{\theta}}. \] \hspace{1cm} (14)

Equation (14) is essentially a special case of Equation (27) in ARRY (2018). It suggests that the gains from openness consist of two parts. The first bracket is the term that refers to the gains from getting access to cheaper varieties that are created and produced abroad, which is an extension to the standard ACR term. The second bracket is the ratio of total...
value created by a country over its total expenditure, which captures a country’s 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.

Notably, Equation (14) cannot be directly applied to compute welfare gains from openness because the necessary data is not available. In particular, the expenditure share of goods that are domestically created and produced, \( \pi_{iii} \), and the expenditure of goods that are domestically created, \( \lambda_{ii} \), are both unobservable in the aggregate data. Instead, these shares have to be imputed by matching the model-generated bilateral trade and MP flows to the data, which depends crucially on the model structure. For example, \( \lambda_{ii} \) would depend on the extent to which multinationals bias their sales towards their home countries, regardless of their production sites. In Section 4, I will explain in detail how headquarters gravity, \( \zeta_{in} \), affects the imputation of \( \pi_{i\ell n} \) and thereby shapes the counterfactual predictions.

### 3.5 “Exact-hat” Algebra

To guide my quantitative analysis in the next section, I express the relative changes in equilibrium outcomes in terms of exogenous shocks, parameters \( \left( \theta, \rho, \sigma \right) \), and the multinationals’ export-platform networks \( \left( X_{i\ell n} \right) \).

First, the labor market clearing condition can be expressed in relative changes:

\[
\hat{w}_{\ell}w_{\ell}L_{\ell} = \left( 1 - \frac{1}{\sigma} \right) \sum_{i,n} X'_{i\ell n} + s \sum_{i,k} X'_{i\ell k\ell} + s^f \sum_{k,n} X'_{\ell kn},
\]

(15)

where

\[
\hat{\pi}_{i\ell n} = \hat{\psi}_{i\ell n} \hat{\lambda}_{in}, \quad \hat{X}_i = \hat{w}_i,
\]

and where

\[
\hat{\psi}_{i\ell n} = \frac{\hat{\xi}_{i\ell n}^{\frac{1}{1+\rho}}}{\hat{\Psi}_{in}^{1+\rho}}, \quad \hat{\Psi}_{in} = \left[ \sum_{\ell=1}^{N} \psi_{i\ell n} \hat{\xi}_{i\ell n}^{\frac{1}{1+\rho}} \right]^{1+\rho},
\]

\[
\hat{\xi}_{i\ell n} = \hat{\gamma}_{i\ell \ell n} \hat{\zeta}_{in} \hat{w}_{\ell}, \quad \hat{\lambda}_{in} = \frac{\hat{M}_i \hat{\Psi}_{in}}{\sum_{k=1}^{N} \lambda_{kn} \hat{M}_k \hat{\Psi}_{kn}}.
\]

Second, the free entry condition can be re-written as

\[
\hat{M}_i \hat{w}_i M_i \hat{w}_i f^e = s^f \sum_{\ell, n} X'_{i\ell n}.
\]

(16)
Finally, to compute welfare changes, I express changes in price indices as

$$\hat{P}_{n}^{-\theta} = \left[ \sum_{k} \lambda_{kn} \hat{M}_{k} \hat{\Psi}_{kn} \right].$$  \hspace{1cm} (17)

With \((\theta, \rho, \sigma)\) in hand, the equation system consisting of Equation 15 and (16) maps counterfactual equilibrium changes one-to-one into multinationals’ export-platform networks, \((X_{i\ell n})\). However, this “exact-hat” algebra cannot be directly applied to compute counterfactual changes exactly because \((X_{i\ell n})\) is not available. Consequently, what lies at the center of my quantitative analysis in the next section is how to impute \((X_{i\ell n})\) based on my model from various data sources about trade, MP, and export-platform sales.

4 Calibration and Quantification

In this section I calibrate the model and perform counterfactuals. First, I calibrate parameters \((\theta, \rho, \sigma)\) from the literature. Then I discuss what information is required for imputing \((X_{i\ell n})\) based on my model. In particular, I show that my model can generate many export-platform networks of multinationals, \((X_{i\ell n})\), that exactly replicate the observed bilateral trade and MP flows. Then I construct bounds on counterfactual changes using this partially identified model. These bounds encompass counterfactual predictions made by the ARRY model, revealing to what extent the ARRY model may mis-estimate welfare consequences of trade and MP shocks. Then I discuss how to narrow these bounds by incorporating additional information on multinationals’ exports. Finally, several policy-motivated counterfactuals are performed and discussed.

\((\theta, \rho, \sigma)\) are calibrated as follows. First, I set \(\sigma = 4\), targeting on the profit share 25%. Second, I calibrate \((\theta, \rho)\) from ARRY (2018). They estimate \(\theta/(1 - \rho)\) using the global sales of the U.S. multinational affiliates and calibrate \(\theta\) to match the coefficients of the standard gravity equation for bilateral trade flows. They get \(\theta = 4.5\) and \(\rho = 0.55\).

4.1 Imputing Export-Platform Networks

As discussed in Section 3.5, trilateral flows \((X_{i\ell n})\) are essential for my counterfactual analysis and are not observed in the aggregate trade and MP data. In this subsection, I will discuss what information is required for imputing \((X_{i\ell n})\) based on my model. Suppose that I have observed trade value from country \(\ell\) to \(n\), \(X_{\ell n}^{TR}\), and MP sales from country \(i\) to \(\ell\),
Let $\tilde{T}_{i\ell} = (M_i T_i)^{-\frac{1}{\gamma}} \gamma_{i\ell}$ and $\tilde{\tau}_{\ell n} = A_{\ell}^{-\frac{1-\rho}{\gamma}} \tau_{\ell n} w_{\ell}$. Then Equation (5) implies that

$$X_{i\ell n} \left( \tilde{T}, \tilde{\tau}, \zeta \right) := \frac{\tilde{T}_{i\ell}^{-\frac{1}{1-\rho}} \tilde{\tau}_{\ell n}^{-\frac{1}{1-\rho}} \zeta_{i\ell n}^{-\frac{1}{1-\rho}} \left[ \sum_k \tilde{T}_{ik}^{-\frac{1}{1-\rho}} \tilde{\tau}_{kn}^{-\frac{1}{1-\rho}} \zeta_{kn}^{-\frac{1}{1-\rho}} \right]^{-\rho} X_n. \tag{18}$$

Equation (18) suggests that $(X_{i\ell n})$ can be expressed in terms of three matrices $\left( \tilde{T}, \tilde{\tau}, \zeta \right)$. Given $(\zeta_{i\ell n})$, $\left( \tilde{T}, \tilde{\tau} \right)$ can be imputed from the bilateral trade and MP flows by solving the following system of equations:

$$\sum_i X_{i\ell n} \left( \tilde{T}, \tilde{\tau}, \zeta \right) X_n = X_{TR}^{TR}, \quad \sum_n X_{i\ell n} \left( \tilde{T}, \tilde{\tau}, \zeta \right) X_n = X_{i\ell n}^{MP}, \quad \sum_{k,n} X_{k\ell n} \left( \tilde{T}, \tilde{\tau}, \zeta \right) X_n = X_{k\ell n}^{MP}. \tag{19}$$

Therefore, imputing $(X_{i\ell n})$ requires bilateral trade and MP flows as well as $(\zeta_{i\ell n})$.

In this paper, I consider the world economy in 2001 comprising of 14 economies: Benelux (Belgium + Luxembourg + the Netherlands), Canada, China, Germany, France, the United Kingdom, India, Ireland, Japan, Korea, Mexico, Taiwan, the U.S., and the rest of the world. The aggregate bilateral trade flows (including domestic sales) come from WIOD. The aggregate bilateral MP flows come from Ramondo et al. (2015).

Notably, ARRY (2018) pointly identify their model by assuming that $\zeta_{i\ell n} = 1$ for all $(i, n)$. Under this assumption, $\left( \tilde{T}, \tilde{\tau} \right)$ are solved from Equation (19) and $(X_{i\ell n})$ are computed accordingly. However, the assumption that $\zeta_{i\ell n} = 1$ for all $(i, n)$ is inconsistent with headquarters gravity documented from the Chinese customs data. To see this more clearly, I input $(X_{i, CHN, n})$ based on the ARRY model, run the regression similar to Column (3) in Table 2, and compare the results with the regression using the Chinese customs data.

The results in Table 5 show clearly that the ARRY model is inconsistent with the headquarters gravity. In fact, due to the proximity-concentration trade-off, 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.

While the assumption that $\zeta_{i\ell n} = 1$ for all $(i, n)$ is not supported by the micro data, in the next subsection I will discuss what counterfactual predictions I can get without imposing this assumption.

---

14 To make a fair comparison, I restrict the data sample in the 14 economies considered above.
Table 5: Headquarters Gravity: Data vs. the ARRY Model

<table>
<thead>
<tr>
<th>Dependent Variable: log($X_{i,CHN,n}$)</th>
<th>Data</th>
<th>ARRY</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(dist$_{in}$)</td>
<td>-.315***</td>
<td>.641***</td>
</tr>
<tr>
<td></td>
<td>(.11)</td>
<td>(.092)</td>
</tr>
<tr>
<td>lang$_{in}$</td>
<td>-.380</td>
<td>.07</td>
</tr>
<tr>
<td></td>
<td>(.32)</td>
<td>(.27)</td>
</tr>
<tr>
<td>legal$_{in}$</td>
<td>.478**</td>
<td>-.254*</td>
</tr>
<tr>
<td></td>
<td>(.23)</td>
<td>(.14)</td>
</tr>
<tr>
<td>OECD$_{in}$</td>
<td>.722</td>
<td>-.575</td>
</tr>
<tr>
<td></td>
<td>(.56)</td>
<td>(.42)</td>
</tr>
<tr>
<td>1{i = n}</td>
<td>1.118***</td>
<td>-1.845***</td>
</tr>
<tr>
<td></td>
<td>(.41)</td>
<td>(.56)</td>
</tr>
</tbody>
</table>

Destination FE ✓ ✓
Origin FE ✓ ✓
R-squared .841 .959
# Obs. 131 144

(Notes: “i” refers to the country of origin and “n” refers to the destination country.)

4.2 Bounding Counterfactuals

What would be my model’s counterfactual predictions without knowing ($\zeta_m$)? In this case, Equation (19) contains $2N^2$ equations but $3N^2$ variables. In other worlds, there are many model parameterizations that are consistent with bilateral trade and MP flows. Without knowing ($\zeta_m$), my model is partially identified and does not yield point estimates on counterfactual predictions.

However, I could characterize counterfactual predictions of this partially identified model by constructing bounds on counterfactual changes. For example, armed with the values of ($\theta, \rho, \sigma$) and data on ($X^R_{i\ell n}, X^{MP}_{i\ell}$), I am interested in the bounds on welfare changes, defined as

$$\max(\min)_{(w, M, \tilde{P}, \tilde{T}, \tilde{\tau}, \tilde{\zeta})} \tilde{W}_1 := \frac{\hat{w}_1}{\tilde{P}_1}$$

s.t. $$(\tilde{w}, \tilde{M}, \tilde{P})$$ satisfy Equation (15), (16), and (17). $$(\tilde{T}, \tilde{\tau}, \tilde{\zeta})$$ satisfy Equation (19). (20)

In Equation (20), I maximize/minimize the changes in country 1’s welfare, taking the system of “exact-hat” algebra and the system for imputing ($X_{i\ell n}$) as constraints. This constrained optimization framework can be used to perform counterfactual experiments based on partially identified models.

As discussed above, the framework of Equation (20) follows the methodology in de Gor-
tari (2019) and 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 a result, focusing on the bounds of counterfactuals is useful in many quantitative exercises.

Notably, it is straightforward to see that the following set is convex:

\[
\left\{ X_{i\ell n} \left( \mathbf{T}, \tilde{\tau}, \zeta \right) : \frac{\sum_i X_{i\ell n} \left( \mathbf{T}, \tilde{\tau}, \zeta \right)}{X_n} = X_{\ell n}^{TR}, \quad \frac{\sum_n X_{i\ell n} \left( \mathbf{T}, \tilde{\tau}, \zeta \right)}{\sum_{k,n} X_{k\ell n} \left( \mathbf{T}, \tilde{\tau}, \zeta \right) = X_{\ell n}^{MP}} \right\}. \tag{21}
\]

Therefore, any level of $\hat{W}_1$ within the bounds defined by Equation (20) is feasible.

Solving the bounds on counterfactuals by Equation (20) 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 set of $\left( \mathbf{T}, \tilde{\tau}, \zeta \right)$ that satisfies the constraints. 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 Equation (20). 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.

### 4.3 Bounds on Gains from Openness

There is one special counterfactual exercise whose computation can be simplified: computing the welfare changes from autarky to the current equilibrium. The key to simplify computation is the closed-form solution to welfare gains from openness provided by Equation (14). The bounds of gains from openness can be computed by

\[
\max(\min) \left( \mathbf{T}, \tilde{\tau}, \zeta \right) \left[ \pi_1^{1-\rho} \lambda_1^{\rho-1} \right] \left( \frac{Y_i^f}{X_1} \right)^{\frac{1}{\lambda}}
\]

s.t. $\pi_{i_1} := \frac{X_{i_1} \left( \mathbf{T}, \tilde{\tau}, \zeta \right)}{X_1}$, $\lambda_{i_1} := \frac{\sum_k X_{ik} \left( \mathbf{T}, \tilde{\tau}, \zeta \right)}{X_1}$, $\left( \mathbf{T}, \tilde{\tau}, \zeta \right)$ satisfy Equation (19). \tag{22}
Since \( \frac{Y_i^f}{X_i} \) is observed in the aggregate MP and trade data, the bounds on gains from openness rely on the estimates of \( \pi_{iii} \) and \( \lambda_{ii} \).

I compute the bounds on welfare gains from openness by solving Problem (22) and leave more general counterfactual exercises to Section 4.5. Figure 4 plots the welfare gains from openness relative to autarky in the ARRY model, which imposes that \( \zeta_{in} = 1 \) for all \((i, n)\), and in my model without restrictions on \( (\zeta_{in}) \). Since the set of constraints in Problem (22) is convex, any value within the bounds is feasible.

The bounds on gains from openness vary substantially across countries. For large countries like the U.S., the range of welfare gains from openness without restrictions on \( (\zeta_{in}) \) lies between 7.3 – 12%, while the gain from openness implied by the ARRY model is 11.6%. The bounds for the U.S. are relatively narrow because it is large and relatively closed. In contrast, for small open economy like Canada, the range without restrictions on \( (\zeta_{in}) \) lies between 11.9 – 57.8%, while the gain from openness implied by the ARRY model is 41.1%. In sum, even without restrictions on \( (\zeta_{in}) \), my model calibrated to bilateral trade and MP data is informative about the gains from openness for large and relatively closed economies, but not so informative about the gains from openness for small open economies.

![Figure 4: Bounds on the Welfare Gains from Openness](image)

(Note: the y-axis presents the percentage welfare changes from autarky to the current equilibrium.)

Comparing to the counterfactual predictions in ARRY (2018), the reason why I have

\[15\] The point estimates under headquarters gravity will be explained in detail in the next subsection.
bounds on gains from openness here is that I do not put restrictions on \((\zeta_i)\). Then how do \((\zeta_i)\) look like under the bounds on gains from openness? Exploring these extremes would tell us to what extent our counterfactual analysis relies on detailed data that characterizes multinationals’ exporting behaviors.

Figure 5 plots \((\zeta_i)\) that maximizes/minimizes the Canadian gains from openness against the bilateral distance between country \(i\) and \(n\). It shows that the gains from openness tend to be low if \((\zeta_i)\) is strongly positively correlated with distance, i.e. the headquarters gravity is strong. Intuitively, strong headquarters gravity implies that most of the domestically consumed varieties are created domestically. In this case, \(\lambda_{ii}\) is large and therefore the gains from openness is low. In contrast, when headquarters gravity is weak (blue dots in Figure 5), foreign multinational affiliates tend to provide a large fraction of varieties consumed by the host country. In this case, shutting down MP will lead to substantial welfare losses. In a nutshell, to understand welfare gains from openness, it is crucial to measure the fraction of consumption goods that are created in foreign countries, which is not directly observed in bilateral trade and MP data.

The variation of bounds across countries is also intuitive. For small open economies like Canada, Ireland, and Benelux, foreign multinational affiliates account for a substantial share in total production. Therefore, whether these MP sales go to their domestic markets or export markets is crucial for welfare gains from openness. In extreme cases of Ireland and Benelux, it is consistent with the observed bilateral trade and MP flows that all varieties consumed in these two countries are created by foreign multinationals. As a result, the upper bounds of their gains from openness go to infinity. In contrast, for large countries like India, Japan, and the U.S., foreign multinational affiliates only account for a small fraction of production, which implies that headquarters gravity has little impacts on their gains from openness.

Figure 4 also suggests that for most countries, the gains from openness implied by the ARRY model are close to their upper bounds, indicating that for most countries the ARRY model tends to over-estimate their welfare gains from openness. Why is this? As discussed above, the upper bounds of gains from openness can exceed those implied by the ARRY model if \(\zeta_i\) is negatively correlated with distance, i.e. foreign multinational affiliates have advantage in serving the host country, while domestic firms have advantage in exporting. However, to replicate the observed trade and MP flows, this negative correlation cannot be too strong. The intuition is that in most countries, domestic firms account for the majority of production. If these firms have advantage in exporting, the exports will be much larger
than their observed levels. In this sense, the bilateral trade and MP flows impose implicit restrictions on \((\zeta_m)\).

4.4 Narrowing the Bounds

Previously, I have shown that without restrictions on \((\zeta_m)\), I can only construct bounds on counterfactual predictions, which could be uninformative for some countries. In this section, I discuss to what extent incorporating information on multinationals’ exports can narrow the bounds and thus provide more precise counterfactual predictions. I will do it in two ways. First, I impose a simple additional restriction on multinationals’ exports that is motivated by Figure 1, showing that even such a simple additional restriction can substantially narrow the bounds on gains from openness. Second, I incorporate the Chinese customs data to pointly identify the model.

4.4.1 Narrowing the Bounds with Simple Additional Restrictions

Unlike bilateral trade and MP flows, aggregate data on multinationals’ exports, or multinationals’ export-platform networks, are scarce. We know little about where multinational affiliates serve their products. Without such information, the bounds on counterfactual predictions could be very wide, as suggested by Figure 1. However, empirical regularities from aggregate data in Figure 1 may help us to rule out a large number of export-platform net-
works of multinationals that replicates the observed bilateral trade and MP flows. Here I consider the following simple restriction:

\[
\frac{\sum_{i \neq \ell} \sum_{n} X_{i\ell n} (\tilde{T}, \tilde{\tau}, \zeta)}{\sum_{i} \sum_{n} X_{i\ell n} (\tilde{T}, \tilde{\tau}, \zeta)} \leq \frac{\sum_{i \neq \ell} \sum_{n \neq \ell} X_{i\ell n} (\tilde{T}, \tilde{\tau}, \zeta)}{\sum_{i} \sum_{n \neq \ell} X_{i\ell n} (\tilde{T}, \tilde{\tau}, \zeta)}, \quad \forall \ell,
\]

i.e. I assume that the foreign multinationals’ export share is greater than or equal to their production share in the host country. This is true for all countries in Figure 1 and is likely to hold for all major economies in the world. Obviously, the additional restriction in Equation (23) does not result in point identification of the model. In other words, there are many model parameterizations that are consistent with the observed bilateral trade and MP flows and satisfy Equation (23).

Figure 6 illustrates the exact bounds on gains from openness with and without the additional restriction Equation (23). It shows that even this very simple additional restrictions can substantially narrows the bounds (notice the log scale). For small open economies like Ireland and Benelux, this restriction 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.

![Figure 6: Bounds on the Welfare Gains from Openness: Additional Restrictions](image)

(Note: the y-axis presents the percentage welfare changes from autarky to the current equilibrium.)
4.4.2 Point Identification of \((\zeta_{in})\) by the Chinese Customs Data

Using the Chinese customs data, I further impose the following restrictions:

\[
\frac{X_{i,\text{CHN},n}(T, \tau, \zeta)}{\sum_k X_{i,\text{CHN},k}(T, \tau, \zeta)} = \frac{X_{i,\text{CHN},n}}{\sum_k X_{i,\text{CHN},k}}. \tag{24}
\]

These \(N^2\) restrictions, associated with the constraints in Equation (20), result in a system with \(3N^2\) variables and \(3N^2\) equations. In particular, \((X_{i,\text{CHN},n})\) provide information on how export-platform sales depend on the home country \(i\) and destination country \(n\), which leads to point identification of \((\zeta_{in})\). Figure 7 shows that the estimated \((\zeta_{in})\) are increasing with the distance between home country \(i\) and destination \(n\). These estimates are consistent with the idea that it is more costly for firms to make sales in the markets farther away from their headquarters, regardless of where they produce. As mentioned previously, I call this point-identified model the HG model.

![Figure 7: Point-Identified \((\zeta_{in})\) and Bilateral Distances](image)

(Note: Distance refers to physical distance between headquarters and destination countries.)

To understand the importance of headquarters gravity to international trade, I eliminate headquarters gravity in China by forcing all foreign multinational affiliates in China to have the same set of export costs with the Chinese domestic firms, i.e. \(\zeta_{in} = \zeta_{\text{CHN},n}\) for \(n \neq \text{CHN}\) and \(\ell = \text{CHN}\). This reduces Chinese exports by 23%. Therefore, the export advantage of foreign multinationals account for about one fourth of the Chinese exports. Consistent with empirical regularities in Section 2, foreign multinationals are important to creating
foreign demand for Chinese labor.

I then perform an out-of-sample validity check by looking at the BMP share, defined as the ratio of MP to total MP flows \(\left(\sum_{n\neq t} X_{itn}/\sum_n X_{itn}\right)\). Figure 8 plots the BMP shares of the U.S. multinationals predicted by the HG model and ARRY model against the ones in the BEA data. Notice that the BMP shares in the BEA data are not used in estimating \((\zeta_{in})\). Figure 8 suggests that the BMP shares of the U.S. multinationals predicted by the ARRY model (average 8.6%) are much lower than the BEA data (average 31.3%), whereas the BMP shares predicted by the HG model (average 23.3%) are much closer to the BEA data. In the presence of headquarters gravity, multinationals have advantage in using their affiliates as export platforms to serve the markets closer to their headquarters, which thereby boosts BMP.

![Figure 8: BMP Shares of the U.S. Multinationals: Model vs. Data](image)

(Note: BEA data is for 1999. The dash line is the 45-degree line.)

The precise estimates on headquarters gravity are crucial for the model’s counterfactual predictions. Figure 4 shows that for most countries the welfare gains from openness predicted by the HG model are much lower than the ones predicted by the ARRY model. Intuitively, headquarters gravity implies that the domestically-created varieties have advantage in serving the domestic market, indicating that \(\lambda_{ii}\) in Equation (14) is larger than implied by the ARRY model. The predictions of general counterfactuals will be discussed in Section 4.5.
4.5 General Counterfactuals

To show the quantitative importance of headquarters gravity, I perform policy-motivated counterfactuals in this section. Unlike welfare gains from openness, the predictions of these general counterfactuals cannot be expressed analytically in terms of \((\pi_{iii}, \lambda_{ii})\). Instead, I have to include the system of “exact-hat” algebra into the constraints and compute the bounds on counterfactual predictions by solving Equation \(\text{(20)}\). Again, I solve the exact bounds using the optimization solver, KNITRO.

4.5.1 Unilateral MP Liberalization into China

In the first policy-motivated counterfactual, I consider unilateral MP liberalization of 10 percent into China, i.e. \(\hat{\gamma}_{i,\text{CHN}} = 0.9\) for all \(i \neq \text{CHN}\). I first compute the bounds of welfare changes without imposing any restriction on \((\zeta_{in})\). Then I contrast counterfactual predictions of the HG model with the ARRY model to illustrate the implications of headquarters gravity for counterfactual general equilibrium outcomes.

![Figure 9: Bounds on the Welfare Gains from Unilateral MP Liberalization into China](image)

(Note: the y-axis presents the percentage welfare changes with a 10% decrease in \(\gamma_{i,\text{CHN}}\) for all \(i \neq \text{CHN}\).)

Figure 9 illustrates the bounds on counterfactual welfare changes as well as welfare changes predicted by the HG model and ARRY model. Notice that the bounds on welfare changes are narrow for some countries. In other words, my model is informative about this counterfactual even without information on multinationals’ exports.
Notably, comparing to the ARRY model, the HG model reduces the Chinese gain from unilateral MP liberalization into China from 0.3% to −0.41% but raises the welfare gains for most of the other countries. To understand the mechanisms behind these differences, I decompose the welfare changes into changes in domestic creation and production share, $\pi_{iii}$, domestic creation share, $\lambda_{ii}$, and specialization in innovation, $Y_i^f/X_i$. The results are presented in Table 6.

In the presence of headquarters gravity, China loses from the unilateral MP liberalization for two reasons. First, headquarters gravity makes China gain less from getting access to varieties created by foreign multinationals since these varieties are better in meeting the demands of foreign consumers. Second, headquarters gravity intensifies the competition from Chinese imports in developed countries, pushing their workers from production into innovation, and thereby making China further specialize in production. In sum, headquarters gravity shifts counterfactual welfare gains from China to developed countries mainly by making China further specialize in production and developed countries further specialize in innovation.

\[
\begin{array}{ccccccccc}
%\Delta \text{ in:} & W_i & \pi_{iii}^{1+\theta} & \lambda_{ii}^{1+\theta} & (Y_i^f/X_i)^{1/\theta} & W_i & \pi_{iii}^{1+\theta} & \lambda_{ii}^{1+\theta} & (Y_i^f/X_i)^{1/\theta} \\
Benelux & .13 & .08 & .10 & -0.05 & .11 & .29 & .40 & -0.57 \\
Canada & .15 & -.04 & -.05 & .25 & .29 & -.06 & -.08 & .43 \\
China & .30 & 1.59 & 1.95 & -3.17 & -.41 & 1.46 & 1.79 & -3.57 \\
Germany & .23 & -.07 & -.09 & .38 & .46 & -.15 & -.23 & .84 \\
France & .11 & .03 & .03 & .05 & .17 & .05 & .06 & .06 \\
Britain & .22 & -.05 & -.06 & .32 & .27 & -.02 & -.03 & .33 \\
India & .03 & .01 & .01 & .02 & .05 & .02 & .02 & .01 \\
Ireland & .06 & .15 & .19 & -.28 & .01 & .27 & .33 & -.58 \\
Japan & .27 & -.01 & -.01 & .28 & .30 & .04 & -.02 & .27 \\
Korea & .14 & -.02 & -.03 & .20 & .29 & .02 & .03 & .24 \\
Mexico & .02 & .03 & .04 & -.05 & -.01 & .04 & .05 & -.10 \\
The Rest of the World & .03 & .00 & -.01 & .04 & .06 & .04 & .04 & -.01 \\
Taiwan & .41 & -.10 & -.12 & .64 & .54 & -.08 & -.10 & .72 \\
United States & .12 & .01 & .02 & .09 & .17 & .02 & .01 & .13 \\
\end{array}
\]

Table 6: Decomposing Gains from Unilateral MP Liberalization into China

4.5.2 US-China Trade War

In the second policy-motivated counterfactual, I investigate the implications of headquarters gravity for consequences of trade shocks. In particular, I consider the recent US-China trade war. Motivated by Trump’s tariff Increase against Chinese imports, I consider a 25 percent increase in the trade cost from China to the U.S., i.e. $\hat{\tau}_{CHN,USA} = 1.25$. Again, I
contrast counterfactual predictions of the HG model with the ARRY model.

<table>
<thead>
<tr>
<th>%∆ in:</th>
<th>ARRY</th>
<th></th>
<th></th>
<th></th>
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<td>$\lambda_{ii}^{-\frac{\pi_{iii}}{\theta}}$</td>
<td>$Y_i^f/X_i$ (^{1/\theta})</td>
<td>$W_i$</td>
<td>$\pi_{iii}^{\frac{1}{\lambda_{ii}^{\theta}}}$</td>
<td>$\lambda_{ii}^{-\frac{\pi_{iii}}{\theta}}$</td>
<td>$Y_i^f/X_i$ (^{1/\theta})</td>
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Table 7: Welfare Effects of Trump’s Tariff Increase against Chinese Imports

Table 7 decomposes the welfare effects of Trump’s tariff increase against Chinese imports into changes in $(\pi_{iii}, \lambda_{ii})$ and specialization in innovation $Y_i^f/X_i$. It shows that headquarters gravity reduces China’s welfare loss from Trump’s tariffs but magnifies welfare losses for most of the developed countries. In the presence of headquarters gravity, a large fraction of so-call Chinese exports to the U.S. are carried out by the Chinese affiliates of foreign multinationals. As a result, these foreign multinationals lose much more from Trump’s tariff increase against Chinese imports than implied by the ARRY model. Take Canada as an example. The ARRY model predicts that it would gain a little from the US-China trade war by 0.0135% ($22.3 Billion), whereas the HG model predicts it would lose by 0.0742% ($122.4 Billion). The loss mainly comes from the decline in innovation. This third-country effect of the US-China trade war applies to Germany, France, Japan, Korea, and Taiwan whose multinationals utilize China as export platforms to serve the U.S. markets.

The U.S. is an outlier: it loses less from Trump’s tariffs in the HG model. This is mainly due to trade diversion: when Trump increases tariffs on imports from China, the U.S. will increase its imports from other countries, especially from Canada and Mexico, which pushes Canada and Mexico into specializing in production and boosts the U.S. innovation.

The main message sent by this counterfactual is that to understand the consequences of trade policies, we do not only need to know how much one country exports to another, but also who carry out these exports. What we have learned from the Chinese customs data is that a substantial fraction of Chinese exports are carried out by foreign multinationals.
Ignoring this fact, we would mis-estimate the global welfare consequences of Trump’s tariff increase against Chinese imports.

5 Conclusion

This paper’s main message is twofold. First, the Chinese customs data suggests that the exporting behaviors of foreign multinational affiliates differ systematically from local firms. In particular, these multinational affiliates bias their sales towards their headquarters. While this regularity, named headquarters gravity, has been documented in specific industries, to the best of my knowledge, it is first documented in this paper for all industries. Second, I show that ignoring this headquarters gravity could substantially bias our quantification of the consequences of trade and MP shocks. This paper is the first attempt to incorporate headquarters gravity into a general equilibrium framework and discuss to what extent incorporating detailed information on multinationals’ exports improves our quantification of globalization.

This message is particularly useful in understanding the consequences of recent trade conflicts. It is evident in the Chinese customs data that a considerable fraction of Chinese exports are carried out by the Chinese affiliates of foreign multinationals. Consequently, these foreign multinationals are exposed disproportionately to Trump’s tariff increase in against Chinese imports. This insight is not only applicable to China: Since foreign multinationals account for a large share of exports in most of the host countries, the complex interdependence of trade and MP is crucial in evaluating the impacts of trade disputes.

The potential avenue for future research is rich. First, I have shown that incorporating detailed information on multinationals’ exports can improve our characterization of multinationals’ export-platform networks and thereby generate more precise counterfactual predictions. While this paper uses the Chinese customs data, incorporating other sources of micro data (e.g. the Orbis data, the BEA data on multinationals) would be ideal for quantifying trade and MP shocks more precisely. 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. In this sense, this paper is only a first step on bringing micro-structure of multinationals’ export-platform networks into general equilibrium frameworks.

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.
References


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Appendix A  Data

A.1 Data Construction

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).

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 percent of foreign firms in China are manufacturers. But these manufacturers are larger than non-manufacturing foreign firms: they account for 45 percent of employees hired by foreign firms in China.
Table A.1: FIESC firms matched with ASCM

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</tr>
<tr>
<td>Matching rate (%)</td>
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<td>21</td>
</tr>
</tbody>
</table>

A.2 Data Quality and Summary Statistics

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.

<table>
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<th>2-digit HS code</th>
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<th>Destination</th>
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<td>Korea</td>
<td>12576</td>
<td>12519</td>
</tr>
<tr>
<td>64</td>
<td>10096</td>
<td>10096</td>
<td>Germany</td>
<td>9777</td>
<td>9751</td>
</tr>
<tr>
<td>95</td>
<td>9087</td>
<td>9082</td>
<td>Netherlands</td>
<td>7323</td>
<td>7278</td>
</tr>
<tr>
<td>94</td>
<td>7569</td>
<td>7559</td>
<td>United Kingdom</td>
<td>6795</td>
<td>6781</td>
</tr>
<tr>
<td>42</td>
<td>6995</td>
<td>6988</td>
<td>Singapore</td>
<td>5804</td>
<td>5791</td>
</tr>
<tr>
<td>39</td>
<td>6702</td>
<td>6697</td>
<td>Taiwan</td>
<td>5009</td>
<td>-</td>
</tr>
<tr>
<td>90</td>
<td>6472</td>
<td>6446</td>
<td>Italy</td>
<td>4014</td>
<td>3992</td>
</tr>
<tr>
<td>Total</td>
<td>267066</td>
<td>266098</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

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

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

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.4 presents some summary statistics of foreign affiliates in China. Several patterns
are confirmed. First, comparing to Chinese firms a larger fraction of foreign affiliates are exporters. Second, a large fraction of foreign affiliates in China export to their headquarters countries. Third, foreign affiliates in China are larger than Chinese firms either in terms of total sales, number of employees, or value-added. Fourth, the value-added share of foreign affiliates in China is not significantly lower than the value-added share of Chinese firms.

<table>
<thead>
<tr>
<th>The U.S. Affiliates in China in 2001</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Chinese Data</strong></td>
</tr>
<tr>
<td>Total Sales</td>
</tr>
<tr>
<td>Sales in China</td>
</tr>
<tr>
<td>Sales to the U.S.</td>
</tr>
<tr>
<td>Sales to other</td>
</tr>
</tbody>
</table>

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

(Note: All values are in million dollars.)

<table>
<thead>
<tr>
<th>Origin</th>
<th>#Firms</th>
<th>#Exporters</th>
<th>#Exp to Origin</th>
<th>Sales</th>
<th>Value-added</th>
<th>Employment</th>
<th>Export</th>
<th>Exp. to origin</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUS</td>
<td>268</td>
<td>161</td>
<td>67</td>
<td>1260</td>
<td>353</td>
<td>45</td>
<td>328</td>
<td>54</td>
</tr>
<tr>
<td>AUT</td>
<td>49</td>
<td>35</td>
<td>13</td>
<td>383</td>
<td>100</td>
<td>17</td>
<td>59</td>
<td>1</td>
</tr>
<tr>
<td>BEL</td>
<td>40</td>
<td>26</td>
<td>13</td>
<td>1414</td>
<td>359</td>
<td>11</td>
<td>118</td>
<td>18</td>
</tr>
<tr>
<td>CAN</td>
<td>243</td>
<td>140</td>
<td>47</td>
<td>1828</td>
<td>387</td>
<td>41</td>
<td>320</td>
<td>18</td>
</tr>
<tr>
<td>DEU</td>
<td>429</td>
<td>299</td>
<td>206</td>
<td>14094</td>
<td>3815</td>
<td>131</td>
<td>1837</td>
<td>611</td>
</tr>
<tr>
<td>DNK</td>
<td>25</td>
<td>17</td>
<td>10</td>
<td>571</td>
<td>160</td>
<td>7</td>
<td>312</td>
<td>148</td>
</tr>
<tr>
<td>ESP</td>
<td>42</td>
<td>20</td>
<td>10</td>
<td>243</td>
<td>65</td>
<td>9</td>
<td>41</td>
<td>17</td>
</tr>
<tr>
<td>FIN</td>
<td>27</td>
<td>21</td>
<td>13</td>
<td>5799</td>
<td>740</td>
<td>8</td>
<td>2449</td>
<td>172</td>
</tr>
<tr>
<td>FRA</td>
<td>191</td>
<td>130</td>
<td>62</td>
<td>2651</td>
<td>707</td>
<td>42</td>
<td>442</td>
<td>100</td>
</tr>
<tr>
<td>GBR</td>
<td>495</td>
<td>339</td>
<td>122</td>
<td>7378</td>
<td>2070</td>
<td>196</td>
<td>2676</td>
<td>141</td>
</tr>
<tr>
<td>ITA</td>
<td>138</td>
<td>81</td>
<td>47</td>
<td>956</td>
<td>253</td>
<td>30</td>
<td>170</td>
<td>36</td>
</tr>
<tr>
<td>JPN</td>
<td>3088</td>
<td>2531</td>
<td>2319</td>
<td>37738</td>
<td>9375</td>
<td>927</td>
<td>20928</td>
<td>12631</td>
</tr>
<tr>
<td>KOR</td>
<td>1247</td>
<td>1049</td>
<td>889</td>
<td>14713</td>
<td>3136</td>
<td>456</td>
<td>10090</td>
<td>2558</td>
</tr>
<tr>
<td>NLD</td>
<td>163</td>
<td>122</td>
<td>45</td>
<td>5279</td>
<td>1045</td>
<td>55</td>
<td>2377</td>
<td>124</td>
</tr>
<tr>
<td>NZL</td>
<td>33</td>
<td>17</td>
<td>2</td>
<td>243</td>
<td>48</td>
<td>9</td>
<td>83</td>
<td>2</td>
</tr>
<tr>
<td>SGP</td>
<td>933</td>
<td>617</td>
<td>336</td>
<td>12155</td>
<td>3189</td>
<td>294</td>
<td>4387</td>
<td>460</td>
</tr>
<tr>
<td>SWE</td>
<td>67</td>
<td>43</td>
<td>21</td>
<td>2815</td>
<td>584</td>
<td>13</td>
<td>414</td>
<td>135</td>
</tr>
<tr>
<td>TWN</td>
<td>3400</td>
<td>2374</td>
<td>1117</td>
<td>14312</td>
<td>3578</td>
<td>743</td>
<td>6598</td>
<td>422</td>
</tr>
<tr>
<td>USA</td>
<td>2341</td>
<td>1515</td>
<td>1028</td>
<td>33415</td>
<td>9394</td>
<td>630</td>
<td>11607</td>
<td>3797</td>
</tr>
</tbody>
</table>

**Table A.4:** Summary Statistics for Manufacturers in China by Origin

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

### A.3 Aggregate Trade and MP Data

I construct bilateral manufacturing trade flows across 13 countries plus the rest of the world in 2001 from World Input-Output Database (WIOD). WIOD has collected sectoral

**Appendix B  Reduced-form Evidence**

**B.1 Comparing headquarters gravity to the Standard Gravity**

In the following reduced-form regression, I replace the destination fixed effect in the firm-level regression of headquarters gravity by the GDP of the destination country and the distance between the destination and China. The results are presented in Table B.5.

<table>
<thead>
<tr>
<th>log(dist,CHN)</th>
<th>log(dist,CHN)</th>
<th>log(dist,CHN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.0506*</td>
<td>-0.0279**</td>
<td></td>
</tr>
<tr>
<td>(0.028)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>lang</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.109**</td>
<td>0.252***</td>
<td></td>
</tr>
<tr>
<td>(0.054)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>legal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.0165</td>
<td>0.166***</td>
<td></td>
</tr>
<tr>
<td>(0.050)</td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td>OECD</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.0931*</td>
<td>0.0768***</td>
<td></td>
</tr>
<tr>
<td>(0.055)</td>
<td>(0.018)</td>
<td></td>
</tr>
<tr>
<td>1{i = n}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.349***</td>
<td>1.198***</td>
<td></td>
</tr>
<tr>
<td>(0.11)</td>
<td>(0.043)</td>
<td></td>
</tr>
<tr>
<td>log(dist,CHN)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.131***</td>
<td>-0.392***</td>
<td></td>
</tr>
<tr>
<td>(0.038)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>log(GDP)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.271***</td>
<td>0.362***</td>
<td></td>
</tr>
<tr>
<td>(0.014)</td>
<td>(0.0047)</td>
<td></td>
</tr>
<tr>
<td>Affiliate FE</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>R-squared</td>
<td>.55</td>
<td>.33</td>
</tr>
<tr>
<td># Obs.</td>
<td>17266</td>
<td>361350</td>
</tr>
</tbody>
</table>

(Notes: “i” refers to the country of origin, “ℓ” refers to the production country, and “n” refers to the destination country. \(x_{iℓn}(ν)\) is the sales of firm \(ν\) originating from \(i\) producing in \(ℓ\) to market \(n\). Processing traders are excluded. Firm located in exporting zones are excluded. Hong Kong, Macau, and Taiwanese firms are excluded. Chinese domestic firms are excluded. The standard errors are clustered at the firm level.)

**B.2 Home Market Advantage of the U.S. Multinational Affiliates**

One limitation of the combined Chinese firm data is that it contains only one production country, China. So a natural question is how general the facts are. As mentioned above, I do not have access to comparable data sets in other countries. However, the U.S. Bureau of
Economic Analysis 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. Figure B.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.

![Graph showing export to U.S. as a share of total export](image)

**Figure B.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.)

**Appendix C  Calibration and Quantification**

The following tables are presented the detailed numbers of gains from openness and from MP liberalization into China.
### Table C.6: Welfare Gains from Openness
(Notes: The numbers are illustrated by Figure 4 and 6.)

<table>
<thead>
<tr>
<th>%Δ in Wi:</th>
<th>No Restrictions</th>
<th>Simple Restrictions</th>
<th>Point Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LB</td>
<td>UB</td>
<td>LB</td>
</tr>
<tr>
<td>Benelux</td>
<td>38.198</td>
<td>∞</td>
<td>38.200</td>
</tr>
<tr>
<td>Canada</td>
<td>11.868</td>
<td>57.826</td>
<td>11.868</td>
</tr>
<tr>
<td>China</td>
<td>0.119</td>
<td>4.340</td>
<td>1.538</td>
</tr>
<tr>
<td>Germany</td>
<td>20.452</td>
<td>45.553</td>
<td>22.881</td>
</tr>
<tr>
<td>France</td>
<td>8.797</td>
<td>20.853</td>
<td>8.797</td>
</tr>
<tr>
<td>Britain</td>
<td>15.013</td>
<td>35.680</td>
<td>17.675</td>
</tr>
<tr>
<td>India</td>
<td>2.340</td>
<td>3.590</td>
<td>2.340</td>
</tr>
<tr>
<td>Ireland</td>
<td>8.417</td>
<td>∞</td>
<td>8.417</td>
</tr>
<tr>
<td>Korea</td>
<td>3.858</td>
<td>8.847</td>
<td>5.812</td>
</tr>
<tr>
<td>Mexico</td>
<td>0.540</td>
<td>8.932</td>
<td>0.540</td>
</tr>
<tr>
<td>The Rest of the World</td>
<td>0.636</td>
<td>62.176</td>
<td>0.636</td>
</tr>
</tbody>
</table>

### Table C.7: Welfare Effects of 10-percent Unilateral MP Liberalization in China
(Notes: The numbers are illustrated by Figure 9.)

<table>
<thead>
<tr>
<th>%Δ in Wi:</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
<th>ARRAY</th>
<th>HG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benelux</td>
<td>-0.035</td>
<td>0.531</td>
<td>0.125</td>
<td>0.113</td>
</tr>
<tr>
<td>Canada</td>
<td>0.132</td>
<td>0.442</td>
<td>0.152</td>
<td>0.290</td>
</tr>
<tr>
<td>China</td>
<td>-0.435</td>
<td>0.299</td>
<td>0.298</td>
<td>-0.413</td>
</tr>
<tr>
<td>Germany</td>
<td>0.077</td>
<td>0.870</td>
<td>0.225</td>
<td>0.461</td>
</tr>
<tr>
<td>France</td>
<td>0.070</td>
<td>0.759</td>
<td>0.109</td>
<td>0.171</td>
</tr>
<tr>
<td>Britain</td>
<td>0.151</td>
<td>0.876</td>
<td>0.221</td>
<td>0.273</td>
</tr>
<tr>
<td>India</td>
<td>0.019</td>
<td>0.101</td>
<td>0.029</td>
<td>0.051</td>
</tr>
<tr>
<td>Ireland</td>
<td>-0.081</td>
<td>0.122</td>
<td>0.057</td>
<td>0.011</td>
</tr>
<tr>
<td>Japan</td>
<td>0.208</td>
<td>0.455</td>
<td>0.266</td>
<td>0.296</td>
</tr>
<tr>
<td>Korea</td>
<td>0.139</td>
<td>0.543</td>
<td>0.144</td>
<td>0.289</td>
</tr>
<tr>
<td>Mexico</td>
<td>-0.043</td>
<td>0.032</td>
<td>0.017</td>
<td>-0.009</td>
</tr>
<tr>
<td>The Rest of the World</td>
<td>-0.051</td>
<td>0.446</td>
<td>0.032</td>
<td>0.063</td>
</tr>
<tr>
<td>Taiwan</td>
<td>0.414</td>
<td>0.705</td>
<td>0.414</td>
<td>0.544</td>
</tr>
<tr>
<td>United States</td>
<td>0.040</td>
<td>0.254</td>
<td>0.124</td>
<td>0.166</td>
</tr>
</tbody>
</table>