The Role of Trade Costs in Global Production Networks. Evidence from China’s Processing Trade Regime

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Abstract
In this paper, we use data from China’s processing trade regime to analyze the role of trade costs on trade within global production networks (GPNs). Under this regime, firms are granted duty exemptions on imported inputs as long as they are used solely for export purposes. As a result, the data provide information on trade between three sequential nodes of a global supply chain: the location of input production, the location of processing (in China) and the location of further consumption. This makes it possible to examine the role of both trade costs related to the import of inputs (upstream trade costs) and trade costs related to the export of final goods (downstream trade costs) on intra-GPN trade. The paper first sets up a three-country general equilibrium model with asymmetric trade costs to develop testable hypotheses related to the impact of upstream and downstream trade costs on intra-GPN trade. The empirical analysis provides empirical support for the model’s predictions.
1. Introduction

Vertical specialization has been one of the most notable trends in the international organization of production during the last few decades. Thanks to reductions in communication, transportation and other trade barriers, multinational firms have sliced up their supply chains and have dispersed their production activities across multiple countries. This means that a single final good is often worked on in many countries, with each sequential node in the supply chain performed in the location that is most advantageous for the process.

A prominent question in the literature on vertical specialization is the role of trade costs on trade within global production networks (GPNs). In a seminal theoretical paper, Yi (2003) has formally demonstrated that intra-GPN trade should be more sensitive to changes in trade costs than regular trade since vertical specialization leads to products crossing borders many more times before reaching the final consumer. Yi (2003) has used this insight to explain how a relatively small reduction in tariffs could explain the rapid growth of world trade in the second half of the twentieth century. Furthermore, Rubin and Tal (2008) and Rubin (2009) have built on this theory to conjecture that rising oil prices will lead to a major slowdown in the growth of world trade and especially intra-GPN trade. Finally, Jacks et al. (2009) and Yi (2009) have used the notion to attribute the large trade collapse during the recent Great Recession to the impact of rising trade costs associated with evaporating credit, increasing non-tariff barriers and home bias in government stimulus plans on global supply chains.
Largely due to data limitations, empirical research on the sensitivity of intra-GPN trade on trade costs has been scant. A notable exception is Hanson et al. (2004), who have examined the role of trade costs for the decisions by U.S. multinationals to export intermediate goods to their foreign affiliates for processing. In this paper, we take advantage of a unique data set on China’s processing trade regime for the period from 1988 to 2008 to analyze the role of trade costs on intra-GPN trade. Under this customs regime, firms are granted duty exemptions on imported raw materials and other inputs as long as they are used solely for export purposes. As a result, the data set provides, for each Chinese processing location, a unique mapping of the source countries where processing inputs are imported from and the destination countries of processed exports. This makes it possible to examine the role of both trade costs related to the import of inputs (upstream trade costs) and trade costs related to the export of final goods (downstream trade costs) on intra-GPN trade. Such mapping of GPNs cannot be conducted with regular trade data since imports are not necessarily used solely for export purposes, but can also be consumed domestically, as we explain in Section 2. 

In Section 3, we identify three stylized facts that suggest that both upstream and downstream trade costs play an important role on China’s processing trade. First, China’s processing exports heavily rely on foreign inputs, with a relatively low share of the value made in China. According to a recent estimate by Koopman et al. (2008), only 18% of China’s processing exports value is produced in China, while the remaining 82% consists of the value of imported processing inputs. Second, the average distance traveled by processing imports (import distance) is shorter than the average distance traveled by processing exports (export distance). In 2008, 75% of China’s processing imports
originated from within the East Asian region, while 62% of the processing exports were destined to non-Asian OECD countries. Third, this spatial pattern is not consistent across processing locations. In a cross-section of 29 Chinese provinces, import distance is negatively correlated to export distance for most years between 1995 and 2008. In other words, locations in China that import their processing inputs from nearby tend to export their processed goods far away, and vice versa.

To explain these stylized facts, we in Section 4 develop a three-country general-equilibrium trade model. In the model, the world consists of three countries: East (for advanced East Asian countries), West (for Europe and North America), and China. Multinational firms from the two advanced regions, East and West, sell goods in each other’s markets. Each firm can serve the other market in one of two ways. It can produce its goods at home and directly export them to the other market. Alternatively, it can indirectly export its goods to the other market by assembling them in the low cost country, China. Since China is located in the vicinity of East, the model provides an explanation for the negative correlation between export and import distance for China’s processing trade: the inputs that China imports from nearby East are processed into final goods and exported to the far-away West; conversely, the inputs that China imports from the far-away West are processed into final goods and exported to the nearby East. Furthermore, the model allows us to develop a number of testable hypotheses relating trade costs to China’s processing trade patterns. First, China’s processing exports should be negatively affected by both an increase in import distance and an increase in export distance. Second, China’s processing exports to East should be more sensitive to export distance and less sensitive to import distance than its processing exports to West. The
intuition underlying the model is the following. For Eastern firms, the key distance factor that determines China’s attractiveness as a processing location is its vicinity to Eastern input suppliers, i.e. import distance. The larger is import distance, the less attractive China becomes as a location for processing activities and therefore the less processed goods China exports. Conversely, for Western firms, the critical determinant of China’s attractiveness as a processing location is its proximity to the East Asian market, i.e. export distance. The larger is export distance, the less attractive China becomes as a location for processing activities. Using China’s bilateral processing trade data, we find support for the theoretical predictions of the model. Specifically, our empirical analysis provides evidence that China’s processing exports are negatively affected by both import and export distance. Furthermore, it shows that processing exports to East Asian countries are more sensitive to export distance and less sensitive to import distance than processing exports to non-Asian OECD countries.

Our paper contributes to two emerging literatures. First, it builds on a theoretical literature on export platform FDI, i.e. on multinational firms that process their final goods in a foreign subsidiary for export to a third-country market.¹ Yeaple (2003) and Ekholm et al. (2007) examine the determinants of export platform FDI by setting up a model with two similar advanced “Northern” countries and a third Southern country in which the final good can be assembled at lower cost. Both studies analyze how firms’ choices of using South as an export platform depends on trade costs, factor-cost differentials, and the fixed costs associated with foreign investment. Grossman et al. (2006) introduce intra-industry firm heterogeneity in this type of setting and examine the role of different

¹ Yeaple (2003) uses the term ”complex integration strategy”.

types of complementarities on export platform activities. Our theoretical framework complements these three studies by using elements of Helpman et al.’s (2004) model structure to derive a closed-form solution of an export platform’s bilateral processing exports. Furthermore, we introduce more realistic assumptions about trade costs by exploiting the empirical regularity that export-platform countries are generally located in the geographical proximity of large markets. For example, China lies in the vicinity of developed East Asia; Mexico neighbors the United States. This allows us to develop testable hypotheses that relate an export platform’s bilateral exports to both export and import distance.

Second, our paper builds on the New Economic Geography literature by theoretically deriving and empirically validating how export platform FDI and intra-GPN trade depends on firms’ foreign market access, foreign supplier access and the complex interaction between both (Redding and Venables, 2004; Amiti and Javorcik, 2008; Redding, 2010; Baldwin and Venables, 2010).

2. Mapping Global Production Networks

Empirical evidence on vertical specialization and the role of trade costs in GPNs is remarkably scant, largely because concrete evidence is difficult to obtain. To measure vertical specialization, one would like to know the number of countries involved in the production process of a specific good, the value added created in each country, and the sequential supply chain linkages between production activities. However, this information is hard to come by. Firms are generally not willing to provide data on the
cost structure of their own supply chain activities, and often do not know the full range of
value chain activities conducted by its suppliers. Furthermore, national statistical
agencies do not generally track the domestic value added of goods that their countries
trade, nor do they track the use of these traded goods, that is, whether they are used for
sales to final consumers, whether they are used for further processing in a specific
industry, and what share of this industry’s output is exported.

In the field of international economics, scholars have used a variety of approaches to gain
insights into the structure of GPNs. One method has been to rely on the highly
disaggregated product codes and descriptions in international trade statistics to classify
traded goods according to their main use. Yeats (2001) and Ng and Yeats (2001), for
example, categorized intermediate goods as those products whose description include the
used the United Nation's "Broad Economic Categories" (BEC) classification to
distinguish between intermediate and final goods. While this approach has been useful to
demonstrate the large and growing role of GPNs in international trade, it faces two
important shortcomings. First, classifying goods according to their product codes is
somewhat arbitrary since product descriptions provide insufficient information to identify
a product’s main use (Hummels et al., 2001). Indeed, some goods, such as tires, can be
used both as a final good by consumers and as an intermediate good by car
manufacturers. Second, even if traded goods were correctly classified as intermediate or

\[\text{Footnote 2:} \text{Dedrick et al. (2010) is a rare study that has been able to capture the value added created by a lead firm and its most important component suppliers for specific electronics products. For this purpose, they have relied on lists of components and their factory prices from industry analysts’ “teardown” reports, which capture the composition of the product at a specific point in time.}\]
final goods, international trade data do not identify in which sector intermediate goods are used, if it is processed for domestic consumption, or if it is used for export purposes. This makes it difficult to accurately link a trade flow with other trade flows within the same GPN.

An alternative approach used to map activities within GPNs is to combine international trade data with input-output (IO) table data. The advantage of IO data is that – for domestic activities – it unambiguously defines intermediate inputs by their use, i.e., in which industry they are put to use and what share of the industry’s output is exported. This information on main use, however, is not available for imported goods in many input-output tables. Lacking this information, researchers have adopted the proportionality assumption to approximate the main use of imports. That is, every domestic sector is assumed to import inputs in the same proportion as its economy-wide use of that input. For example, if an industry such as electronics relies on semiconductors and 10% of all semiconductors are imported, it is assumed that 10% of the semiconductors used by the electronics industry is imported. With this assumption, scholars have been able to link the flow of imported inputs to the flow of exported goods within the same global production network. Hummels et al. (2001) and Johnson and Noguera (2009) have used this approach to quantify the import content embodied in a country’s exports. Recent studies, then again, have questioned the accuracy of the proportionality assumption. Winkler and Milberg (2009) have shown that, in Germany, the cross-sectoral variation in the use of imported inputs differs significantly from the cross-sectoral variation in the use of domestic inputs. Koopman et al. (2008) show that China’s policy preferences for processing exports has led to a significant difference in the
intensity of imported inputs in the production for processing exports than in other productions (for domestic final sales and non-processing exports).

A third approach has been to use firm-level data on multinationals to measure the dispersion of GPNs. Collinson and Rugman (2008), Rugman et al. (2009) and Rugman and Oh (2009), for example, use data on the geographic distribution of assets for large multinational firms to measure the dispersion of GPNs. Hanson et al. (2005) use BEA data on U.S. multinationals to estimate the drivers of trade in intermediate inputs for further processing between parent firms and their foreign affiliates. These studies, however, give an incomplete and potentially biased picture of the organization of GPNs since many multinationals outsource a large portion of their manufacturing activities to external firms (Gereffi, 1999; Gereffi et al., 2005; Swenson, 2006; Bonham et al., 2007). If these outsourced activities are more dispersed geographically than the assets owned by the multinational firms, the existing estimates on the dispersion of upstream activities will be biased.

In this paper, we will exploit a unique data set that allows us to overcome some of the shortcomings in the existing literature. Specifically, we will exploit a data set collected by the General Administration of Customs of the People’s Republic of China on China’s processing trade regime. Under this regime, firms are granted duty exemptions on imported raw materials and other inputs as long as they are used solely for export purposes. Since imported processing inputs may not be consumed domestically, the processing trade data provides, for each processing location, a unique mapping of the source countries where processing inputs are imported from and the destination countries of processed exports. This makes it possible to directly link imported inputs to exported
products within the same GPNs, without relying on the proportionality assumption. Furthermore, since the processing trade data incorporate both intra-firm and arm’s length trade, it provides a more complete measure of trade flows within GPNs. In the next section, we provide an overview of the processing trade data and identify three stylized facts that relate import and export distance to processing trade patterns.

3. China’s Processing Trade Regime

China’s processing trade regime was installed in the mid-eighties in order to both attract foreign direct investment and promote exports. Under the regime, firms were granted duty exemptions on imported raw materials and other inputs as long as they are used solely for export purposes. Largely ignored by many scholars, the regime was much more far-reaching than similar systems introduced in other East Asian countries. Unlike in its neighboring countries, China’s concessionary provisions were not geographically limited within strictly policed export processing zones, but rather applied over its entire territory (Naughton, 2006). As a result, China’s processing trade regime has turned into an important part of its overall trade performance. As it is illustrated in Figure 1, between 1988 and 2008, the share of processing exports (i.e. exports conducted under the processing regime) in China's total exports has risen from 30% to 51%, while the share of processing imports in total imports has increased from 27% to 38%.

[Figure 1 about here]

A special characteristic of China’s processing exports is that it more heavily relies on imported inputs than China’s non-processing exports. According to recent estimates by Koopman et al. (2008), only 18.1% of China’s processing export value is produced in
China, while the remaining 81.9% consists of the value of imported inputs (see Figure 2). In comparison, the domestic content share of China’s non-processing exports stood at a much higher 88.7%, meaning that imported inputs only represented 11.3% of the export value.

[Figure 2 about here]

In this section, we are primarily interested in the geographic characteristics of China’s processing trade regime. To analyze the countries of origin of processing imports and the destination countries of processing exports, an important data issue that needs to be addressed is that 90% of China’s trade with its largest trading partner, Hong Kong, are re-exported elsewhere (Feenstra et al., 1999; Feenstra et al., 2004; Ferrantino and Wang, 2007). This can significantly affect the analysis since it biases the true source country of processing imports and the true destination country of processing exports that are shipped through Hong Kong. To account for these re-exports, we link the processing trade data from China’s Customs Statistics to a data set from the Hong Kong Census and Statistical Office on Hong Kong re-exports. This allows us to estimate the country of origin of processing imports re-exported through Hong Kong and the destination country of processing exports re-exported through Hong Kong. A comparison of columns 1-2 and 3-4 in Table 1 illustrates the impact of adjusting for re-exports through Hong Kong on China’s processing trade with its major trading partners. It almost doubles the share of processing imports originating from China’s other major trading partners and increases by a quarter the share of processing exports destined to these same countries.

[Table 1 about here]
China’s processing trade regime heavily relies on East Asian inputs. As it is shown in Figure 3, China heavily sources its inputs from its neighboring East Asian countries, with 75.1% of its processing imports originating from within East Asia in 2008. By contrast the United States, EU-19 and Canada contributed relatively little to the supply of processing inputs, together accounting for less than 19% of processing imports in 2008. This asymmetric sourcing pattern of processing inputs has become more pronounced over time. Between 1988 and 2008, the share of processing imports originating from China’s most important East Asian trading partners has risen from 59.6% to 75.1%, while the share of processing imports originating from non-Asian OECD countries has decreased from 37.7% to 18.7% over the same period.

[Figure 3 about here]

Conversely, the majority of processing exports are destined to non-Asian OECD countries, except for an interlude between 1992 and 1997. As it is shown in Figure 4, the share of processing exports destined to non-Asian OECD countries has risen from 54.7% in 1997 to 59.4% in 2008. On the contrary, the share of processing exports destined within the East Asian region has declined from 36.0% to 28.3% during the same period.

[Figure 4 about here]

This unbalanced processing trade pattern is generally attributed to the reorganization of GPNs in East Asia (Yoshida and Ito, 2006; Gaulier et al., 2007; Haddad, 2007). With rising costs in Japan and the Newly Industrialized Economies (NIEs) – Taiwan,
Singapore, South Korea and Hong Kong – East Asian firms are increasingly using China as a lower cost export platform. Instead of directly exporting their final goods to the Western markets, these firms now export high value intermediate goods to their processing plants in China and then export it on to the West after assembly. As a result, it is argued that a triangular trade pattern has emerged in GPNs in which China heavily relies on processing inputs from East Asia, while predominantly sending processed goods to the West.

Data on the bilateral intensity of China’s processing trade provide further evidence of this triangular trade structure. As it is shown in Figure 5, East Asian countries more intensively supply China with processing inputs than countries outside of East Asia. Except for Indonesia and Vietnam, more than 35% of China’s imports from its major East Asian trading partners were processing imports in 2007 (see Figure 5). Almost 40% of its imports from Japan and between 40% and 60% of its imports from the Newly Industrialized Economies (South Korea, Taiwan and Singapore) were aimed at supplying inputs for processing industries. This is a significantly higher share than for Western countries. The share of processing imports in China’s total imports from the EU-19, Canada and the United States amounted to 15.4%, 17.6% and 25.0%, respectively.

[Figure 5 about here]

At the same time, China more intensively supplies processed goods to developed countries than to its East Asian neighbors. As it is shown in Figure 6, more than 50% of the exports that China sends to the United States, the EU-19 and Japan are processing exports. For most developing East Asian countries the number is significantly lower.
The triangular trade pattern suggests that China is primarily used as an export platform by East Asian firms that sell their goods to Western markets. However, in a cross-section of 29 Chinese provinces, the weighted average distance traveled by processing imports (import distance) has been negatively correlated to the weighted average distance travelled by processing exports (export distance) for most years between 1995 to 2008. In other words, locations in China that import their processing inputs from nearby tend to export their processed goods far away and vice versa.

4. Trade Costs and Intra-GPN Trade

To understand the role of trade costs on China’s processing trade, we in subsection 4.1 develop a theoretical model that builds on a recent literature about export platform FDI (Yeaple, 2003; Grossman et al., 2006; Ekholm et al., 2007). In section 4.2 and 4.3, we set up the empirical specification and empirically test the hypotheses that come from the model. In section 4.4, we analyze the impact of growth rebalancing on China’s processing trade.

4.1. Theoretical framework

Consider a world with three countries. There are two advanced countries, East and West, which have high wages and large markets for differentiated products. In addition, there is a third country China that has low wages and no local market for differentiated products.4 Households in the two advanced countries consume goods produced by two industries.

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4 The assumption that China does not have a market for the industry’s output is not limiting since, by the very nature of the processing trade regime, processed goods are not allowed to be sold on the Chinese market.
One industry manufactures homogeneous products in a perfectly competitive environment, while the other produces differentiated goods under monopolistically competitive conditions. Consumers’ preferences are characterized by the utility function

\[ U = q_0 + \left[ \int_0^n q(v)^\alpha \, dv \right]^{1/\alpha}, \quad 0 < \alpha < 1, \]  

(1)

Where \( q_0 \) is a homogeneous good, \( q(v) \) is the \( v \)th variety in the differentiated goods sector and \( n \) is the measure of varieties in the industry. With this utility function, the elasticity of substitution between any pair of differentiated goods is \( \varepsilon = 1/(1 - \alpha) \). Maximizing the utility function subject to the consumer’s expenditure generates the demand function that a firm producing variety \( v \) faces in advanced country \( i \):

\[ q^i(v) = A^i p(v)^{-\varepsilon}, \]  

(2)

where the demand level \( A^i \) is exogenous from the point of view of the individual firm.\(^5\)

The monopolistically competitive firm charges the following price for its product:

\[ p^i(v) = \frac{c(v)}{\alpha}, \]  

(3)

where \( c \) denotes the firm’s marginal unit production cost and \( 1/\alpha \) represents the markup factor.

The countries differ in several ways. First, advanced country firms are more productive than Chinese firms in producing the homogeneous good \( x_0 \). We assume that one unit of labor is needed to produce one unit of the homogeneous good in \( East \) and \( West \), but that \( 1/w>1 \) units of labor are needed to produce one unit of the good in \( China \). We also assume that the homogeneous good is produced in equilibrium in all three countries and

\(^5\) As is well known, \( A^i = Y^i / \left[ \int_0^{n^i} p^i(v)^{1-\varepsilon} \, dv \right] \) in general equilibrium, where \( n^i \) is the measure of varieties available in country \( i \) and \( p^i(v) \) is the price of variety \( v \).
take this good to be the numéraire. This implies that $w^E = w^W = 1 > w^C = w$, where $w^i$ is the wage in country $i$. Second, the market size for differentiated products differs across countries. We denote by $Y^i$ the number of households in country $i$ that consume differentiated products and assume that $Y^W, Y^E > 0$ and $Y^C = 0$. Third, China is located closer to East than to West, while West is equidistant to both East and China. Denote $\tau^{ij}$ as the melting-iceberg trade cost of shipping goods from country $i$ to country $j$, where $\tau^{ii} = 1$ and $\tau^{ij} = \tau^{ji} > 1$ for $i \neq j$. We assume that trade costs increase linearly with distance so that $\tau^{EC} = t < \tau^{WC} = \tau^{WE} = \tau$ (see Figure 7). These geographic assumptions reflect the notion that China acts as the low-cost processing platform in the vicinity of East. To see this, note the differential impact that an increase in trade costs $t$ and $\tau$ play in our model. A rise in $t$ increases trade costs only between East and China, thus making it less attractive to indirectly export through China. Conversely, a rise in $\tau$ increases the trade costs between West and China as well as West and East, thus reducing the incentives of both direct and indirect exports.

[Figure 7 about here]

In the remainder of the model, we focus on the differentiated goods industry. To simplify notation, we will in the rest of the model drop the $v$’s. In the differentiated goods industry, we assume that firms are heterogeneous and can only enter as producers of differentiated products in the two advanced countries and that such firms must locate their headquarters and produce their intermediate goods in their country of origin. Entry requires a firm to bear a fixed fee $F_e$, measured in labor units. With this fee, the entrant acquires the design for a differentiated product and draws a labor-per-unit-output
coefficient of $a$ from a cumulative Pareto distribution $G(a)$ with shape parameter $z$. Upon observing this draw, the firm decides either to exit the industry or to start producing. If it decides to produce, it bears an additional fixed cost $f_D$ of initiating production operations. There are no other fixed costs when the firm sells only for the domestic market. If the firm chooses to export to the foreign market, however, it bears an additional fixed cost $f_X$ of forming a distribution and servicing network in the foreign country. Finally, if it sets up a processing plant abroad, it bears one additional fixed cost $f_O$.

The marginal cost structure of a product depends on the firm’s organizational form. Each firm needs to produce its intermediate good in its home country at cost $w^l = a$, where $a$ equals the firm’s labor-per-unit-output coefficient. The final good can then be processed in any country $l \in \{E, W, C\}$ at an extra ad valorem cost $w^l$. The combination of production costs and trade costs implies that the unit cost of producing an intermediate good in country $j$, processing it into a final good in country $l$ and delivering the final goods to country $i$ equals:

$$c^{jli} = ax^j w^l \tau^{li}, \quad (4)$$

To maximize the number of organizational forms that coexist in the industry, we take on the following assumption:

$$(tw)^{1-\varepsilon} < \frac{f_D + f_O + f_X}{f_D + f_X} \quad (5)$$

This assumption ensures that at least one domestic firm processes its final goods locally and at least one foreign firm produces its goods locally. Dropping this assumption does not alter the key results of the model. The assumption in equation (5) then implies that, in equilibrium, there are four types of firms that sell their final goods in advanced country $i$:
- **Type-D firms** are domestic firms, headquartered in country $i$, that process and sell their final goods in their home country.
- **Type-O firms** are domestic firms, headquartered in country $i$, that offshore their final good processing to China and sell in their home country.
- **Type-X firms** are foreign firms that are headquartered in country $j \neq i$, process their final goods in advanced country $j \neq i$ and export to $i$.
- **Type-T firms** are foreign firms that are headquartered in advanced country $j \neq i$, process their final goods in China and then export to country $i$. For this type of firms, there is a triangular trade pattern.

Using equations (1)-(4), we can derive the operating profits that the four types of firms face in the markets *East* and *West*:

**Table 2: Profit functions**

<table>
<thead>
<tr>
<th>Type</th>
<th>$\pi^E$</th>
<th>$\pi^W$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type-D firm</strong></td>
<td>$\pi_D^E = a^{1-\varepsilon}B^E - f_D$</td>
<td>$\pi_D^W = a^{1-\varepsilon}B^W - f_D$</td>
</tr>
<tr>
<td><strong>Type-O firm</strong></td>
<td>$\pi_O^E = (at^2w)^{1-\varepsilon}B^E - f_O - f_D$</td>
<td>$\pi_O^W = (at^2w)^{1-\varepsilon}B^W - f_O - f_D$</td>
</tr>
<tr>
<td><strong>Type-X firm</strong></td>
<td>$\pi_X^E = (at)^{1-\varepsilon}B^E - f_X - f_D$</td>
<td>$\pi_X^W = (at)^{1-\varepsilon}B^W - f_X - f_D$</td>
</tr>
<tr>
<td><strong>Type-T firm</strong></td>
<td>$\pi_T^E = (at\tau w)^{1-\varepsilon}B^E - f_O - f_X - f_D$</td>
<td>$\pi_T^W = (at\tau w)^{1-\varepsilon}B^W - f_O - f_X - f_D$</td>
</tr>
</tbody>
</table>

where $B' = (1 - \alpha)A^1/\alpha^{1-\varepsilon}$.

Note that if $B^E = B^W$ in Table 2, the profit functions for Type-D firms, Type-X firms and Type-T firms are identical in *East* and *West*. For Type-O firms, however, $\pi_O^E > \pi_O^W$. Since trade costs are higher between *West* and China than between *East* and China (see Figure 7), it is more costly for Western firms to offshore to China than for Eastern firms.
In Figure 8, we depict the profit functions of the four firm-types that are selling in country $i$. In this figure, $a^{1-\varepsilon}$ is represented on the horizontal axis. Since $\varepsilon > 1$, this variable increases monotonically with labor productivity $1/a$, and can be used as a productivity index. All four profit functions are increasing with this productivity index: more productive firms are more profitable for all four firm types.

Figure 8 illustrates that domestic and foreign firms can be ranked according to productivity. Consider first the domestic firms in country $i$. For a given productivity level, type-$D$ firms face a lower fixed cost but a higher marginal cost than type-$O$ firms. This implies that domestic firms with a productivity level below $(a_D^i)^{1-\varepsilon}$ expect negative operating profits and exit the industry, firms with productivity levels between $(a_D^i)^{1-\varepsilon}$ and $(a_O^i)^{1-\varepsilon}$ become type-$D$ firms, and firms with productivity levels above $(a_O^i)^{1-\varepsilon}$ become type-$O$ firms. In other words, the most productive domestic firms offshore their production to China (Type-$O$), while the less productive firms produce their final goods locally (Type-$D$).

Foreign firms face a similar pattern. For a given productivity level, type-$X$ firms face a lower fixed cost but a higher marginal cost than type-$T$ firms. This means that foreign firms with productivity levels below $(a_X^i)^{1-\varepsilon}$ do not sell their products in country $i$; foreign firms with productivity between $(a_X^i)^{1-\varepsilon}$ and $(a_T^i)^{1-\varepsilon}$ become type-$X$ firms; while those with a productivity higher than $(a_T^i)^{1-\varepsilon}$ become type-$T$ firms. In other words, the most productive foreign firms offshore their production to China (Type-$T$),
while the less productive foreign firms produce their final goods in their home country
\((Type-X)\).

Using the profit functions in Table 2, it is straightforward to derive that the cutoff
coefficients \((a_k^{1-\varepsilon})\) depicted in Figure 8 solve the following equations:

Table 3: Cut-off conditions

<table>
<thead>
<tr>
<th></th>
<th>Market East</th>
<th>Market West</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type-D firm</td>
<td>((a_D^E)^{1-\varepsilon}B^E = f_D)</td>
<td>((a_D^W)^{1-\varepsilon}B^W = f_D)</td>
</tr>
<tr>
<td>Type-O firm</td>
<td>((a_O^E)^{1-\varepsilon}B^E((t^2w)^{1-\varepsilon} - 1) = f_O)</td>
<td>((a_O^W)^{1-\varepsilon}B^W((\tau^2w)^{1-\varepsilon} - 1) = f_O)</td>
</tr>
<tr>
<td>Type-X firm</td>
<td>((\tau a_X^E)^{1-\varepsilon}B^E = f_D + f_X)</td>
<td>((\tau a_X^W)^{1-\varepsilon}B^W = f_D + f_X)</td>
</tr>
<tr>
<td>Type-T firm</td>
<td>((\tau a_T^E)^{1-\varepsilon}B^E((tw)^{1-\varepsilon} - 1) = f_O)</td>
<td>((\tau a_T^W)^{1-\varepsilon}B^W((tw)^{1-\varepsilon} - 1) = f_O)</td>
</tr>
</tbody>
</table>

Free entry ensures equality between the expected operating profits of a potential entrant
and the entry cost \(F_e\). The free entry condition then provides implicit solutions for the
cutoff coefficients \(a_k^i\) and the demand levels \(B^i\) in every country.

The industry sales of firm-type \(k\) in country \(i\) amounts to the joint revenue of all type \(k\)
firms in country \(i\). Using equations (2) and (3), it is straightforward to show that firm
revenues in country \(i\) can be expressed as \(R_k^i = \frac{c^k}{1-\alpha} B^i\), where \(c\) is given by equation (4).

By taking the integral of all firms of type \(k\) operating in country \(i\), the industry sales of
each firm type \(k\) in country \(i\) equals:

Table 4: Industry sales

<table>
<thead>
<tr>
<th></th>
<th>Market East</th>
<th>Market West</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type-D firm</td>
<td>(\Omega_D^E = \frac{B^E[V(a_O) - (t^2w)^{1-\varepsilon}V(a_O)]}{1-\alpha})</td>
<td>(\Omega_D^W = \frac{B^W[V(a_O) - (\tau^2w)^{1-\varepsilon}V(a_O)]}{1-\alpha})</td>
</tr>
</tbody>
</table>
Table 4 provides us with sufficient information to derive a closed form solution for China’s processing exports. As it is shown in Figure 9, processing exports from China to country $i$ equals the aggregate sales of Type-O domestic firms and Type-T foreign firms in country $i$, i.e. the sum of $\Omega^0_i + \Omega^T_i$.

In the appendix, we derive two testable hypotheses related to China’s processing exports:

**Hypothesis 1**: *Ceteris paribus, China’s bilateral processing exports are negatively affected by both an increase in import distance and an increase in export distance.*

The intuition behind this hypothesis is straightforward. Since China’s processing exports by both Type-O and Type-T firms rely on imported inputs, and since the cost of importing inputs is a function of distance, an increase in import distance raises the price of Chinese processing exports, thus leading to a reduction the bilateral export value. Similarly, an increase in export distance negatively affects processing exports by increasing costs.

The implications for the empirical specification are nonetheless important. Empirical studies in the field of international economics such as gravity models do generally not take into account the role of import distance on exports. In this respect, our results are in line with the New Economic Geography literature that highlights that a country’s exports
not only rely on foreign market access, but also on supplier access (Redding and Venables, 2004).

We also derive that:

**Hypothesis 2:** *Ceteris paribus, China’s processing exports to East are (i) more sensitive to export distance and (ii) less sensitive to import distance than its processing exports to the West.*

This result is largely driven by the differential impact that \( t \) and \( \tau \) have on the processing exports of type-\( T \) foreign firms. Type-\( T \) foreign firms’ processing exports to both *East* and *West* are more sensitive to an increase in \( t \) than to an increase in \( \tau \). The differential impact is related to the assumption that *China* is the low-cost processing platform in the vicinity of *East*. On the one hand, an increase in \( t \) only raises the trade costs related to using *China* as an export platform. As a result, it reduces the attractiveness of triangular exports through *China*, thus inducing some foreign firms to substitute from a Type-\( T \) firm to a Type-\( X \) firm. This leads to an increase in the relative market share of type-\( X \) firms to type-\( T \) firms in country \( i \). On the other hand, an increase in \( \tau \) raises the trade costs for both Type-\( X \) firms and Type-\( T \) firms. In our model, it therefore leaves the relative market share of type-\( X \) firms to type-\( T \) firms unchanged.

Since \( t \) and \( \tau \) have opposing roles for type-\( T \) firms’ processing exports to East and West, the differential impact leads to Hypothesis 2. When exporting to West, \( t \) reflects the trade costs related to import distance and \( \tau \) reflects the trade costs related to export distance. Conversely, when exporting to East, \( t \) reflects the trade costs related to export distance and \( \tau \) reflects the trade costs related to import distance. This implies that type-\( T \) firms’
processing exports to East are (i) more sensitive to export distance and (ii) less sensitive to import distance than its processing exports to the West.

Finally, we show in the appendix that Hypothesis 2, not only applies for processing exports by Type-T firms, but to total processing exports by both Type-T and Type-O firms. Since for Type-O firms import distance is identical to export distance, type-O firms’ processing exports are equally sensitive to import distance as to export distance, and very similar in magnitude. Hypothesis 2 therefore continues to hold.

4.2. Empirical Specification

To test Hypotheses 1 and 2, we estimate an augmented gravity model on Chinese provinces’ processing exports with their foreign trading partners (adjusted for Hong Kong re-exports) for the period 1988-2008. Specifically, we estimate the following equation:

\[
\ln X_{ijt} = \alpha + \lambda_i + \mu_t + v_{jt} + \beta_1 \ln XD_{ij} + \beta_2 \ln MD_{it} + \beta_3 East_j \times \ln XD_{ij} + \beta_4 East_j \times \ln MD_{it} + Z_{it} \gamma + \epsilon_{ijt},
\]

where the natural log of processing exports from a Chinese province \( i \) to a destination country \( j \) in year \( t \), \( \ln X_{ijt} \), is the dependent variable; \( XD_{ij} \) is export distance between province \( i \) and country \( j \); \( MD_{it} \) is the weighted import distance for province \( i \) in period \( t \); \( Z_{it} \) refers to a standard vector of time-varying province-specific control variables, \( East_j \) is a dummy variable that equals 1 if the destination country is an East Asian country and is 0 otherwise, \( \lambda_i \) is a province fixed effect, \( \mu_t \) is a time fixed effect, \( v_{jt} \) is a country x time fixed effect, and \( \epsilon_{ijt} \) is a normally distributed error term.\(^6\)

\(^6\) Our data consists of China’s East Asia neighbors (Indonesia, Malaysia, Thailand, Japan, Singapore, South Korea, Philippines, Taiwan, and Hong Kong) and the Non-Asian OECD countries (Australia, Canada,
Our model includes two independent distance variables to capture the role of trade costs. To measure export distance \((XD_{ij})\), we use the arc distance between the Chinese port closest to province \(i\) and the destination country \(j\). To measure import distance \((MD_{ij})\), we need to take into account that multiple inputs from various countries are used in the production of a specific export good. As a consequence, we measure import distance using the following formula:

\[
MD_{it} = \sum_j \frac{M_{ijt}}{\sum_i M_{ijt}} . XD_{ij},
\]

where \(M_{ijt}\) is province \(i\)’s imports from country \(j\) in period \(t\); and \(XD_{ij}\) is the arc distance between the Chinese port closest to province \(i\) and the source country \(j\).

To analyze if China’s processing exports to East Asian countries are more sensitive to export distance and less sensitive to import distance than its processing exports to Western countries, we introduce a dummy variable, \(East_j\), that equals 1 if the country of destination is an East Asian country and 0 if the destination market is a non-Asian OECD country. We then introduce interaction terms between \(East_j\) and our two distance variables \(\ln XD_{ij}\) and \(\ln MD_{it}\) as independent variables in our model. Hypothesis 1 will be confirmed if \(\ln XD_{ij}\) and \(\ln MD_{it}\) both have a negative effect on processing exports. Hypothesis 2 will be validated if (i) the coefficient on the interaction term between \(East_j\) and \(\ln XD_{ij}\) is significantly negative and (ii) the coefficient on the interaction term between \(East_j\) and \(\ln MD_{it}\) is significantly positive.

We estimate the effect of distance on processing exports using a set of controls that are standard in gravity models. Specifically, we use data from *China’s Statistical Yearbook* United States, and EU-19) since as shown in Table 1 the share of its processing imports and exports from these trading partners accounts for most of its trade with 95.4% and 87.8%, respectively.
to control for the time-varying variables GDP per capita, population size and wages for Chinese provinces and destination markets. To construct a specification that captures multilateral resistance, we follow Rose and van Wincoop (2001) and Feenstra (2004) by adding both province-fixed effects and country*time fixed effects. Finally, we use time fixed effects to account for economic shocks common to all country pairs.

### 4.3. Regression Results

Table 5 presents our OLS estimation results of equation (6). Column 1 includes the independent variables that are generally used in gravity equations. Column 2 adds import distance $\ln MD_{it}$ as an independent variables. Column 3 includes the dummy variable $East_j$ and the interaction terms.

[Table 5 about here]

The results provide support for Hypotheses 1 and 2. First, we find evidence for Hypothesis 1. Specifically, in column 2, both coefficients on import distance and export distance are negative and statistically significant. In column 3, the coefficient on import distance remains negative and statistically significant, but the coefficient on export distance becomes insignificant.

The results also confirm Hypothesis 2. Specifically, we find that in column 3 the coefficient on $East_j \times XD_{ij}$ is negative and statistically significant, while the coefficient on $East_j \times MD_{it}$ is positive and statistically significant. In line with Hypothesis 2, this suggests that processing exports destined to East Asian countries are more sensitive to export distance and less sensitive to import distance than processing exports destined to non-Asian OECD countries.
4.4. Robustness Tests

The OLS results do not take into account the potential endogeneity of import distance and GDP per capita. To account for this, we follow Sissoko (2004) and Carrère (2006) in using the Hausman and Taylor (1981) estimation model to select the appropriate instruments. The corresponding Hausman test leads us to reject the null hypothesis at the 0.01 level of significance and conclude that the model with the internal instruments provides most efficient estimates. The results are presented in Table 6. Column 1 replicates the OLS regression results in column 3 of Table 5. Columns 2-4 provide the Hausman-Taylor estimates for different combinations of endogenous variables. The results continue to provide supporting evidence for Hypotheses 1 and 2.

[Table 6 about here]

Another estimation issue arises from the potential presence of industrial clustering in particular regions and the level of aggregation in our analysis. First, there might be structural differences between the processing trade patterns of coastal and internal provinces. As is shown in Figure 10, 97.2% of processing exports and 97.6% of processing imports are conducted by the ten coastal provinces listed in the figure.

[Figure 10 about here]

Provinces may also be specialized in different industries. To measure this, we can calculate a variant of Finger and Kreinin’s (1979) export similarity index that measures the overlap of a province’s processing export bundle with that of Guangdong.\footnote{The export similarity index is defined as $ESI_{i,j} = \sum_i \min(s_{i,j}, s_{i,g}) \times 100$, where $s_{i,j}$ and $s_{i,g}$ are HS8 industry $i$’s shares in province $j$’s and Guangdong’s processing exports. The index varies between zero and 100, with zero indicating complete dissimilarity and 100 representing identical export composition.}
motivation for using Guangdong as benchmark is that this coastal province accounts for over 40% of China’s processing trade (see figure 10). From Table 7, we see that the processing export composition differs significantly across provinces. Compared to Guangdong, Ningxia (an internal province) has an export similarity index of only 0.12%, while Jiangsu (a coastal province) has an export similarity index of 41.30%. At the same time, the table suggests that the coastal provinces are more similar in comparison to the internal provinces. The averages of the export similarity indices are 25.44 for the coastal provinces and 4.55 for the internal provinces.

[Table 7 about here]

Ideally we should control for these structural differences between provinces by disaggregating our analysis at the industry level. However, we are limited by the lack of available data. Specifically, it is not possible to disaggregate the analysis at the industry level because we do not have the necessary input-output information regarding the combination of inputs that are used to produce specific exports. For example, semiconductors imported into a processing location can be used to produce both cars and computers. The processing trade data identifies the value of semiconductors that are imported by a certain location but not in which industry they are put to use.

To at least partially address these estimation issues, we re-estimate equation (6) at the county level (instead of the province level), while restricting the analysis to the counties in the coastal provinces that have more similar export bundles (see Table 7). To control for unobserved heterogeneity across counties and over time, we include in equation (16)

---

8 The coastal provinces are commonly considered to include: Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan.
both county*year fixed effects and country*year fixed effects. While the inclusion of country*year fixed effects implies that we can no longer estimate the coefficient on import distance, we can still estimate the coefficients on the interaction effects between $East_j \ln XD_{ij}$ and $East_j \ln MD_{it}$. The results of the county-level analysis are presented in Table 8 for the years 1997-2000, 2001-2004, and 2005-2008, respectively. The results provide support for Hypothesis 2. In particular, the coefficient on $East_j \ln XD_{ij}$ is negative and significant, while the coefficient on $East_j \ln MD_{it}$ is positive and significant.

[Table 8 about here]

In sum, we find robust evidence that China’s processing exports not only depend on downstream trade costs (export distance), but also on upstream trade costs (import distance). Specifically, we find that processing exports are negatively affected by both import and export distance. Furthermore, processing exports destined to East Asian countries are more sensitive to export distance and less sensitive to import distance than processing exports destined to non-Asian OECD countries.

5. Conclusion

What role do trade costs have on intra-GPN trade? Recent theoretical work has demonstrated the importance of this question, yet it has proven to be hard to empirically evaluate. We have tackled this question by using a unique data set on China’s processing trade regime. Under this customs regime, firms are granted duty exemptions on imported raw materials and other inputs as long as they are used solely for export purposes. As a result, the data set provides information on trade between three sequential nodes of a

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9 China’s Customs Statistics only provides county-level data starting in 1997. We have run the regressions in intervals of 4 years due to constraints in computing power.
global supply chain: the location of input production, the location of processing (in China) and the location of further consumption. This makes it possible to examine the role of both trade costs related to the import of inputs (upstream trade costs) and trade costs related to the export of final goods (downstream trade costs) on intra-GPN trade.

In a first step to evaluate the role of trade costs on China’s processing trade, we have developed a three-country industry-equilibrium model in which heterogeneous firms from two advanced countries, East and West, sell their products in each other’s markets. Each firm can use two modes to serve the foreign market. It can directly export its products from its home country. Alternatively, it can indirectly export to the foreign market by assembling its product in a third low-cost country, China, which is assumed to be located closer to East than to West. Our model illustrates that China’s processing exports should not only depend on downstream trade costs (export distance), but also on upstream trade costs (import distance), and the interaction of both. Using China’s bilateral processing trade data, we have found empirical support for this complex impact of these trade costs on intra-GPN trade.
In this appendix, we derive the closed form solution for China’s processing exports to country $i$, $\Omega_D^i + \Omega_T^i$, where $\Omega_k^i$ denotes the aggregate industry sales of type-$k$ firms in industry $i$ (see text). This will allow us to derive Hypotheses 1 and 2.

Consider first the derivation of $\Omega_D^i$ and $\Omega_T^i$. In our model, four types of firms sell their products in advanced country $i$: type-$D$ domestic firms, type-$O$ domestic firms, type-$X$ foreign firms and type-$T$ foreign firms. The representative consumer spends amount $Y^i$ on industry output:

$$Y^i = \Omega_D^i + \Omega_O^i + \Omega_X^i + \Omega_T^i, \quad (A-1)$$

where $\Omega_k^i$ denotes the aggregate industry sales of type-$k$ firms in industry $i$. If we divide both sides of equation (A-1) by $\Omega_D^i$ and rearrange, we obtain:

$$\Omega_D^i = \frac{Y^i}{1 + \sigma_{b,O}^i + \sigma_{k,O}^i + \sigma_{T,O}^i}, \quad (A-2)$$

where $\sigma_{k,l}^i$ captures the relative market share of type-$k$ firms to type-$l$ firms in country $i$. In other words,

$$\sigma_{k,l}^i = \frac{\Omega_k^i}{\Omega_l^i}. \quad (A-3)$$

Similarly, If we divide both sides of equation (A-1) by $\Omega_T^i$ and rearrange, we obtain:

$$\Omega_T^i = \frac{Y^i}{1 + \sigma_{b,T}^i + \sigma_{X,T}^i + \sigma_{O,T}^i}. \quad (A-4)$$

To derive a closed-form solution for $\Omega_D^i$ and $\Omega_T^i$, we can then plug in the industry sales $\Omega_k^i$ from Table 4 on page 16 into equation (A-3) and then into (A-2). Furthermore, we can use the assumption that firms randomly draw a labor-per-unit-output coefficient of $a$ from a cumulative Pareto distribution $G(a)$ with shape parameter $z$. In that case, Helpman
et al. (2004) show that $V(a)$, is also Pareto with the shape parameter $z - (\varepsilon - 1)$. The Pareto distribution implies that

$$
\frac{V(a_1)}{V(a_2)} = \left(\frac{a_1}{a_2}\right)^{z-(\varepsilon-1)}
$$

(A-5)

for every $a_1$ and $a_2$ in the support of the distribution of $a$. Inserting equation (A-5) into equations (A-2) and using the cutoff conditions in Table 3 then yields:

<table>
<thead>
<tr>
<th>Table A-1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Components of $\Omega_T^t$</strong></td>
</tr>
<tr>
<td>$1 + \sigma_{X,T}^t$</td>
</tr>
<tr>
<td>$\sigma_{D,T}^t + \sigma_{X,T}^t$</td>
</tr>
</tbody>
</table>

| **Components of $\Omega_0^t$** | | |
| $1 + \sigma_{D,0}^t$ | $\frac{f_0}{f_D 1 - (t^2w)^{\varepsilon-1}} \frac{(t^2w)^{\varepsilon-1}}{1 - (t^2w)^{\varepsilon-1}} \frac{z-(\varepsilon-1)}{\varepsilon-1} (t^2w)^{\varepsilon-1}$ | $\frac{f_0}{f_D 1 - (t^2w)^{\varepsilon-1}} \frac{(t^2w)^{\varepsilon-1}}{1 - (t^2w)^{\varepsilon-1}} \frac{z-(\varepsilon-1)}{\varepsilon-1} (t^2w)^{\varepsilon-1}$ |
| $\sigma_{X,0}^t + \sigma_{T,0}^t$ | $\frac{f_0}{f_D + f_x} \frac{(t^2w)^{\varepsilon-1}}{1 - (t^2w)^{\varepsilon-1}} \frac{1}{t} \frac{z-(\varepsilon-1)}{\varepsilon-1} (t^2w)^{\varepsilon-1}$ | $\frac{f_0}{f_D + f_x} \frac{(t^2w)^{\varepsilon-1}}{1 - (t^2w)^{\varepsilon-1}} \frac{1}{t} \frac{z-(\varepsilon-1)}{\varepsilon-1} (t^2w)^{\varepsilon-1}$ |

Using equation (A-5) and Table (A-1), it is relatively straightforward to prove Hypotheses 1 and 2.
Bibliography


Figure 1: Proportion of processing trade in China’s total trade, 1988-2008

Source: Authors’ calculations using China’s Customs Statistics.
Figure 2: Domestic and foreign content share of China’s processing and non-processing exports

Source: Koopman et al. (2008).
Figure 3: Share of Processing Imports, by region of origin, 1988-2008

Source: authors’ calculations, using China’s Customs Statistics
Figure 4: Share of Processing Exports, by region of destination, 1988-2008

Source: authors’ calculations, using China’s Customs Statistics
Figure 5: Processing imports as a share of China’s total imports, by country of origin, 2007 (%)

Source: authors’ calculations, using China’s Customs Statistics
Figure 6: Processing exports as a share of China’s total exports, by destination country, 2007 (%)

Source: authors’ calculations, using China’s Customs Statistics
Figure 7: Geographical assumptions

ASIA

East

-China

West
Figure 8: Profit functions for the four firm-types

$\pi_i^j$ $\pi_D^i$ $\pi_O^i$ $\pi_T^i$ $\pi_X^i$

$-f_D$ $(a_D)^{-\varepsilon}$ $(a_O)^{-\varepsilon}$ $(a_X)^{-\varepsilon}$ $(a_T)^{-\varepsilon}$

$-(f_X + f_D)$

$-(f_O + f_D)$

$-(f_O + f_X + f_D)$
Figure 9: China’s processing trade, by firm type

PROCESSING EXPORTS TO EAST

East

Processing exports to China

West

Processing exports to West

TYPE-O FIRM

TYPE-T FIRM

TYPE-O FIRM

TYPE-T FIRM
Figure 10: Share of processing trade 2008, by province

The diagram shows the percentage of processing trade for various provinces in China in 2008, categorized into coastal and internal trade. The chart illustrates the distribution of trade across different regions, with coastal provinces generally having a higher percentage of processing trade compared to internal provinces.
### Table 1

The origin and destination of China’s processing import and export, 2008

<table>
<thead>
<tr>
<th>Region</th>
<th>Share of processing imports originating from Unadjusted for HK re-exports</th>
<th>Share of processing exports destined to Adjusted for HK re-exports</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>East Asia</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HK</td>
<td>85.0</td>
<td>71.2</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>45.3</td>
<td>-</td>
</tr>
<tr>
<td>Japan</td>
<td>11.3</td>
<td>18.7</td>
</tr>
<tr>
<td>South Korea</td>
<td>11.3</td>
<td>21.9</td>
</tr>
<tr>
<td>Singapore</td>
<td>2.9</td>
<td>4.6</td>
</tr>
<tr>
<td>Taiwan</td>
<td>8.6</td>
<td>13.3</td>
</tr>
<tr>
<td>Malaysia</td>
<td>1.8</td>
<td>3.2</td>
</tr>
<tr>
<td>Thailand</td>
<td>1.4</td>
<td>4.9</td>
</tr>
<tr>
<td>Philippines</td>
<td>1.5</td>
<td>2.5</td>
</tr>
<tr>
<td>Vietnam</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td>Indonesia</td>
<td>0.5</td>
<td>1.4</td>
</tr>
<tr>
<td>Macau</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td><strong>Non-Asian OECD</strong></td>
<td><strong>10.4</strong></td>
<td><strong>20.0</strong></td>
</tr>
<tr>
<td>United States</td>
<td>4.3</td>
<td>6.2</td>
</tr>
<tr>
<td>EU-19</td>
<td>4.8</td>
<td>0.9</td>
</tr>
<tr>
<td>Canada</td>
<td>0.5</td>
<td>0.8</td>
</tr>
<tr>
<td>Australia</td>
<td>0.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Other</td>
<td>0.5</td>
<td>0.9</td>
</tr>
<tr>
<td><strong>ROW</strong></td>
<td><strong>4.6</strong></td>
<td><strong>8.8</strong></td>
</tr>
</tbody>
</table>

Authors’ calculations using China’s Customs Statistics Data
Tables 2, 3 and 4 are included in the text.
### Table 5

**Regression results, 1988-2008**

<table>
<thead>
<tr>
<th>Dependent variable: log of bilateral processing exports, by province</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>GDP per capita (province)</td>
<td>1.655***</td>
</tr>
<tr>
<td></td>
<td>[0.132]</td>
</tr>
<tr>
<td>Population (province)</td>
<td>3.968***</td>
</tr>
<tr>
<td></td>
<td>[0.215]</td>
</tr>
<tr>
<td>Wage (province)</td>
<td>-0.541***</td>
</tr>
<tr>
<td></td>
<td>[0.112]</td>
</tr>
<tr>
<td>Export Distance</td>
<td>-0.505***</td>
</tr>
<tr>
<td></td>
<td>[0.043]</td>
</tr>
<tr>
<td>Import Distance</td>
<td>-0.170***</td>
</tr>
<tr>
<td></td>
<td>[0.058]</td>
</tr>
<tr>
<td>East*Export Distance</td>
<td>-0.570***</td>
</tr>
<tr>
<td></td>
<td>[0.233]</td>
</tr>
<tr>
<td>East *Import Distance</td>
<td>0.576***</td>
</tr>
<tr>
<td></td>
<td>[0.070]</td>
</tr>
<tr>
<td>Year Dummy</td>
<td>Yes</td>
</tr>
<tr>
<td>Province Dummy</td>
<td>Yes</td>
</tr>
<tr>
<td>Country-Year Dummy</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>17306</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.835</td>
</tr>
</tbody>
</table>

*Notes*: Robust standard errors are in parentheses. * means significant at 10%; ** means significant at 5%; *** means significant at 1%. Constant not reported.
### Table 6

Regression results, 1988-2008

Dependent variable: log of bilateral processing exports, by province

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>Hausman Taylor Estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)(^*)</td>
</tr>
<tr>
<td>GDP per capita (province)</td>
<td>1.609***</td>
<td>1.7137***</td>
</tr>
<tr>
<td></td>
<td>[0.133]</td>
<td>[0.102]</td>
</tr>
<tr>
<td>Population (province)</td>
<td>3.850***</td>
<td>3.7072***</td>
</tr>
<tr>
<td></td>
<td>[0.213]</td>
<td>[0.196]</td>
</tr>
<tr>
<td>Wage (province)</td>
<td>-0.612***</td>
<td>-0.4870***</td>
</tr>
<tr>
<td></td>
<td>[0.114]</td>
<td>[0.104]</td>
</tr>
<tr>
<td>Export Distance</td>
<td>0.101</td>
<td>-0.1498</td>
</tr>
<tr>
<td></td>
<td>[0.223]</td>
<td>[0.215]</td>
</tr>
<tr>
<td>Import Distance</td>
<td>-0.336***</td>
<td>-0.3255***</td>
</tr>
<tr>
<td></td>
<td>[0.061]</td>
<td>[0.057]</td>
</tr>
<tr>
<td>East*Export Distance</td>
<td>-0.620***</td>
<td>-0.3650</td>
</tr>
<tr>
<td></td>
<td>[0.233]</td>
<td>[0.224]</td>
</tr>
<tr>
<td>East*Import Distance</td>
<td>0.588***</td>
<td>0.6246***</td>
</tr>
<tr>
<td></td>
<td>[0.069]</td>
<td>[0.070]</td>
</tr>
<tr>
<td>Year Dummy</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Province Dummy</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Country-year Dummy</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>17285</td>
<td>17285</td>
</tr>
<tr>
<td>R²</td>
<td>0.837</td>
<td>1791.36</td>
</tr>
</tbody>
</table>

**Notes:** Robust standard errors are in parentheses. * means significant at 10%; ** means significant at 5%; *** means significant at 1%.

Column 2: endogenous variables = GDP per capita (province), GDP per capita (country), import distance.
Column 3: endogenous variables = import distance.
Column 4: endogenous variables = GDP per capita (province), GDP per capita (country).
### Table 7

Export Similarity Index Relative to Guangdong, by province, 2008

<table>
<thead>
<tr>
<th>Coastal Provinces</th>
<th>Export Similarity Index</th>
<th>Internal Provinces</th>
<th>Export Similarity Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beijing</td>
<td>31.01</td>
<td>Hebei</td>
<td>20.07</td>
</tr>
<tr>
<td>Tianjin</td>
<td>31.50</td>
<td>Shanxi</td>
<td>45.87</td>
</tr>
<tr>
<td>Liaoning</td>
<td>27.37</td>
<td>Inner Mongolia</td>
<td>9.26</td>
</tr>
<tr>
<td>Shanghai</td>
<td>45.43</td>
<td>Jilin</td>
<td>18.22</td>
</tr>
<tr>
<td>Jiangsu</td>
<td>46.12</td>
<td>Heilongjiang</td>
<td>25.82</td>
</tr>
<tr>
<td>Zhejiang</td>
<td>38.80</td>
<td>Anhui</td>
<td>23.25</td>
</tr>
<tr>
<td>Fujian</td>
<td>39.30</td>
<td>Jiangxi</td>
<td>22.87</td>
</tr>
<tr>
<td>Shandong</td>
<td>35.11</td>
<td>Henan</td>
<td>14.62</td>
</tr>
<tr>
<td>Hainan</td>
<td>15.69</td>
<td>Hubei</td>
<td>25.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hunan</td>
<td>13.60</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Guangxi</td>
<td>18.88</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sichuan</td>
<td>24.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Guizhou</td>
<td>21.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Yunnan</td>
<td>20.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Shaanxi</td>
<td>17.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gansu</td>
<td>7.66</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Qinghai</td>
<td>5.79</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ningxia</td>
<td>3.42</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Xinjiang</td>
<td>14.84</td>
</tr>
</tbody>
</table>

**Average Coastal**: 34.48  **Average Internal**: 18.53
Table 8

Regression results, 1988-2008

Dependent variable: log of bilateral processing exports, by coastal county

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Export Distance</td>
<td>0.941***</td>
<td>0.622***</td>
<td>0.691***</td>
</tr>
<tr>
<td></td>
<td>[0.225]</td>
<td>[0.223]</td>
<td>[0.244]</td>
</tr>
<tr>
<td>East*Export Distance</td>
<td>-1.578***</td>
<td>-1.391***</td>
<td>-1.641***</td>
</tr>
<tr>
<td></td>
<td>[0.235]</td>
<td>[0.232]</td>
<td>[0.254]</td>
</tr>
<tr>
<td>East *Import Distance</td>
<td>0.358***</td>
<td>0.228***</td>
<td>0.152***</td>
</tr>
<tr>
<td></td>
<td>[0.045]</td>
<td>[0.044]</td>
<td>[0.045]</td>
</tr>
<tr>
<td>County-year dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Country-year dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>25,754</td>
<td>28,709</td>
<td>32,507</td>
</tr>
<tr>
<td>R²</td>
<td>0.748</td>
<td>0.753</td>
<td>0.710</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors are in parentheses. * means significant at 10%; ** means significant at 5%; *** means significant at 1%.