

The Role of Trade Costs in Global Production Networks

Evidence from China's Processing Trade Regime

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Abstract

In a seminal contribution, Yi (2003) has shown that vertically specialized trade should be more sensitive to changes in trade costs than regular trade. Yet empirical evidence of this remains remarkably scant. This paper uses 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 authors show that intra-GPN trade differs from regular trade in that it not only depends on downstream trade costs, but also on upstream trade costs and the interaction of both. Moreover, intra-GPN trade is more sensitive to oil price movements and business cycle movements than regular trade. Finally, the paper analyzes three channels through which intra-GPN trade have amplified the trade collapse during the recent Global Recession.

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

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1. Introduction

Vertical specialization has been one of the most notable trends in the international organization of production during the last few decades (Helpman, 2006; Spencer, 2006; Desai, 2009). 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, Meissner and Novy (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.¹

Largely due to data limitations, empirical research on the sensitivity of intra-GPN trade on trade costs has been scant.² 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,

¹ This argument has been contested by Hoekman, Martin and Mattoo (2009) and Kee, Neagu and Nicita (2010), among others. See the discussion in section 6.

² A notable exception is Hanson, Mataloni and Slaughter (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.

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, Wang and Wei (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.³

To explain the role of trade costs on intra-GPN trade, we in Section 4 develop a three-country general-equilibrium trade model.⁴ 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

³ In this paper, "province" encompasses all of China's first-tier administrative divisions: provinces, municipalities and autonomous regions. We have excluded Tibet and Ningxia from our analysis since they have no processing trade in at least one year of our data sample. Furthermore, we treat Hong Kong SAR, China; Macau SAR, China and Taiwan, China as foreign economies.

⁴ Our model builds on the recent export platform FDI literature by Yeaple (2003), Grossman, Helpman and Szeidl (2006) and Ekholm, Forslid and Markusen (2007). It is a generalized version of the model developed by Ma, Van Assche and Hong (2009).

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.

In Section 5, we take advantage of the panel structure of the processing trade data to investigate whether rising oil prices have rendered intra-GPN trade more sensitive to distance-related trade costs. We find evidence that *China*'s processing exports indeed have become more sensitive to both import and export distance in times of rising oil prices. We also find that processing exports are more sensitive to oil price movements than non-processing exports. Specifically, an increase in oil prices tends to reduce the

share of processing exports in total exports, and especially when destined for far away countries. These results are in line with Yi's (2003) theory that intra-GPN trade is more sensitive to changes in trade costs than regular trade.

In Section 6, we use the processing trade data to analyze the impact of the recent Great Recession on intra-GPN trade. This analysis has become particularly relevant in light of the great collapse in trade during the crisis, which was significantly larger than the drop in world GDP. While there is a general consensus among trade economists that GPNs played an important role in the great trade collapse, there continues to be a heated debate through which channels. Analyzing China's processing trade data, we find evidence for the existence of three channels: a compositional effect, a trade cost effect and a bullwhip effect. First, in line with the *compositional effect*, we find that the sectors that contributed most to China's exports collapse are those where processing trade is more prevalent. Second, we show that, within industries, processing exports consistently dropped more than non-processing exports during the Great Recession. This is consistent with the *trade cost effect*, since intra-GPN trade should be more sensitive to trade costs than regular trade. Third, in line with the *bullwhip effect*, we show that in virtually all industries, the drop in demand for China's processing exports led to a magnified drop in processing imports.

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.⁵ Furthermore, national statistical

⁵ Dedrick, Kraemer and Linden (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

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 words “parts” or “components”. Lemoine and Ünal-Kesenci (2004) and Zebregs (2004) 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, Ishii and Yi, 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 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

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.

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, Ishii and Yi (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, Wang and Wei (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, Li and Oh (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, Mataloni and Slaughter (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, Humphrey and Sturgeon, 2005; Swenson, 2006; Bonham, Gangnes and Van Assche, 2007; Desai, 2009). 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 economies. 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, Wang and Wei (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 SAR, China, are re-exported elsewhere (Feenstra, Hai, Woo and Yao, 1999; Feenstra, Hanson and Lin, 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 SAR, China. To account for these re-exports, we follow Ma, Van Assche and Hong (2009) by linking the processing trade data from China's Customs Statistics to a data set from Hong Kong SAR, China's Census and Statistical Office on its re-exports. This allows us to estimate the country of origin of processing imports re-exported through Hong Kong SAR, China and the destination country of processing exports re-exported through Hong Kong SAR, China. A comparison of columns 1-2 and 3-4 in Table 1 illustrates the impact of adjusting for re-exports through Hong Kong SAR, China 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 economies.

[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 neighboring East Asian economies, with 75.1% of its processing imports originating from within East Asia in 2008. By contrast

the United States, EU-19⁶ 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 economies 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, Lemoine and Ünal-Kesenci, 2007; Haddad, 2007). With rising costs in Japan and the Newly Industrialized Economies (NIEs) – Taiwan, China; Singapore; South Korea and Hong Kong SAR, China – 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.

⁶ The EU-19 include all European Union countries prior to the accession of the 10 candidate countries on 1 May 2004, plus the four eastern European member countries of the OECD, namely Czech Republic, Hungary, Poland, Slovak Republic.

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 economies 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 were aimed at supplying inputs for processing industries. This is a significantly higher share than for Western economies. 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 economies 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 economies the number is significantly lower.

[Figure 6 about here]

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 (Ma, Van Assche and Hong, 2009). 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, Helpman and Szeidl, 2006; Ekholm, Forslid and Markusen, 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 framework⁷

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.⁸ Households in the two advanced countries consume goods produced by two industries. 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

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

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 :

$$q^i(v) = A^i p(v)^{-\varepsilon}, \quad (2)$$

where the demand level A^i is exogenous from the point of view of the individual firm.⁹

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

$$p^i(v) = \frac{c(v)}{\alpha}, \quad (3)$$

⁷ This is a generalized version of the model developed by Ma, Van Assche and Hong (2009).

⁸ 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.

⁹ 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 .

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 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 τ^{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).¹⁰ 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 τ 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 τ 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

¹⁰ A recent debate has emerged on whether trade costs are truly a linear function of distance (e.g, Brun, Carrère, Guillaumont and de Melo, 2005; Coe, Subramanian and Tamirisa, 2007). In this paper, we follow the standard approach in gravity regressions of using distance as a proxy for trade costs.

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 .¹¹ 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 $w^j = a$, 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:

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

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.¹² 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 :

¹¹ Our model features intra-industry firm heterogeneity as developed by Melitz (2003).

¹² Ma, Van Assche and Hong (2009) show that hypotheses 1 and 2 hold in the more restrictive model where firms cannot offshore production to China for sale in their home country.

- *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

	Market East	Market West
Type-D firm	$\pi_D^E = a^{1-\varepsilon} B^E - f_D$	$\pi_D^W = a^{1-\varepsilon} B^W - f_D$
Type-O firm	$\pi_O^E = (at^2w)^{1-\varepsilon} B^E - f_O - f_D$	$\pi_O^W = (a\tau^2w)^{1-\varepsilon} B^W - f_O - f_D$
Type-X firm	$\pi_X^E = (a\tau)^{1-\varepsilon} B^E - f_X - f_D$	$\pi_X^W = (a\tau)^{1-\varepsilon} B^W - f_X - f_D$
Type-T firm	$\pi_T^E = (attw)^{1-\varepsilon} B^E - f_O - f_X - f_D$	$\pi_T^W = (artw)^{1-\varepsilon} B^W - f_O - f_X - f_D$

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

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.¹³ All four profit functions are increasing with this productivity index: more productive firms are more profitable for all four firm types.

[Figure 8 about here]

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 $(a_k^i)^{1-\varepsilon}$ depicted in Figure 8 solve the following equations:

Table 3: Cut-off conditions

	Market East	Market West
Type-D firm	$(a_D^E)^{1-\varepsilon} B^E = f_D$	$(a_D^W)^{1-\varepsilon} B^W = f_D$

¹³ This graphical approach of presenting the results is adopted from Helpman, Melitz and Yeaple (2004).

Type-O firm	$(a_O^E)^{1-\varepsilon} B^E ((t^2 w)^{1-\varepsilon} - 1) = f_o$	$(a_O^W)^{1-\varepsilon} B^W ((\tau^2 w)^{1-\varepsilon} - 1) = f_o$
Type-X firm	$(\tau a_X^E)^{1-\varepsilon} B^E = f_D + f_X$	$(\tau a_X^W)^{1-\varepsilon} B^W = f_D + f_X$
Type-T firm	$(\tau a_T^E)^{1-\varepsilon} B^E ((t w)^{1-\varepsilon} - 1) = f_o$	$(\tau a_T^W)^{1-\varepsilon} B^W ((t w)^{1-\varepsilon} - 1) = f_o$

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 $R_k^i = \frac{c_k^{1-\varepsilon}}{1-\alpha} B^i$, 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

	Market East	Market West
Type-D firm	$\Omega_D^E = \frac{B^E [V(a_D) - (t^2 w)^{1-\varepsilon} V(a_O)]}{1-\alpha}$	$\Omega_D^W = \frac{B^W [V(a_D) - (\tau^2 w)^{1-\varepsilon} V(a_O)]}{1-\alpha}$
Type-O firm	$\Omega_O^E = \frac{B^E (t^2 w)^{1-\varepsilon} V(a_O)}{1-\alpha}$	$\Omega_O^W = \frac{B^W (\tau^2 w)^{1-\varepsilon} V(a_O)}{1-\alpha}$
Type-X firm	$\Omega_X^E = \frac{B^E \tau^{1-\varepsilon} [V(a_X) - (t w)^{1-\varepsilon} V(a_T)]}{1-\alpha}$	$\Omega_X^W = \frac{B^W \tau^{1-\varepsilon} [V(a_X) - (t w)^{1-\varepsilon} V(a_T)]}{1-\alpha}$
Type-T firm	$\Omega_T^E = \frac{B^E (t \tau w)^{1-\varepsilon} V(a_T)}{1-\alpha}$	$\Omega_T^W = \frac{B^W (t \tau w)^{1-\varepsilon} V(a_T)}{1-\alpha}$

where $V(a) = \int_0^a x^{1-\varepsilon} dG(x)$.

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 $\Omega_O^i + \Omega_T^i$.

[Figure 9 about here]

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 τ 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 τ . 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 τ 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 τ 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 τ reflects the trade costs related to export distance. Conversely, when exporting to East, t reflects the trade costs related to export distance and τ 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 SAR, China re-exports) for the period 1988-2008. Specifically, we estimate the following equation:

$$\ln X_{ijt} = \alpha + \lambda_i + \mu_t + \nu_{jt} + \beta_1 \ln XD_{ij} + \beta_2 \ln MD_{it} + \beta_3 East_j * \ln XD_{ij} + \beta_4 East_j * \ln MD_{it} + \mathbf{Z}_{it}\boldsymbol{\gamma} + \varepsilon_{ijt}, \quad (6)$$

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 ; \mathbf{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 is an East Asian economy, and is 0 otherwise and ε_{ijt} is a normally distributed error term.¹⁴

¹⁴ Our data consists of China's East Asia neighbors (Indonesia, Malaysia, Thailand, Japan, Singapore, South Korea, Philippines, Taiwan, China and Hong Kong SAR, China) and the Non-Asian OECD countries (Australia, Canada, 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.

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_{it}), we need to take into account that multiple inputs from various economies are used in the production of a specific export good. As a consequence, we measure import distance using the following formula:

$$MD_{it} = \sum_j \frac{M_{ijt}}{\sum_j M_{ijt}} \cdot XD_{ij} , \quad (7)$$

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 economies 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 economy of destination is an East Asian economy 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 standard set of controls. Specifically, we use data from, respectively, *China's Statistical Yearbook* to include controls for GDP per capita and population size for Chinese provinces. We also use data from *China's Statistical Yearbook* to add a control for Chinese provincial wages.

Anderson and van Wincoop (2003, 2004) highlighted the importance of controlling for multilateral resistance in gravity models, i.e. the fact that bilateral flows not only depend on bilateral trade barriers but also on trade barriers across all trading partners. To construct a specification that captures multilateral resistance, we follow Rose and van Wincoop (2001) and Feenstra (2004) by adding both exporter-specific and importer-specific fixed effects. Ideally these fixed effects should be time-varying since the

multilateral resistance term may vary over time (Egger, 2008). The inclusion of time-varying exporter-specific fixed effects, however, would mean that no time-varying parameters specific to an exporting province such as import distance can be estimated. As a robustness check, we include time-varying importer-specific effects. Finally, we use time fixed effects to account for economic shocks common to all country pairs.¹⁵

There is a potential endogeneity bias in that omitted variables could be correlated with gravity variables (GDP per capita, population, distance) and the level of bilateral trade. We follow Sissoko (2004) and Carrère (2006) in using the Hausman and Taylor (1981) estimation model to select the appropriate instruments.

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 $East_j * \ln XD_{ij}$ is negative and statistically significant, while the coefficient on $East_j * \ln MD_{it}$ is positive and statistically significant. In line with Hypothesis 2, this suggests that processing exports destined to East Asian economies are more sensitive to export distance and less sensitive to import distance than processing exports destined to non-Asian OECD countries.

¹⁵ Other studies have argued for the inclusion of pair fixed effects to control for unobserved characteristics of pairs of countries, but this would mean that no time-invariant parameters such as export distance elasticity can be estimated (Baldwin and Taglioni, 2006).

The OLS results do not take into account the potential endogeneity of import distance and GDP per capita. To account for this, we apply the instrumental variables estimation proposed by Hausman and Taylor (1981). 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]

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

4.4. Growth Rebalancing and China's processing trade

The model can also be used to analyze the impact on China's processing trade patterns of a shift in final goods demand from Western countries to East Asia. This exercise is of particular interest since many scholars consider the rebalancing of East Asia's growth away from heavy dependence on external demand towards increased reliance on intra-regional demand to be a key global policy priority to forestall the reemergence of global imbalances (Prasad, 2009; Petri, 2010; International Monetary Fund, 2010). Prior to the Great Recession, the large current account deficits of the United States and a few other advanced economies, combined with the large current account surpluses of oil-exporting countries and emerging Asian markets such as China, were considered a key source of global economic instability (Suominen, 2010).

As it has been demonstrated in Section 3, China's processing trade regime has played an important role in fueling China's bilateral trade surplus with many Western economies.¹⁶ Whereas China heavily relies on processing inputs from within the East Asian region, it predominantly sends its processed final goods to non-Asian OECD countries. This imbalance can be replicated in our theoretical model by assuming that the market size of *West* is significantly larger than the market size of *East*. From equation (A-4) and Table A-1 in the appendix, this benchmark scenario implies that China's processing trade is dominated by Eastern *Type-T* firms that produce their components in *East*, process their final goods in *China* and export to *West*.

Growth rebalancing can then be modeled as a counterfactual scenario in which there is an increase in the relative market size of *East* compared to *West*.¹⁷ Using equation (A-4) and Table A-1, it is straightforward to show that this will weaken the observed triangular trade pattern through two channels. First, and most obviously, it will increase the share of *China*'s processing exports destined to *East*. Second, since processing exports destined to *East* rely more heavily on Western components than processing exports destined to *West*, it will decrease the share of *China*'s processing imports originating from *East*. Indeed, in the extreme counterfactual where the market size of *East* and *West* are symmetric, the triangular trade pattern completely disappears, with *China* both importing a disproportionate share of its processing inputs from *East* and exporting a disproportionate share of its processed final goods to *East*.

5. Oil Prices and Intra-GPN Trade

The sensitivity of intra-GPN trade to changes in trade costs has been a prominent question in the literature of vertical specialization. In a seminal theoretical contribution, 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. He used this insight to explain how a relatively small reduction in tariffs could explain the rapid

¹⁶ See also Van Assche, Hong and Sloomakers (2008).

¹⁷ We do not consider a growth in China's market since, by the nature of the processing trade regime, processed goods are not allowed to be sold on the Chinese market.

growth of world trade in the second half of the twentieth century. Conversely, 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. In this section, we will attempt to gain insights into this latter conjecture, by using the panel data structure of the processing trade data to analyze the sensibility of intra-GPN trade to changes in oil prices.

5.1. Trends in oil prices and transportation costs

Oil prices have risen dramatically in the last decade. As it is shown in Figure 10, while crude oil prices were relatively stable and even declined over the period 1980-1999, they have rapidly increased over the period 1999-2008, growing at an annualized rate of 20.6%. During the Great Recession of 2008-2009, the oil prices have retreated (see Figure 10), but this is likely a temporary phenomenon. As the global economy comes out of the recession and as peak oil is reached, oil prices are expected to return to and even exceed its pre-crisis levels. Peak oil refers to the attainment of the maximum conventional oil output (i.e. excluding heavy oil from tar sands, oil shale etc.), expressed in terms of millions of barrels of crude oil extracted per day (Deffeyes, 2001). There is a general consensus among oil experts that peak oil will be reached prior to 2015 (De Almeida and Silva, 2009). When this occurs, the gap between oil production and demand is expected to increase. As a consequence, the price of oil is expected to both rise significantly and become more volatile.

[Figure 10 about here]

Rubin and Tal (2008) have argued that the rise of oil prices is likely to lead to significant hikes in international transportation and thus will lead to a major slowdown in the growth of world trade. As supporting evidence, they highlight that, hand-in-hand with the oil price hikes, the cost to ship a standard 40-foot container from Shanghai to the U.S. eastern seaboard has risen from US\$3,000 in 2000 to US\$8000 in 2008. Other studies, however, have estimated that the sensitivity of shipping freight rates to oil prices remains relatively low, thus limiting the threat that rising oil prices will lead to a significant reduction in the growth of intra-GPN trade. Hummels (2007) and UNCTAD (2010)

estimate an elasticity of maritime cargo costs with respect to fuel prices between 0.20 and 0.40. Mirza and Zitouna (2009) estimate an even lower elasticity of freight rates to oil prices ranging from 0.02 to 0.15.

To analyze if rising oil prices have made intra-GPN trade more sensitive to distance, we will analyze the following hypothesis:

Hypothesis 3: *Ceteris paribus, a rise in oil prices increases China's processing exports' sensitivity to export distance, import distance and local distance.*

Since intra-GPN trade is conjectured to be especially sensitive to changes in trade costs (Yi, 2003), we will also investigate if increases in oil prices have a significantly larger impact on processing exports than on non-processing exports. Specifically, we will test the following hypothesis:

Hypothesis 4: *Ceteris paribus, a rise in oil prices reduces the share of China's processing exports in total exports, and especially for far away destinations.*

5.3. Empirical specification

To test hypotheses 3, we estimate the following equation for the years 1988-2008:

$$\ln X_{ijt} = \alpha + \beta_1 \ln XD_{ij} + \beta_2 \ln MD_{it} + \beta_3 t * \ln LD_i + \beta_4 t * \ln XD_{ij} + \beta_5 t * \ln MD_{it} + \beta_6 \ln Oil_t * \ln LD_i + \beta_7 \ln Oil_t * \ln XD_{ij} + \beta_8 \ln Oil_t * \ln MD_{it} + \mathbf{Z}_{ijt} \boldsymbol{\gamma} + \varepsilon_{ijt}, \quad (8)$$

where t refers to a time trend, Oil refers to average crude oil prices in US\$/barrel, and all other variables are defined in section 4.2. Equation (8) differs from equation (6) in three ways. First, to simplify the interpretation of the results, we have eliminated the variable $East_j$ and its interactions with export distance and import distance. Second, to account for time-varying trends in the elasticity of processing exports with respect to the three distance variables, we have included interaction terms between trend t and the three distance variables.¹⁸ Third, to account for the impact of oil prices on processing exports, we have interacted $\ln Oil$ with the three distance variables. Hypothesis 3 will be

¹⁸ See Brun, Carrère, Guillaumont and de Melo (2005) and Disdier and Head (2008) for a similar approach.

confirmed if the coefficients on the interaction terms $\ln Oil_t * \ln LD_i$, $\ln Oil_t * \ln XD_i$ and $\ln Oil_t * \ln MD_i$ all are negative.

To test Hypothesis 4, we estimate the equation:

$$\ln S_{ijt} = \alpha + \beta_1 \ln LD_i + \beta_2 \ln XD_{ij} + \beta_3 \ln OIL_t + \beta_4 \ln OIL_t * \ln LD_i + \beta_5 \ln OIL_t * \ln XD_{ij} + \beta_6 t + \beta_7 t * \ln LD_i + \beta_8 t * \ln XD_{ij} + \mathbf{Z}_{ijt}\boldsymbol{\gamma} + \varepsilon_{ijt}, \quad (9)$$

where the dependent variable S_{ijt} is the share of processing exports in total exports from province i to country j in year t , and all independent variables as previously defined. It is important to note that we have dropped import distance (MD) as an independent variable in equation (9). For reasons explained in Section 2, China's Customs Statistics data allow us to identify the distance from which inputs are imported (import distance) for processing trade, but not for regular non-processing trade. Hypothesis 4 will be confirmed if the coefficients on $\ln Oil_t$ and on the interaction terms of both $\ln Oil_t * \ln LD_i$ and $\ln Oil_t * \ln XD_{ij}$ are negative.

5.3. Regression Results

The results from the estimation of equations (8) and (9) are presented in Table 7. In columns 1 to 3, the dependent variable is the natural log of bilateral processing exports; in columns 4 to 6, the dependent variable is the natural log of the share of processing exports in total exports.

[Table 7 about here]

The results provide partial support for Hypothesis 3. In column 3, the coefficients on both $\ln Oil_t * \ln XD_{ij}$ and $\ln Oil_t * \ln MD_{it}$ are negative and statistically significant, suggesting that oil price hikes do make China's processing exports more sensitive to import and export distance. The coefficient on $\ln Oil_t * \ln LD_i$, however, is positive and significant.

The results for the control variables in columns 1, 2 and 3 are similar to those in the benchmark specification. Processing exports are larger for more populated provinces, with higher GDP per capita, lower internal distance and lower wages. In addition,

processing exports are greater for destinations that are more populated and have a higher GDP per capita. Furthermore, we find a general trend for processing exports to become more sensitive to internal and import distances over time.

The results in columns 5 and 6 of Table 7 provide supporting evidence for Hypothesis 4. In column 5, the coefficient on $\ln Oil_t * \ln XD_{ij}$ is negative, which suggests that a rise in oil prices reduces the share of China's processing exports in total exports especially for far away destinations. Conversely, the coefficient on $\ln Oil_t * \ln LD_i$ is not significant.

The coefficients on the other control variables in columns 4, 5 and 6 suggest that the share of processing exports in total exports is larger for more populated provinces, closer to the coast with lower wages. The share is also larger when destined for richer, less populated countries that are further away. Finally, we find an upward trend for the share of processing exports in total exports, but this trend is smaller for internal provinces and faraway destinations.

In conclusion, we find evidence that China's processing exports become more sensitive to both import and export distance in times of rising oil prices, but not more sensitive to internal distance. We also find supporting evidence that processing exports are more sensitive to changes in trade costs related to oil price movements than non-processing exports. Specifically, an increase in oil prices tends to reduce the share of processing exports in total exports, and especially when destined for far away countries.

6. Intra-GPN Trade and the Great Recession

Finally, we can use the processing trade data to examine the impact of the Great Recession on intra-GPN trade flows. This analysis has become particularly relevant in light of the collapse in trade during the crisis, which was significantly larger than the drop in world GDP. A number of scholars have attributed the disproportionate trade collapse to vertical specialization. Barry Eichengreen, for example, stated that “the most important factor is probably the growth of global supply chains, which has magnified the impact of declining final demand on trade” (International Economy, 2009). Bems, Johnson and Yi (2009) argue that “international supply chains are a leading contender for explaining why the great collapse was so great.”

The channels through which vertical specialization exacerbated the trade collapse, however, have become the source of a heated debate. Using a simple Barbie doll example, O'Rourke (2009) demonstrated that vertical specialization cannot automatically explain why world trade overshoot the drop in world GDP. The fact that components of the Barbie doll cross borders multiple times in the production of a final doll for US consumers does not necessarily imply that a drop in Barbie sales should lead to a disproportionate drop in trade. To explain the role of vertical specialization in the trade collapse, scholars have therefore focused on three additional effects: a compositional effect, a trade cost effect and a bullwhip effect.

A number of studies have argued that vertical specialization has exacerbated the trade collapse through a *compositional effect* (Francois and Woerz, 2009; Levchenko, Lewis and Tesar, 2009; and Eaton, Kortum, Neiman and Romalis, 2010). Vertical specialization has primarily taken place in durable goods sectors (consumer electronics, automobile and transport equipment, office equipment and computers, etc.), thus making trade and especially intra-GPN trade more intensive in durable goods than overall GDP. This compositional change has made trade more sensitive to business cycle fluctuations.¹⁹ In times of recession, households and companies tend to hold off first and foremost their purchases of durable goods, not only because tightening budget constraints render high ticket-item goods unaffordable for some, but also because consumers and firms want to postpone their purchases until it is known with more certainty whether and when the economic climate will improve. Since an economic crisis leads to a disproportionate drop in the demand for durable goods, the compositional effect can explain the lopsided collapse in trade compared to GDP. This assertion was backed up by Levchenko, Lewis and Tesar (2009) who found that, during the crisis, U.S. imports fell more in sectors that are intensively used as intermediate inputs.

A second set of studies have argued that another part of the story is the rising trade costs associated with evaporating credit, increasing non-tariff barriers and home bias in government stimulus plans (Yi, 2009; and Jacks, Meissner and Novy, 2009). Jacks, Meissner and Novy (2009) estimate that trade costs have on average increased by 11%

¹⁹ Engel and Wang (2008) found that U.S. durable goods imports are more sensitive to business cycles than nondurable goods imports.

between the second quarter of 2008 and the first quarter of 2009. Since intra-GPN trade is especially sensitive to changes in the trade costs (Section 5; Yi, 2003), this can explain the magnified fall in trade compared to GDP.

A final explanation that has received less attention is the role of bullwhip effects in global supply chains on the trade collapse (Escaith and Gonguet, 2009; Escaith, Lindenberg and Miroudot, 2010; Ma and Van Assche, 2010). The bullwhip effect is one of the most researched and documented symptoms in the field of supply chains management (Lee, Padmanabhan and Wang, 1997; Cachon, Randall and Schmidt, 2007). It states that, when a downstream firm is confronted with a drop in demand for its final products, its first reaction is to run down its inventories. Thus a slowdown in downstream activities transforms itself into an amplified reduction in the demand for inputs that are located upstream.²⁰ Since fluctuations in final demand get amplified as one moves upstream along the supply chain, this provides an alternative explanation of the magnified fall in trade compared to GDP.

Due to the data limitations highlighted in Section 2, most of the above-mentioned studies have relied on indirect measures to evaluate the role of vertical specialization on the trade collapse. In this section, we will use data on China's processing trade regime to evaluate if there is direct evidence of a compositional effect, trade cost effect and bullwhip effect in GPNs during the Great Recession.

The dataset that we will use in this section differs from the rest of the paper in an important way. Instead of using annual data, we will rely on processing trade data for the first quarter of 2008 and the first quarter of 2009. Since the Great Recession hit China's exports in the last quarter of 2008, the quarterly data allow us to analyze the initial impact of the Great Recession on China's processing trade. As it is shown in Table 8, the initial impact of the crisis was huge. In the first quarter of 2009, demand for China's exports experienced a stunning contraction of 19.9% compared to the previous year, from US\$304 billion to US\$243 billion. We now turn to the analysis of the three effects.

²⁰ Mason-Jones and Towill (2000) provide the following explanation of a bullwhip effect: "If demand for products is transmitted along a series of inventories using stock control ordering, then the demand variation will increase with each transfer".

[Table 8 about here]

6.1.1. Compositional effect

To verify if the trade collapse during the Great Recession was concentrated in industries with large vertical specialization, we first need to identify in which type of industry China's processing exports are most prevalent. For this purpose, we use the Organization of Economic Cooperation and Development's (OECD) technology classification (Hatzichronoglou, 1997) to disaggregate China's exports into four categories: *high technology* exports, *medium-high technology* exports, *medium-low technology* exports, *low technology* exports. In Figure 10, we depict the share of processing exports in China's total exports for each technology category. The figure shows that vertical specialization is more prevalent in the higher technology categories than in the lower technology categories. In 2007, processing exports accounted for 84.9% of *high-technology* exports; 45.6% of *medium-high-technology* exports; 26.6% of *medium-low-technology* exports; and 29.8% of *low technology* exports.

[Figure 11 about here]

The higher technology categories are also the industries that saw a larger exports collapse during the Great Recession. As it is shown in Table 8, *high technology* exports dropped 24.1% in the first quarter of 2009 compared to a year earlier; *medium-high technology* exports dropped 22.0%; *medium-low technology* exports dropped 21.6%; *low technology* exports dropped 8.9%.

Furthermore, the higher technology categories are also the industries that contributed most to the drop in China's exports during the Great Recession. As it is shown in Table 8, *high technology* exports, which accounted for almost one third of China's exports in the first quarter of 2008, contributed to 37.6% of the exports collapse; *medium-high technology* exports contributed to 25.4%; *medium-low technology* exports contributed to 16.0%; *low technology* exports contributed to 10.9%; and *other non-manufacturing* exports contributed to 10.1%

In sum, we find evidence of a compositional effect in China's exports during the Great Recession. The sectors that contributed most to the export collapse are those where vertical specialization is more prevalent.²¹

6.1.2. Trade cost effect

Next, we want to investigate if there is evidence of a trade cost effect in China's trade during the Great Recession. As we have shown in Section 5, intra-GPN trade is generally more sensitive to trade costs than regular trade. If trade costs have risen significantly during the Great Recession, we therefore should find that processing exports have consistently dropped more than non-processing exports from the first quarter of 2008 to the first quarter of 2009.

To adequately control for compositional effects, we conduct the analysis at the most disaggregated level in China's trade data – the HS 8-digit level. Specifically, we examine whether, at the HS 8-digit level, there is evidence that the share of China's processing exports in total exports has significantly declined from the first quarter of 2008 to the first quarter of 2009. The results are presented in Table 9. In line with the trade cost effect, the t-test on equality of means finds that the share of processing exports in total exports was significantly lower in the first quarter of 2009 than a year earlier.

[Table 9 about here]

In sum, we find evidence of a trade cost effect in China's exports during the Great Recession. After controlling for compositional effects, processing exports have consistently dropped more during the Great Recession than non-processing exports.

6.1.3. Bullwhip effect

Finally, we want to investigate whether there is a bullwhip effect in intra-GPN trade. In other words, we want to analyze if the percentage decline in China's processing imports exceeded the percentage decline in processing exports during the Great Recession. A first indication of a bullwhip effect is that, despite China's relatively robust economic growth

²¹ In line with this result, Aziz and Li (2008) demonstrate that China's increasing specialization in electronics exports has led to an overall rise in the income elasticity of China's exports.

in 2008 and 2009, the percentage drop in China's processing imports was larger than that of processing exports in the first quarter of 2009 compared to a year earlier.²² China's processing exports dropped 23.7%, while processing imports declined 36.2% (see Table 10).

[Table 10 about here]

The evidence of a bullwhip effect is confirmed when the analysis is disaggregated to the industry level. As it is shown in Table 10, in 15 out of the 20 industries the percentage change in processing imports had been more pronounced than the percentage change in processing exports.

The existence of a bullwhip effect in China's processing trade helps to explain at least partially the resilience of China's economy in the realm of the great trade collapse (Ma and Van Assche, 2009). When the crisis hit China in the second half of 2008, its economy was able to rapidly pass on the negative export demand shock to its input suppliers through a reduction in demand for processing inputs. Indeed, since the drop in imports was larger than the drop in exports in the first quarter of 2009 compared to a year earlier, China's net exports actually increased.

The largest sufferers of the bullwhip effect in China's processing trade were its East Asian neighbors. As it is shown in Figure 9, the Great Recession has hit most severely China's imports from economies that more intensively supply China with its processing inputs, that is, its East Asian neighbors. With the exception of Vietnam and Indonesia, more than 40% of China's imports from its major East Asian trading partners were processing imports in 2006, which is a significantly higher share than for countries outside of East Asia. These East Asian countries have witnessed the largest import decline in the realm of the recent global economic crisis. Compared to the previous year, China's imports from its major East Asian trading partners have all declined between 25% and 61% in the first quarter of 2009. In contrast, China's imports from its major non-Asian trading partners have dropped less than 20%.

²² In the first and second quarter of 2009, China's GDP has expanded at an annualized rate of 6.1% and 7.9%, respectively.

[Figure 12 about here]

In sum, we find supporting evidence that GPNs have exacerbated the great trade collapse during the Great Recession through three channels: a compositional effect, a trade cost effect and a bullwhip effect. First, in line with the *compositional effect*, we find that the sectors that contributed most to the Chinese exports collapse are those where processing trade is more prevalent. Second, we show that, within industries, processing exports consistently dropped more than non-processing exports during the Great Recession. This is in line with the *trade cost effect* since intra-GPN trade should be more sensitive to trade costs than regular trade. Third, in line with the *bullwhip effect*, we show that in virtually all industries, the drop in demand for China's processing exports led to a magnified drop in processing imports.

7. 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 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 trade costs on intra-GPN trade.

A key theoretical prediction by Yi (2003) is 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. Rubin and Tal (2008) and Rubin (2009) have built on this theory to conjecture that rising oil prices will increase trade costs, thus leading to a major slowdown in the growth of world trade and especially intra-GPN trade. To test this conjecture, we have used the panel data structure of the processing trade data to analyze the sensibility of intra-GPN trade to changes in oil prices. We have found evidence that China's processing exports indeed have become more sensitive to both upstream and downstream trade costs in times of rising oil prices. Furthermore, in line with Yi's (2003) theoretical prediction, China's processing exports have been found to be more sensitive to oil price movements than non-processing exports.

Finally, we have used the processing trade data to analyze the role of GPNs in the large trade collapse during the recent Great Recession. In line with the predictions of many trade economists, we found that the Great Recession led to a disproportionate drop in China's processing exports compared to non-processing exports, thus suggesting that GPNs played a key role in the trade decline. Part of this was a compositional effect. The sectors that contributed most to China's exports collapse were those where processing exports were more prevalent. However, even within highly disaggregated industries, we have found that processing exports consistently dropped more than non-processing exports, thus suggesting that intra-GPN trade is more sensitive to business cycle fluctuations than regular trade. Furthermore, in line with the bullwhip effect, we showed that in virtually all industries, the drop in demand for China's processing exports led to a magnified drop in processing imports, thus feeding the trade collapse.

Our analysis provides new insights into the success of China's export-oriented growth strategy. To a large extent, prior studies have attributed China's dramatic exports rise to

domestic factors – its relatively low labor costs coupled with its aggressive export promotion policies. Our study, however, suggest that another key driver has been China’s geographic location within the dynamic East Asian region. Specifically, its proximity to East Asian input suppliers (supplier access) and its vicinity of large and growing East Asian consumer markets (market access) both have strongly boosted its attractiveness as an export-processing platform.

There are nonetheless policy actions that developing countries can take to deepen their integration into global production networks. Since intra-GPN trade is negatively affected by both upstream and downstream trade costs, and since intra-GPN trade is more sensitive to trade costs than regular trade, trade-cost reducing policies should be considered an integral part of any export-oriented growth strategy.

Appendix

In this appendix, we derive the closed form solution for China's processing exports to country i , $\Omega_O^i + \Omega_T^i$, where Ω_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 Ω_O^i and Ω_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:

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

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

$$\Omega_O^i = \frac{Y^i}{1 + \sigma_{D,O}^i + \sigma_{X,O}^i + \sigma_{T,O}^i}, \quad (\text{A-2})$$

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

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

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

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

To derive a closed-form solution for Ω_O^i and Ω_T^i , we can then plug in the industry sales Ω_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, Melitz and Yeaple (2004) show that $V(a)$, is also Pareto with the shape parameter $z - (\varepsilon - 1)$. The Pareto distribution implies that

$$\frac{V(a_1)}{V(a_2)} = \left(\frac{a_1}{a_2}\right)^{z - (\varepsilon - 1)} \quad (\text{A-5})$$

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 A-1

	<i>Market East</i>	<i>Market West</i>
Components of Ω_T^i		
$\mathbf{1} + \sigma_{X,T}^i$	$\left[\frac{f_o}{f_D + f_X} \frac{(tw)^{\varepsilon-1}}{1 - (tw)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (tw)^{\varepsilon-1}$	$\left[\frac{f_o}{f_D + f_X} \frac{(tw)^{\varepsilon-1}}{1 - (tw)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (tw)^{\varepsilon-1}$
$\sigma_{D,T}^i + \sigma_{O,T}^i$	$\left[\frac{f_o}{f_D} \frac{(t\tau w)^{\varepsilon-1}}{1 - (t\tau w)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (t\tau w)^{\varepsilon-1}$	$\left[\frac{f_o}{f_D} \frac{(t\tau w)^{\varepsilon-1}}{1 - (t\tau w)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (t\tau w)^{\varepsilon-1}$
Components of Ω_0^i		
$\mathbf{1} + \sigma_{D,0}^i$	$\left[\frac{f_o}{f_D} \frac{(t^2w)^{\varepsilon-1}}{1 - (t^2w)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (t^2w)^{\varepsilon-1}$	$\left[\frac{f_o}{f_D} \frac{(\tau^2w)^{\varepsilon-1}}{1 - (\tau^2w)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (\tau^2w)^{\varepsilon-1}$
$\sigma_{X,0}^i + \sigma_{T,0}^i$	$\left[\frac{f_o}{f_D + f_X} \left(\frac{t^2w}{\tau} \right)^{\varepsilon-1} \frac{1}{1 - (t^2w)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} \left(\frac{t^2w}{\tau} \right)^{\varepsilon-1}$	$\left[\frac{f_o}{f_D + f_X} \frac{(\tau w)^{\varepsilon-1}}{1 - (\tau^2w)^{\varepsilon-1}} \right]^{\frac{z-(\varepsilon-1)}{\varepsilon-1}} (\tau w)^{\varepsilon-1}$

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

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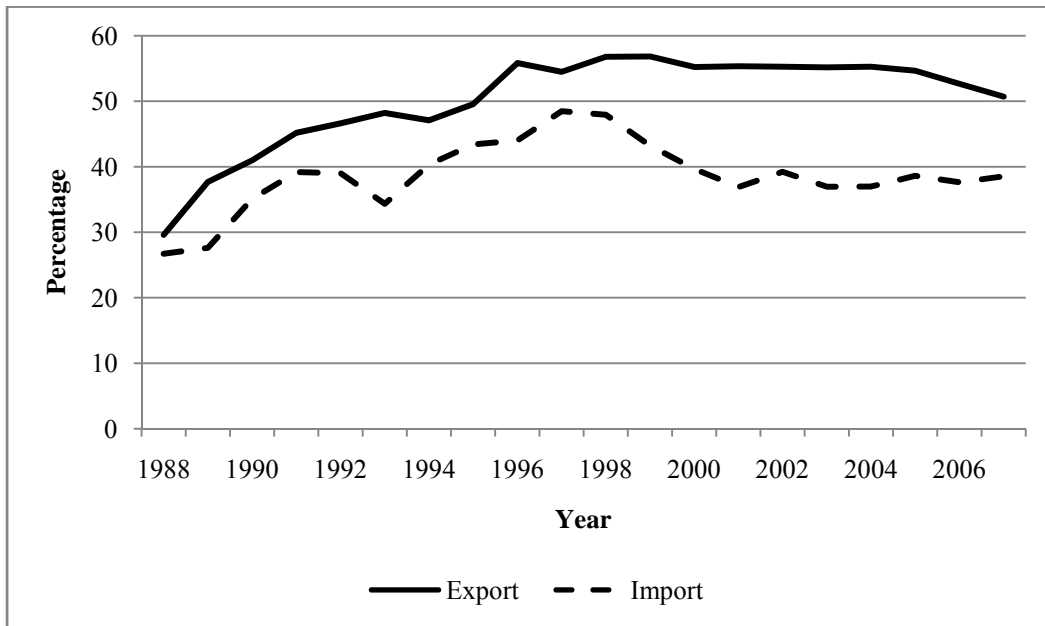
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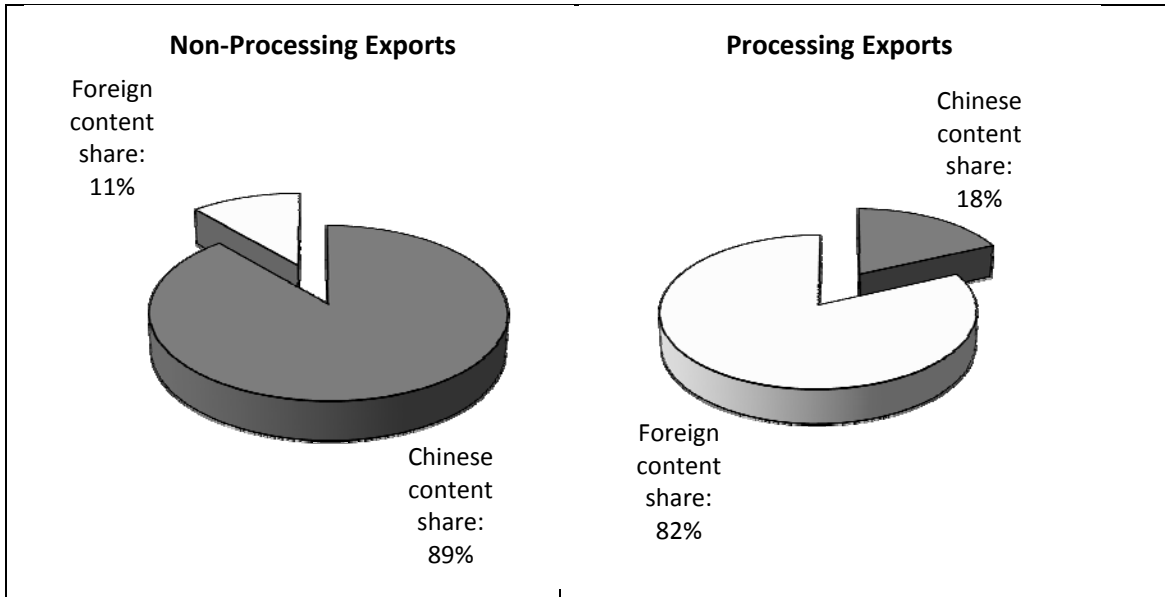
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Figure 1: Proportion of processing trade in China's total trade, 1988-2008



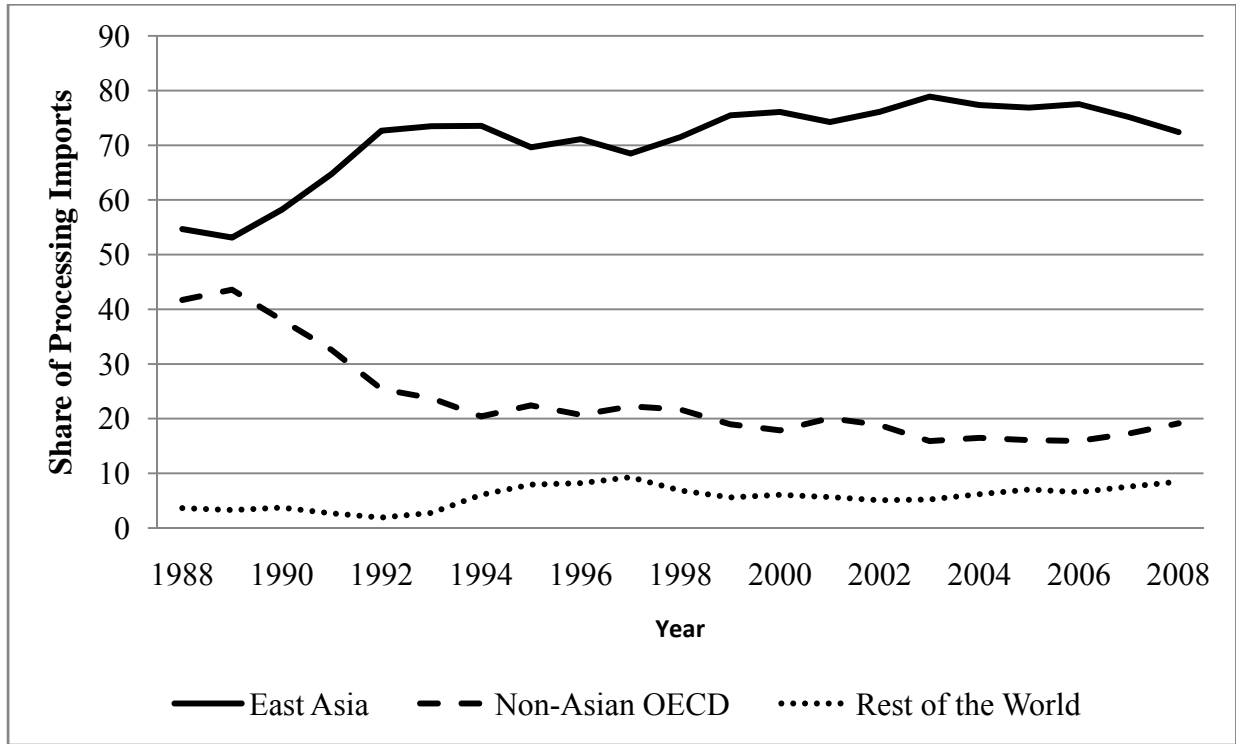
Source: Authors' calculations using China's Customs Statistics.

Figure 2: Domestic and foreign content share of China's processing and non-processing exports



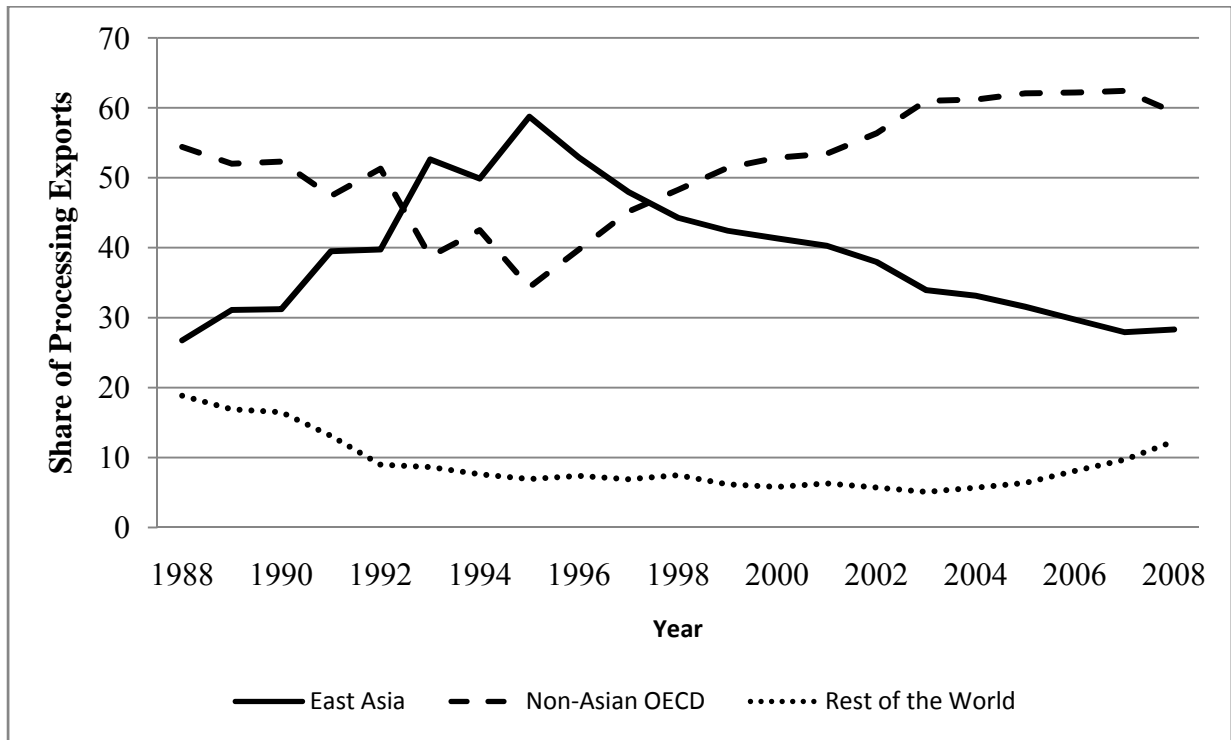
Source: Koopman, Wang and Wei (2008).

Figure 3: Share of Processing Imports, by region of origin, 1988-2008



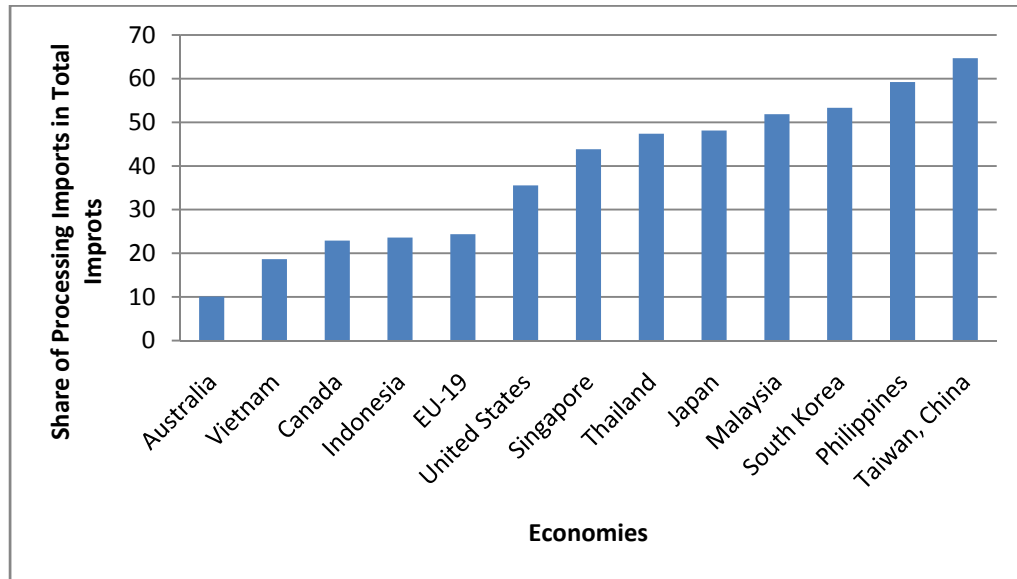
Source: authors' calculations, using China's Customs Statistics

Figure 4: Share of Processing Exports, by region of destination, 1988-2008



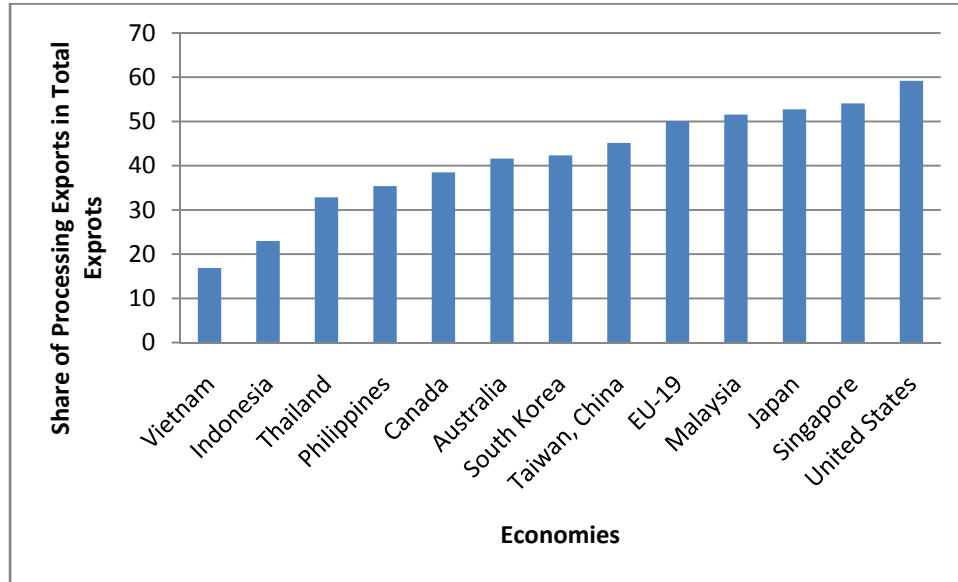
Source: authors' calculations, using China's Customs Statistics

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

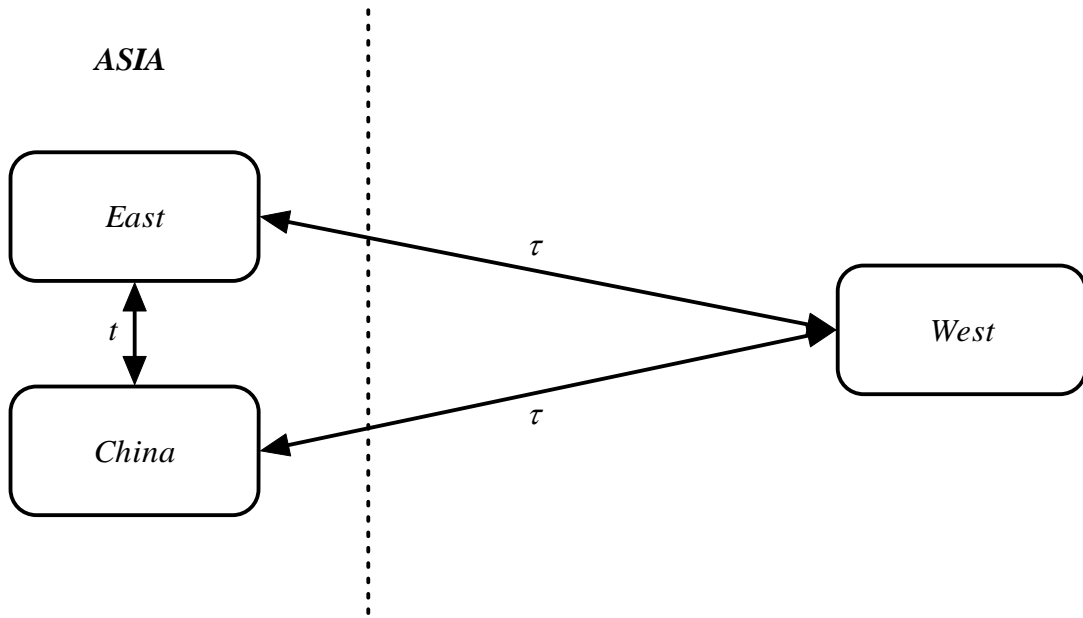


Figure 8: Profit functions for the four firm-types

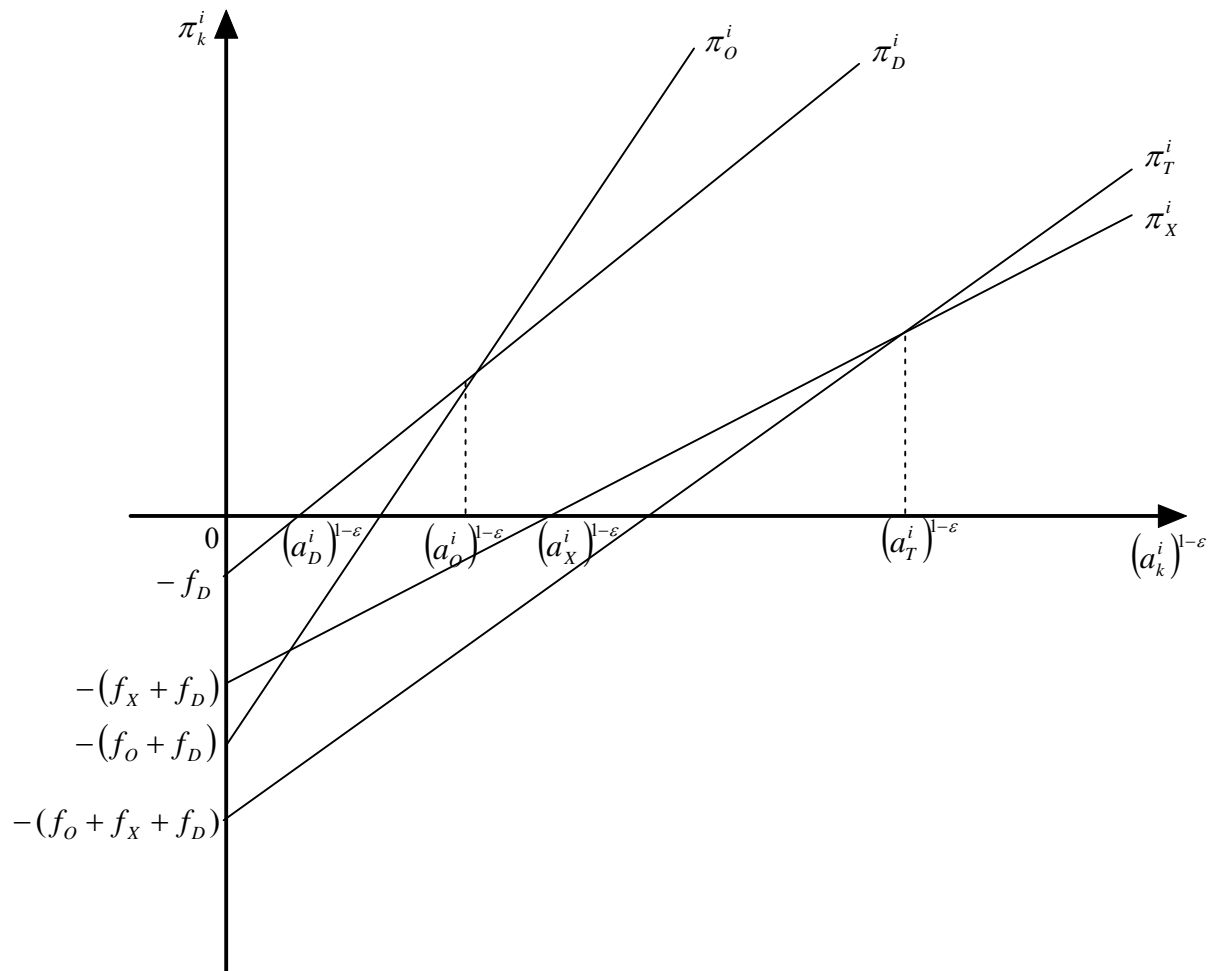


Figure 9: China's processing trade, by firm type

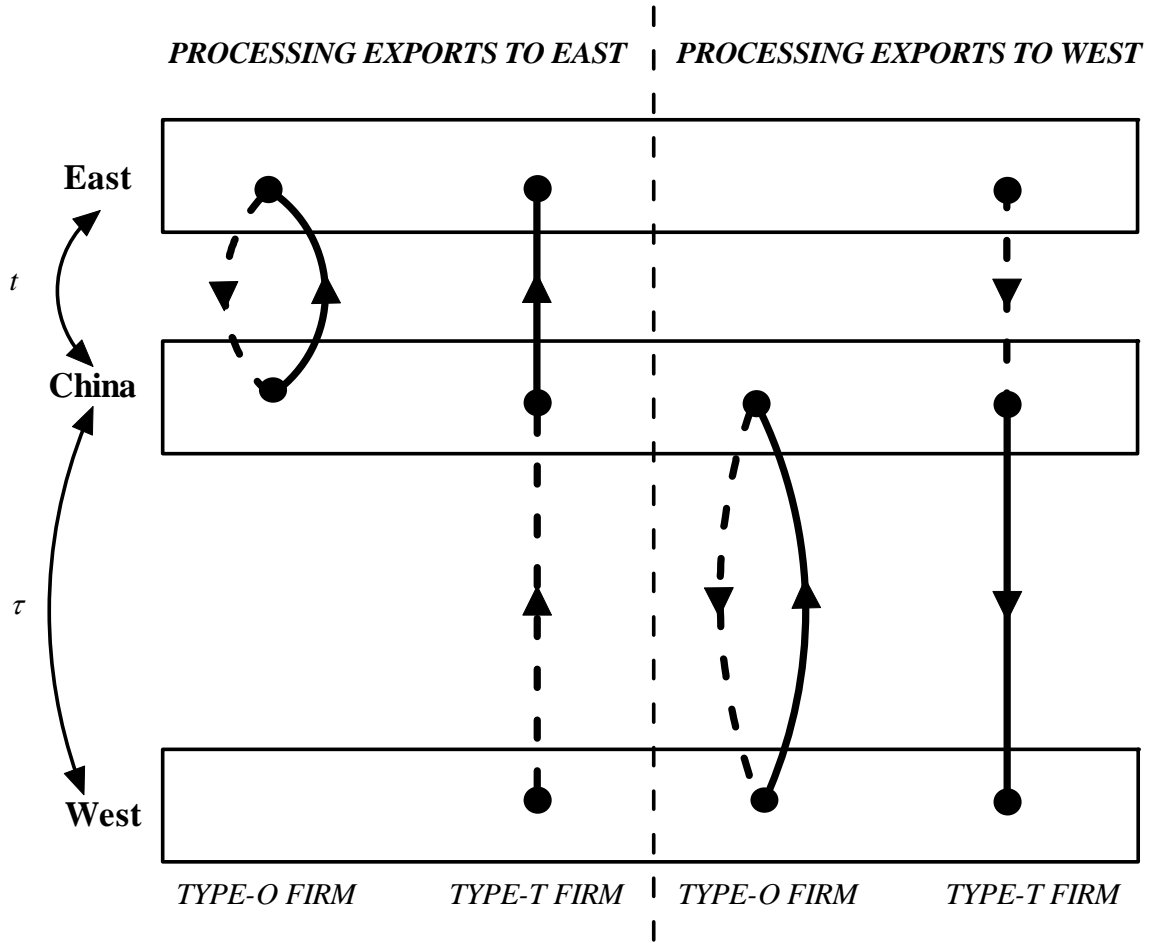
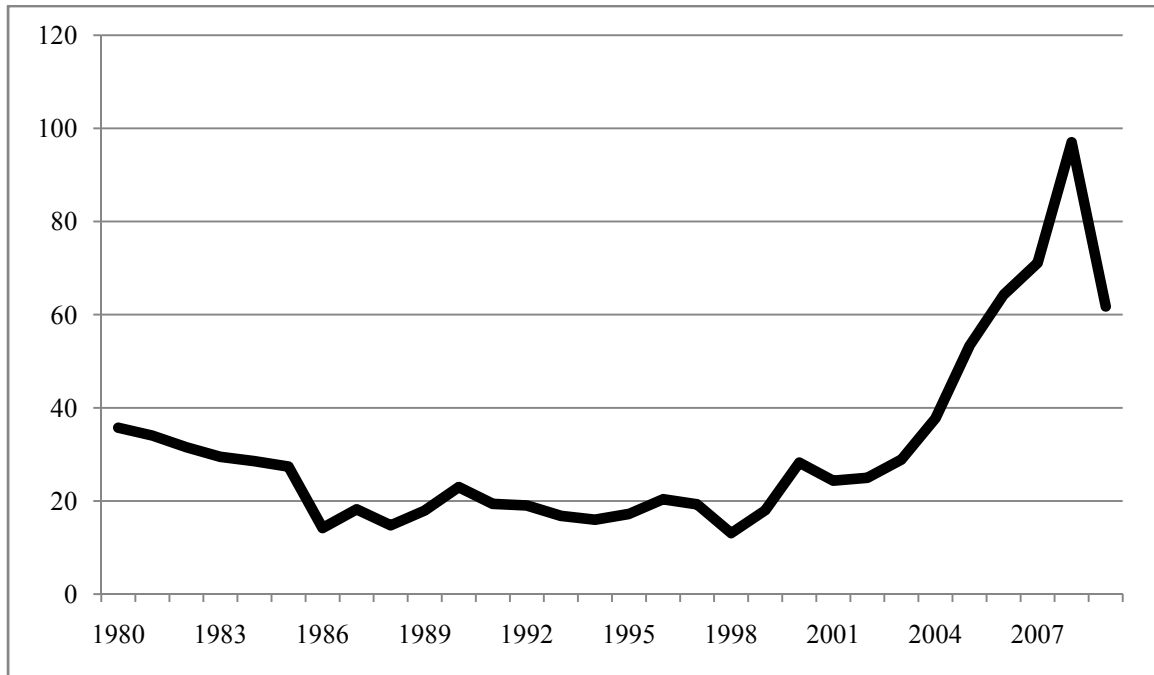
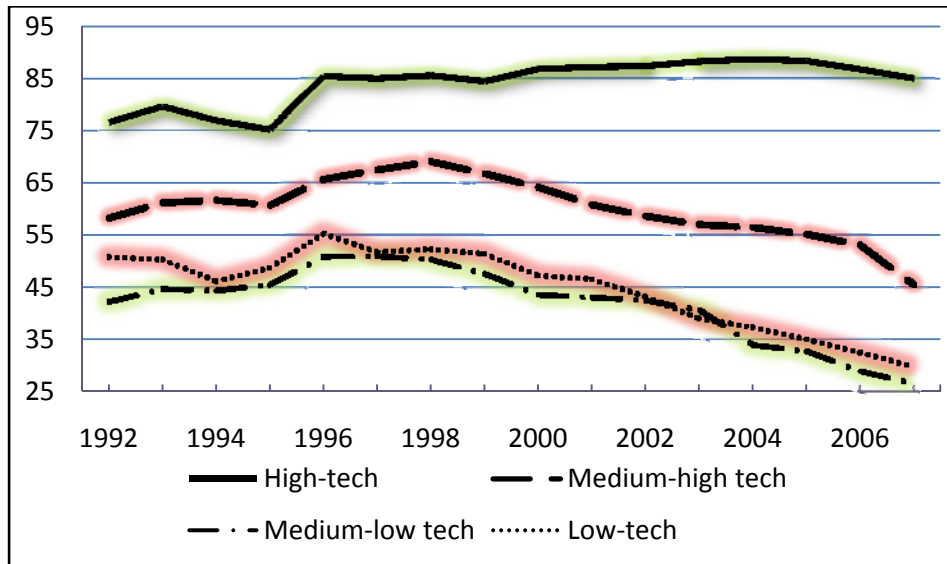


Figure 10: Average crude oil prices, US\$/barrel, 1980-2009



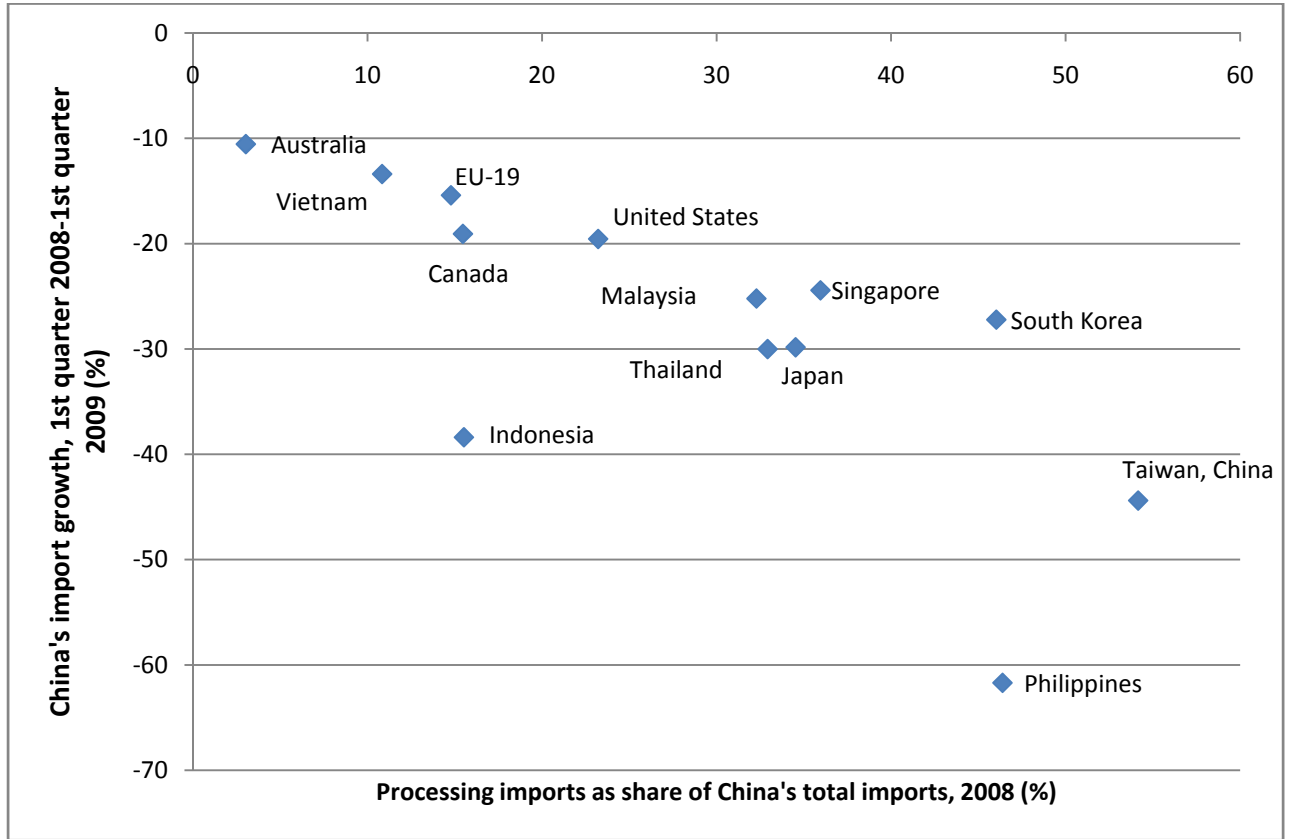
Source: IMF International Financial Statistics

Figure 11: Share of processing exports in China's total exports, by technology level (%)



Source: authors' calculations, using China's Customs Statistics

Figure 12: Intensity of China's processing imports (2008) versus severity of China's imports contraction (08Q1-09Q1), by economy of origin.



Source: Authors' calculations using China's Customs Statistics.

Table 1

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

	Share of processing imports originating from		Share of processing exports destined to	
	Unadjusted for HK re-exports	Adjusted for HK re-exports	Unadjusted for HK re-exports	Adjusted for HK re-exports
East Asia	85.0	71.2	49.3	28.2
Hong Kong SAR, China	45.3	-	29.3	-
Japan	11.3	18.7	8.2	11.6
South Korea	11.3	21.9	4.2	6.0
Singapore	2.9	4.6	2.3	3.3
Taiwan, China	8.6	13.3	1.6	2.2
Malaysia	1.8	3.2	1.4	1.9
Thailand	1.4	4.9	0.7	1.0
Philippines	1.5	2.5	0.5	0.7
Vietnam	0.1	0.3	0.3	0.5
Indonesia	0.5	1.4	0.5	0.8
Macau	0.3	0.3	0.2	0.3
Non-Asian OECD	10.4	20.0	42.1	59.6
United States	4.3	6.2	18.2	25.7
EU-19	4.8	0.9	19.4	27.5
Canada	0.5	0.8	1.3	1.8
Australia	0.3	0.5	1.2	1.7
Other	0.5	0.9	2.0	2.8
ROW	4.6	8.8	8.6	12.2

Authors' calculations using China's Customs Statistics Data

Tables 2, 3 and 4 are included in the text.

Table 5

Regression results, 1988-2008

Dependent variable: log of bilateral processing exports			
OLS			
	(1)	(2)	(3)
GDP per capita (province)	1.655*** [0.132]	1.601*** [0.133]	1.609*** [0.133]
Population (province)	3.968*** [0.215]	3.884*** [0.216]	3.872*** [0.213]
Wage (province)	-0.541*** [0.112]	-0.616*** [0.114]	-0.621*** [0.114]
Export Distance	-0.505*** [0.043]	-0.504*** [0.043]	0.087 [0.223]
Import Distance		-0.170*** [0.058]	-0.342*** [0.061]
East*Export Distance			-0.570*** [0.233]
East *Import Distance			0.576*** [0.070]
Year Dummy	Yes	Yes	Yes
Province Dummy	Yes	Yes	Yes
Country-Year Dummy	Yes	Yes	Yes
Observations	17306	17299	17299
R ²	0.835	0.836	0.836

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				
	OLS	Hausman Taylor Estimator		
	(1)	(2) ^a	(3)	(4)
GDP per capita (province)	1.609*** [0.133]	1.7137*** [0.102]	1.5666*** [0.101]	1.7733*** [0.103]
Population (province)	3.872*** [0.213]	3.7072*** [0.196]	3.3027*** [0.187]	4.0353*** [0.204]
Wage (province)	-0.621*** [0.114]	-0.4870*** [0.104]	-0.3337*** [0.102]	-0.5698*** [0.105]
Export Distance	0.087 [0.223]	-0.1498 [0.215]	-0.3401 [0.212]	-0.0270 [0.217]
Import Distance	-0.342*** [0.061]	-0.3255*** [0.057]	-0.3377*** [0.057]	-0.3158*** [0.057]
East*Export Distance	-0.570*** [0.233]	-0.3650 [0.224]	-0.1662 [0.221]	-0.4919** [0.226]
East *Import Distance	0.576*** [0.070]	0.6246*** [0.070]	0.6412*** [0.070]	0.6299*** [0.070]
Year Dummy	Yes	Yes	Yes	Yes
Province Dummy	Yes	Yes	Yes	Yes
Country-year Dummy	Yes	Yes	Yes	Yes
Observations	17299	17285	17285	17285
R ²	0.837			
Hausman test HT vs. GLS (χ^2)		1791.36	10354.41	6004.33

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
Regression results, 1988-2008

Dependent variable:	log of bilateral processing exports			log of share of processing exports		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita (province)	1.601*** [0.133]	1.309*** [0.132]	1.279*** [0.133]	-0.007 [0.079]	-0.070 [0.080]	-0.080 [0.080]
GDP per capita (country)	1.928*** [0.229]	1.828*** [0.231]	1.839*** [0.231]	0.411*** [0.123]	0.365*** [0.123]	0.378*** [0.123]
Population (province)	3.866*** [0.214]	2.753*** [0.230]	2.785*** [0.236]	1.280*** [0.124]	0.973*** [0.141]	1.014*** [0.145]
Population (country)	1.148*** [0.150]	1.124*** [0.150]	1.124*** [0.149]	-0.125** [0.062]	-0.135** [0.061]	-0.135** [0.061]
Wage (province)	-0.608*** [0.114]	-0.826*** [0.115]	-0.851*** [0.117]	-0.543*** [0.071]	-0.619*** [0.072]	-0.634*** [0.073]
Export Distance	-0.512*** [0.042]	-0.272*** [0.103]	0.492 [0.332]	0.048** [0.024]	0.169*** [0.060]	0.908*** [0.192]
Import Distance	-0.160*** [0.057]	0.785*** [0.117]	1.654*** [0.325]			
Oil Price * Export Distance			-0.307** [0.128]			-0.299*** [0.076]
Oil Price * Internal Distance			0.061*** [0.023]			0.014 [0.011]
Oil Price * Import Distance			-0.352*** [0.131]			
Trend * Export Distance		-0.021*** [0.008]	0.001 [0.012]		-0.011** [0.005]	0.011 [0.007]
Trend * Internal Distance		-0.008*** [0.001]	-0.012*** [0.002]		-0.004*** [0.001]	-0.005*** [0.001]
Trend * Import Distance		-0.073*** [0.009]	-0.045*** [0.014]			
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Province Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Country-year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17285	17285	17285	19605	19605	19605
R-squared	0.836	0.839	0.839	0.426	0.427	0.428

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

Table 8

Technology category	Exports value (US\$ billion)		Growth rate (%) 08Q1-09Q1	Share of exports (%)		Contribution to total export growth (%) 08Q1-09Q1
	08Q1	09Q1		08Q1	09Q1	
High technology	94.6	71.8	-24.1	31.1	29.5	37.6
Medium-high technology	70	54.6	-22.0	23.0	22.5	25.4
Medium-low technology	44.9	35.2	-21.6	14.8	14.5	16.0
Low technology	73.8	67.2	-8.9	24.3	27.6	10.9
Other	20.5	14.4	-29.8	6.7	5.9	10.1
Total	303.8	243.2	-19.9	100.0	100.0	100.0

Authors' calculations using China's Customs Statistics Data

Table 9

Variables	Number of observations	Mean	Standard error
Share of processing exports in total exports, 08Q1	4760	0.31	0.004
Share of processing exports in total exports, 09Q1	4760	0.29	0.004
Difference	9520	0.020***	0.003

Notes: * means significant at 10%; ** means significant at 5%; *** means significant at 1%.

Table 10: China's Processing Trade in Crisis, by industry

	Processing exports (US\$ billion)		Processing exports growth (%)	Processing imports (US\$ billion)		Processing imports growth (%)	Bullwhip effect
	08Q1	09Q1	08Q1-09Q1	08Q1	09Q1	08Q1-09Q1	
High technology	78.32	57.23	-26.9	45.88	29.03	-36.6	YES
Aircraft	0.21	0.23	8.6	0.11	0.09	-17.8	NO
Pharmaceuticals	0.37	0.36	-3.3	0.08	0.09	24.0	NO
Office and computing machinery	30.70	23.80	-22.4	3.59	2.43	-32.5	YES
Radio, TV and comm. Equipment	38.50	27.80	-27.7	29.70	20.20	-31.9	YES
Medical, precision and optical ins.	8.54	5.05	-40.9	12.40	6.22	-49.8	YES
Medium-high technology	34.01	24.90	-26.9	13.59	9.79	-27.9	YES
Electrical machinery	10.50	7.43	-29.4	6.27	4.34	-30.7	YES
Motor vehicles	3.37	1.37	-59.4	0.26	0.17	-35.0	NO
Chemicals	2.47	2.01	-18.4	2.10	1.41	-32.9	YES
Other transport equipment	0.87	0.79	-9.5	0.07	0.06	-13.1	YES
Machinery and equipment	16.80	13.30	-21.0	4.89	3.81	-22.0	YES
Medium-low technology	12.67	12.04	-5.1	10.12	5.69	-43.8	YES
Shipbuilding and repairing	3.36	5.30	57.5	0.01	0.04	377.6	YES
Rubber and plastic products	4.57	3.59	-21.5	1.59	1.09	-31.5	YES
Petroleum products	0.05	0.04	-14.7	0.04	0.18	395.9	NO
Non-metallic mineral products	0.71	0.49	-31.1	0.66	0.37	-44.5	YES
Metal products	3.98	2.62	-34.3	7.82	4.01	-48.7	YES
Low technology	22.69	19.38	-14.6	6.57	4.69	-28.7	YES
Manufacturing	8.17	6.79	-16.9	0.73	0.52	-27.7	YES
Paper and paper products	1.38	0.98	-29.0	1.28	0.72	-44.0	YES
Printing and publishing	0.32	0.32	-1.3	0.06	0.05	-13.3	YES
Food, beverages and tobacco	1.32	1.35	2.5	0.71	0.50	-29.5	NO
Textiles, apparel and leather	11.50	9.94	-13.5	3.80	2.90	-23.8	YES
Other	4.55	2.63	-42.3	11.80	6.85	-41.8	NO
Total	152.24	116.18	-23.7	87.95	56.06	-36.2	YES

Source: Authors' calculations using China's Customs Statistics