

research paper series

China and the World Economy

Research Paper 2011/13

*Trading Partners, Traded Products, and Firm Performance:
Evidence from China's Exporter-Importers*

By

Zheng Wang and Zhihong Yu

The Authors

Zheng Wang is a doctoral candidate at The Leverhulme Centre for Research on Globalisation and Economic Policy (GEP), University of Nottingham.

Zhihong Yu is an RCUK research fellow of GEP and research fellow at CESifo, Munich.

Acknowledgements

Financial support from The Leverhulme Trust under Programme Grant F/00 114/AM is greatly acknowledged. Zhihong Yu also thanks the British Academy and Sino-British Fellowship Trust for financial support.

Trading Partners, Traded Products, and Firm Performances: Evidence from China's Exporter-Importers

by

Zheng Wang and Zhihong Yu

Abstract

In this study we explore a newly available unique dataset that links China's international trade transactions to a comprehensive firm-level data in China's manufacturing sector, and establish a number of interesting stylized facts linking firms' key economic performance to their exporting-importing behaviour. One novelty of our analysis is we distinguish between ordinary trade and processing trade; the latter involves importing inputs and materials to be assembled and re-exported to the overseas market. Several novel patterns emerge. First, we discover significant heterogeneity *within* two-way traders – in terms of size, productivity and factor intensity – depending on their engagement in processing exports/imports. Whilst the existing literature typically finds that two-way traders are larger and more productive than one-way traders, we show that pure processing two-way traders are actually the least productive and exhibit the lowest capita/skill intensity compared to one way traders. By contrast, firms conducting both ordinary and processing trade are the largest, most productive and capital intensive among all trading firms. Second, consistent with the market hierarchy hypothesis, larger and more productive firms trade with a larger number of trade partners with tougher market conditions characterized by longer distances and smaller market size. Remarkably, this pattern is highly symmetric between exports and imports, as well as ordinary and processing trade. Third, firms with greater capital and skill intensities source their inputs from countries with higher income per capita, and this pattern holds only for ordinary imports but not processing imports. Fourth, larger firms trade a larger number of products with greater average product complexity as proxied by Nunn's contract intensity measure. Fifth, controlling firm size, more productive and capital intensive firms export less complex products but import more complex ordinary inputs. Whilst some of the above findings confirm existing stylized facts reported for other countries, some patterns we discover are new to the literature and remain to be reconciled with the heterogeneous firm trade theory.

JEL Classification: F12, F13

Key Words: Firm Heterogeneity, Exports and Imports, Traded Products, Trade Partners, Factor Intensity

Outline

1. Introduction
2. Data
3. Exporting, importing, processing trade, and firm performance
4. Trading partners and performance of China's exporters and importers
5. Traded products and performance of China's exporters and importers
6. Conclusions

Non-Technical Summary

In this study we explore a newly available unique dataset that links China's international trade transactions to a comprehensive firm-level data in China's manufacturing sector, and establish a number of interesting stylized facts linking firms' key economic performances to their exporting-importing behaviour. One novelty of our analysis is we distinguish between ordinary trade and processing trade; the latter involves importing inputs and materials to be assembled and re-exported to the overseas market. Several novel patterns emerge. First, we discover significant heterogeneity *within* two-way traders – in terms of size, productivity and factor intensity – depending on their engagement in processing exports/imports. Whilst the existing literature typically finds that two-way traders are larger and more productive than one-way traders, we show that pure processing two-way traders are actually the least productive and exhibit the lowest capita/skill intensity compared to one way traders. By contrast, firms conducting both ordinary and processing trade are the largest, most productive and capital intensive among all trading firms. Second, consistent with the market hierarchy hypothesis, larger and more productive firms trade with a larger number of trade partners with tougher market conditions characterized by longer distances and smaller market size. Remarkably, this pattern is highly symmetric between exports and imports, as well as ordinary and processing trade. Third, firms with greater capital and skill intensities source their inputs from countries with higher income per capita, and this pattern holds only for ordinary imports but not processing imports. Fourth, larger firms trade a larger number of products with greater average product complexity as proxied by Nunn's contract intensity measure. Fifth, controlling firm size, more productive and capital intensive firms export less complex products but import more complex ordinary inputs. Whilst some of the above findings confirm existing stylized facts reported for other countries, some patterns we discover are new to the literature and remain to be reconciled with the heterogeneous firm trade theory.

1. Introduction

Ever since the pioneering study by Bernard and Jensen (1999), the last decade has seen a surge of empirical researches using firm-/plant- level production and trade data to reveal the importance of firm heterogeneity in international trade. As was summarised in Bernard et al. (2007), a well-established empirical regularity emerging from this literature is that, across a wide range of countries and industries, exporting firms have superior performances (higher productivity, larger size, greater capital and skill intensity etc.) compared to their non-exporting counterparts. These new empirical findings have motivated the development of heterogeneous firm trade theories (HFT) led by Melitz (2003) to accommodate such stylised facts and generate new insights on the role of firms in international trade. Despite its importance, one limitation of the “first-wave” microeconomic trade studies is that the data typically only report the total value of exports at the firm level, without further detailed information on the destinations and products being exported. Further, the early works almost exclusively focus on firms’ exporting statuses, with little attention paid to their linkages to firm-level import activities.

The latest developments in the literature thus see the emergence of the “second-wave” microeconomic researches exploring much more disaggregated and detailed firm-transaction-level data, which report not only the countries and products traded by individual firms, but also information on both exports and imports.¹ The availability of this new strand of data leads to the possibility of exploring a series of new questions, including the comparison of firm performances across their trading statuses in terms of exporting and importing, as well as the linkages between firm level characteristics and the profiles of their trade partners or traded products. A number of new empirical regularities begin to emerge from this strand of research. For example, two-way traders, i.e. firms that engage in both exporting and importing, are typically found to have superior performances (larger, more productive, paying higher wages etc.) than one-way traders that either only export or import; firms with exceptional characteristics also on average transact with a larger number of countries and products with greater value of shipment per country or product (e.g. Bernard et al., 2009; Kasahara and Lapham, 2006, 2008; Muûls and Pisu, 2009; Castellani et al., 2010; Vogel and Wagner, 2010, for a review of the literature).

This paper contributes to this fast growing literature by presenting novel empirical evidence on the relation between firm performances (productivity, size, wage, and capital/skill intensity) and the

¹ See, for example, Eaton et al. (2004) and Lawless (2009) for multi-destination exporters; Bernard et al. (forthcoming) for multi-product exporters; Manova and Zhang (2009a), Bernard et al. (2009), Kasahara and Lapham (2006, 2008), Muûls and Pisu (2009), Castellani et al. (2010), Vogel and Wagner (2010), and Kugler and Verhoogen (2009) for studies on exporters and importers.

characteristics of their trade partners and traded products on both export and import sides for China, which is the world's largest exporter in 2010. One contribution of our paper is that we investigate whether there is a special role played by processing trade, which represents the trade activity of importing all or part of the inputs (including raw materials, parts and components, accessories etc.) from abroad and re-exporting the finished products after processing or assembly by enterprises within China. From a theoretical point of view, processing traders might behave quite differently from ordinary traders in their export-import activities; this is because the former are by definition two-way traders (simultaneous exporter-importers), and specialise in a relatively narrow range of labour-intensive production activities, i.e. assembling or processing for their foreign buyers, whose performances and trade activities might, as a result, depart from those of ordinary traders who make relatively independent export-import decisions as was assumed in the standard HFT theory associated with high fixed entry costs. From an empirical point of view, for many developing countries processing trade plays a non-trivial and sometimes vital role in their export performances. In China, 60% of its total trade is processing trade during the period 2000-2006 (Fernandes and Tang, 2011). In Mexico, more than a quarter of manufacturing goods are produced in foreign-owned export-processing plants, known as *Maquiladoras*, in 2004 (Heid et al., 2011). According to International Labour Organisation (ILO), worldwide 60 million workers are employed in 3,500 export processing zones spanning 130 countries (Boyenge, 2007).

Distinct from previous research, in this study we are able to investigate the above questions by merging two very comprehensive micro level datasets. The first is the transaction-level data covering the entire population of Chinese exporters and importers. The second is the firm-level production and accounting data covering medium- and large- size enterprises in China's manufacturing sector. The merged data allows us to directly link various indicators of firm performances, such as productivity and factor intensity, to their export or import activities, including where they export to or import from and what kinds of products they trade. Relevant to our question of interest, one unique feature of the merged dataset is that it distinguishes between transactions under different tax regimes, including processing exports or imports, which enables us to explicitly investigate firms' engagement in processing trade and how it is related to their key performance indicators, such as value-added based productivity, wage, and capital/skill intensity.

Through our analysis, we discover a number of interesting results, some of which confirm findings in previous research, whilst others are new to the literature. First, we discover significant heterogeneity *within* two-way traders – in terms of size, productivity and factor intensity – depending on their engagement in processing exports/imports. Whilst the existing literature typically finds that two-way traders are larger and more productive than one-way traders, we show that pure processing two-way traders are actually the least productive and exhibit the lowest capita/skill intensity compared to other traders. By contrast, firms conducting both ordinary and processing trade are the largest, most productive and capital intensive among all trading firms.

Second, consistent with the market hierarchy hypothesis, larger and more productive firms trade with a larger number of trade partners with on average “tougher” market conditions characterized by longer distances and smaller market size (measured by GDP or GDP per capita). Remarkably, this pattern is highly symmetric between exports and imports, as well as between ordinary and processing trade. Third, firms with greater capital and skill intensities source their inputs from countries with higher income per capita, and this pattern holds only for ordinary imports. Fourth, larger firms trade a larger number of products with greater average product complexity as proxied by Nunn’s contract intensity measure. Fifth, controlling firm size, more productive and capital intensive firms export less complex products but import more complex ordinary inputs.

The remainder of this paper is structured as follows. The next section and Appendix A provide details of the data we use and construct. In Section 3 we compare firm-level performances across different trading statuses in terms of exporting/importing as well as engagements in processing trade. Section 4 and 5 analyse the characteristics of firms’ trading partners and traded products, respectively, and the links to their various performance indicators. Section 6 concludes.

2. Data

In this paper we explore a unique dataset that links Chinese manufacturing firms to their international transactions in both exports and imports. Two original sources of data are used to construct this dataset: the firm-level production data drawn from China’s Annual Survey of Industrial Firms (CASIF), and the transaction-level trade data from Chinese Customs Trade Statistics (CCTS).

a. Firm-Level CASIF Dataset

The CASIF dataset is compiled by the National Bureau of Statistics in China (NBS) from 2002-2006. Firms included in CASIF are those qualified as “above-scale” firms, which consist of the whole population of state-owned firms, and all non-state firms with annual sales above 5 million Chinese yuan (CNY).² Because this threshold is in nominal terms, there exists the possibility that the sample will get larger over time purely because of price changes. On average, more than 200 thousand firms are included each year and they account for around 95% of total Chinese industrial output and 98% of industrial exports, covering 39 2-digit industries, of which 30 belong to manufacturing industries, and spreading across all 31 provinces and municipalities. In practice, the NBS implemented standard procedures to ask firms to report required details on their production activities, accounting statement, and other basic characteristics such as ownership structure, location

² The exchange rate is around 1USD=8.27CNY between 2002 and 2005, so the sales threshold is equivalent to around 600,000 USD.

and industry. In addition, firms are also required to report the value of exports *out of* their total outputs, including those exported by the firms themselves or through independent trading intermediaries.³ We clean the dataset by excluding observations according to the following criteria:

- firms in non-manufacturing industries (2-digit GB/T industry code >43 or <13) and tobacco (GB/T code 16);
- observations with negative values of the following variables: output, sales, exports, capital, or intermediate inputs;
- observations with total asset less than total fixed assets or total liquid assets, or with total sales less than exports.

b. Transaction-level CCTS Dataset

The second source is the transaction-level data on exports and imports from the Chinese Customs Trade Statistics (CCTS) collected by the General Administration of Customs of China (CACC). All exports and imports transactions going through the Chinese Customs from 1 January 2002 to 31 December 2006 are included. The value of this data set is mainly in the rich information it contains, which includes main firm registry information, such as firm identifier, ownership, etc., as well as transaction information, including the dates of transaction, 8-digit HS product code, value of imports and exports, quantity of goods, customs regimes, means of transportation, custom identifier, the origin or destination of the trading country.⁴ For the purpose of this study, we aggregate exports and imports for each firm by year, product (8-digit HS level), country (import origin or export destination) and trade regime (ordinary, processing etc).⁵

c. Matched Firm-Transaction Dataset

Each firm in the CASIF and the CCTS has a unique identifier code. However, the unique firm identifier codes in these two datasets are based on different systems. The 9-digit identifier in the firm-level CASIF dataset is based on the Enterprise Legal Person Coding system, which is designated by the local administrative authorities, whereas the CCTS data uses the 10-digit Enterprise Customs Coding system. It is therefore impossible to merge these two datasets directly by their original identifier codes. In order to link firms' transaction information to their production data, we develop a method to match firms by some common variables appearing in both datasets,

³ See Upward et al. (2010) for a more detailed description of the dataset. Other previous studies using this dataset include Cai and Liu (2009), Hsieh and Klenow (2009), Girma et al. (2009), Lu et al. (2009), and Yu (2011).

⁴ Previous studies using this dataset include Manova and Zhang (2009a, b).

⁵ For every export/import transaction the Chinese Customs records the tax regime to which the transaction belongs. There are in total 18 types of trade regimes, but 96% and 83% of China's total exports and imports, respectively, are under either "ordinary trade" or "processing trade" regime during 2002-2006 (author's own calculation based on the CCTS dataset). See the next section for the definitions for ordinary or processing trade regime.

including firm names, postcode, and telephone number.⁶ We finally obtain a matched CASIF-CCTS dataset including 79,730 unique firms and 238,118 observations during the years 2002-2006. As can be seen from Table 1, this matched data covers a non-trivial portion of China's total trade; nearly 50% and 40% of China's total exports and imports, respectively, are represented by firms in our matched data. In the rest of this paper, all the results we report are based on this merged sample.

[Insert Table 1 here]

d. Product- and Country- Level Data

One purpose of this study is to examine how the heterogeneity of trading firms - in terms of size, productivity, factor intensity etc., is linked to the complexity of the products they trade. The measure of product complexity used in this paper is the Nunn measure of contract intensity (Nunn, 2007). The reason we adopt the Nunn measure rather than the Rauch measure (Rauch, 1999) is that the latter is a category variable whilst the former is a continuous variable constructed using both the Rauch measure and the US input-output (IO) table. Since we will be controlling for 4-digit industry so as to focus on the intra-industry variation across firm characteristics, the Nunn measure provides us with much larger variation across firms in the complexity of the products they trade compared to the Rauch measure. However, one issue with the Nunn measure is that it is constructed using US IO table 1997 and HS97 code system, whereas our transaction data is based on HS2002. As part of this project we updated the Nunn measure to HS2002 using US IO table 2002.⁷ Finally, the country-level data, including distance to China, GDP, GDP per capita, are all from standard sources including CEPII and World Bank Development Indicator.

3. Exporting, Importing, Processing Trade and Firm Performances

In this section we explore the linkages between firms' trading status (exporter, importer, two-way traders etc.) and their key economic characteristics, such as size, productivity, and factor intensity, etc. Previous studies found robust evidence that two way traders have superior performances than one way traders (e.g. Kasahara and Lapham, 2006, 2008; Muûls and Pisu, 2009; Haller, 2010; Castellani et al., 2010). We examine whether such patterns hold for China, with an

⁶ In this paper, we use an improved method that is similar to albeit slightly different from that used in Upward et al. (2010). The main matching variable is firms' names, complemented by other common variables in both datasets such as postcodes and telephone numbers. Firm name is a reliable match variable as it suffers the least from missing value problems, and it is by law that no firms can have the same name in the same administrative region and the vast majority of all firms contain their local region name as part of their firm name. Details of the matching procedure are described in the appendix.

⁷ Full details of the construction of the updated version of the Nunn measure are reported in appendix, and the data is available from the authors upon request.

important distinction between processing traders and ordinary traders. Processing traders are those involved in “inward processing trade” for which firms import raw materials or other intermediate inputs from abroad, with tariff exemptions on the imported inputs or other tax preferences from the governments, and then process or assemble these inputs into finished or semi-finished products to be re-exported to foreign markets.⁸ By contrast, “ordinary trade” refers to those exports/imports transactions under normal tariff regime without preferential tax treatments. Processing trade accounts for a large share of China’s total foreign trade; since year 1996 at least 50% of China’s total manufacturing exports are processing exports.⁹ As shown below, once we further break down two-way traders according to their engagements in processing trade, we reveal some interesting findings that are quite different from those found in the previous literature for industrialized countries where (inward) processing trade hardly exist.

a. Classification of Trading Status with Processing Trade

A common practice in the existing literature is to classify trading firms into three mutually exclusive categories, i.e. one-way exporters (XJ) that has positive exports but zero imports, one-way importers (MJ) with zero exports but positive imports, and two way traders (XM) with positive exports and imports. In the case of China, however, two-way traders could be a very heterogeneous group due to the existence of processing traders which, by definition, conduct two-way trade. For this reason, we further break down “two-way traders” into three sub-categories: two-way ordinary traders (XMO), two-way pure processing traders (XMP), and two-way mixed traders (XMOP). XMO are defined as two-way traders of which the entire exports and imports are ordinary trade, XMP are two-way traders of which the entire exports and imports are processing trade, whereas XMOP are two-way traders whose exports/imports involve both ordinary and processing trade.

Table 2 reports the number of firms in our sample broken down by the new classification of trading status and ownership, where firms’ registration type information retrieved from the CASIF data is used to identify three broad categories of ownership: domestic-owned, Hong Kong, Macau and Taiwan (HMT)-owned, and foreign-owned (excluding HMT-owned). Several interesting points are worth noting. First, the majority of all trading firms (nearly 60%) conduct two-way trade, whilst only 30% (10%) are one-way exporters (importers). These shares, however, vary significantly across firms with different types of ownership. Among domestic firms, only 36 % engage in two-way trade, whilst the ratio is about 70% for HMT- and foreign-owned firms. In contrast, the majority of domestic firms (56%) are one-way exporters, whereas a small fraction (20%) of HMT-

⁸ The “processing trade” regime can be further broken down into “pure assembly trade”, and “processing with imported materials trade”; under the former regime foreign buyers provide the Chinese supplier with raw materials, parts or components free of charge for assembly and re-exporting, whilst under the later regime the Chinese firms independently purchase the intermediate inputs from the foreign markets, and retain the ownership of these inputs which have to be processed for re-exporting.

⁹ See Koopman et al. (2008, Table 1) for the shares of processing trade in China for various years.

and foreign-owned firms export only. It is also noteworthy that one-way importers are in minority (10%), and the share is stable across ownership types. These patterns are very similar to those reported in Manova and Zhang (2009b) using the whole CCTS data (which thus includes both manufacturing and non-manufacturing goods) for 2005.¹⁰ Second, when we further break down two-way traders into ordinary (XMO) and processing traders (XMP or XMPOP), as can be seen from the last row of Table 2, more than 70% of the two-way traders engage in processing trade,¹¹ with the majority $(35.5\%/(35.52+5.52)=85\%)$ of them conducting both ordinary and processing trade. Looking across ownership types, it is clear that processing traders dominate among HMT- and foreign-owned firms, whilst more than half of domestic firms do not engage in processing trade at all. Note also that only a small fraction $(5.43\%/57.06\% =8\%)$ of all two-way traders conduct processing trade only, and these “pure processing traders” are highly concentrated in HMT-owned firms. These findings are consistent with the notion that the China’s export-oriented inward FDI is largely driven by foreign firms exploiting China’s comparative advantage in labour-intensive processing/assembly activities, which generates large amount of two-way trade, and has significantly contributed to China’s fast growth in both exports and imports in the last decade.¹²

[Insert Table 2 here]

b. Exporters, Importers, Processing Trade and Firm-Level Performances

One empirical regularity emerging from the existing importer-exporter literature is that two-way traders have superior performances over one-way traders (Bernard et al., 2007; Muûls and Pisu, 2009; Castellani et al., 2010; Volgel and Wagner, 2009; Kasahara and Lapman, 2006, 2008). There is robust evidence that even within the narrowly defined industries, firms engaging in both exporting and importing are larger and more productive than one-way traders, whilst the relative performances between only exporters and only importers remain ambiguous. In this section we compare a number of key firm-level characteristics across different types of trading firms in China.¹³ The novelty of our analysis is that we distinguish between processing traders and ordinary traders within the two-way trader category. Such distinction is non-trivial, as more than 70% of two-way traders in our sample are engaged in (inward) processing trade, and these firms may

¹⁰ Such similarity also provides some reassurance that our matching does not generate systematic biases towards one particular type of traders compared to the CCTS data which covers the entire population of China’s traders.

¹¹ More precisely, the share of processing traders in two way trades is $(5.53+35.52/57.06)=71.9\%$.

¹² See Upward et al. (2010) for further details of the role of processing trade in China’s export expansion from 2000-2007.

¹³ It is noteworthy that unlike previous studies that report the premia of traders relative to non-trading firms, we focus on the performance differences between firms that were already engaged in international trade. This is because the CASIF firm-level data does not report firm-level imports, so we are unable to properly identify “non-traders” in the CASIF sample, especially in terms of their importing status.

exhibit very different firm-level characteristics (e.g. productivity and skill intensity) from ordinary traders. To our knowledge, none of the previous studies mentioned above have made such a distinction.

c. Descriptive Analysis

We begin by providing some basic descriptive statistics on various firm characteristics across trading categories in Table 3.¹⁴ Consistent with previous literature, we find two-way traders are larger than one-way exporters or importers, in terms of number of employees, total output and total value added, although the difference between one-way importers and two-way traders is very small in terms of output and value added. Further, one-way importers are also unambiguously larger than one-way exporters in all three size measures.

[Insert Table 3 here]

However, when we break down two-way traders into three sub-groups according to their processing trade status, new patterns emerge. First, in terms of firm size, pure processing two way traders (XMP) are *smaller* than one-way importers in terms of employment, and even smaller than one-way exporters as well in total output and value added. By contrast, both two-way ordinary traders and two-way mixed traders are larger than one-way exporters or importers. Hence, the relative size of two-way to one-way traders depends on the former's engagement in processing trade. Second, in terms of productivity, as far as total factor productivity (TFP) is concerned, two-way traders as a whole are more productive than one-way importers, which are in turn more productive than one-way exporters. Note, however, that pure processing two-way traders turn out to exhibit the *lowest* TFP, whilst two-way ordinary traders or mixed traders are the most productive groups of firms. Such productivity hierarchy still holds when productivity is measured by value-added per worker, but with one important exception – only importers now become the most productive group, with a large lead over two-way ordinary traders. Using the notations defined in section 3.1 and Table 2, the ordering of firms' trading status in terms of VA per worker can be summarised as: MJ > XMO > XMOP > XJ > XMP. Interestingly, this pattern of ordering holds consistently when we move to other firm characteristics including capital intensity, skill intensity and wage per workers.

To summarise, these descriptive statistics revealed the existence of significant heterogeneity in firm characteristics within the two-way traders group. In particular, pure processing two-way traders are typically smaller, less productive, and less skill and capital intensive than all other

¹⁴ Statistics shown in Table 3 are for traders in year 2004, because only in that year the data allows us to break down workers by skill/unskilled labour forces in terms of their levels of education. As shown in column (1), the composition of trading status for 2004 is very similar to the whole sample as reported in the last row of Table 2.

trading firms including one-way traders, with the only exception that they employ more workers than one-way exporters. Furthermore, while two-way ordinary or mixed traders are larger and have higher TFP than all other types of traders, one-way importers, exhibit highest capital and skill intensity, greatest value added per worker, and pay highest wages.

d. Regression Analysis

Of course, the patterns shown above are unconditional on firms' industry, location etc., so it is likely that these results are mainly driven by industrial or provincial compositions, rather than intra-industry firm heterogeneity as emphasised in the theoretical literature. Now we conduct descriptive regression analysis controlling for these effects.

More formally, we run the following two pooled OLS regressions to examine heterogeneous firms' performances in relation to their export-import and processing trade statuses:

$$\ln P_{it} = \alpha + \beta_1 MJ_{it} + \beta_2 XM_{it} + \theta \vec{Z}_{it} + \epsilon_{it}, \quad (1)$$

$$\ln P_{it} = \alpha + \beta_1 MJ_{it} + \beta_3 XMO_{it} + \beta_4 XMP_{it} + \beta_5 XMOP_{it} + \theta \vec{Z}_{it} + \epsilon_{it}, \quad (2)$$

where $\ln P_{it}$ denotes the logarithm of firm level performance measures including total employment, total real output, total real value added, TFP, real value added per worker, capital stock per worker, skill intensity and wage per worker,¹⁵ MJ_{it} , XM_{it} , XMO_{it} , XMP_{it} and $XMOP_{it}$ are dummy variables denoting firms' trading status including, respectively, one-way importers, two-way traders, two-way ordinary traders, two-way processing traders and two-way mixed traders conducting both ordinary and processing trade, and finally \vec{Z}_{it} is a set of control variables including year dummies, ownership dummies, county(6-digit)-industry(4-digit GB/T) pair wise fixed effects.¹⁶ Note that one-way exporters (XJ_{it}) is the omitted category, so coefficients $\beta_1 - \beta_5$ indicates the percentage difference in firm-level performances between each trade category and one-way exporters [$100 \cdot \exp(\beta) - 1$], once differences in industry, location and ownership are controlled for.

The main results for the two sets of regressions are reported in Table 4, and we also report the F-test for the statistical difference between relevant coefficients of the trading status dummies of each regression in Table B1 of Appendix B. We first examine firms' differences in size. As is shown in column (1)-(3) of Table 4, consistent with the patterns reported in the previous descriptive analysis, it is clear that two-way traders as a whole are larger than one-way importers, which are in

¹⁵ Output, value added are all in real terms in 2000 price deflated by ex-factory price index at the 2-digit industry level obtained from China Statistical Yearbooks of various years.

¹⁶ In the CASIF data, the location of each firm can be identified by a 6-digit indicator at the county-level within China, which is far more disaggregated at the provincial-level commonly used in previous studies. During our sample period, there are around 3,000 counties in China. There are also more nearly 480 4-digit industries for firms in our sample. In total, there are nearly 50,000 industry-county pairs for each regression, see the last row of Table 4 for details.

turn larger than one-way exporters in output and value added, although not in terms of employment.

¹⁷ Interesting patterns emerge, however, when we further break down two-way traders into three sub-categories according to their engagement in processing trade. First, pure processing two-way traders (XMP) are larger than one-way importers or exporters in terms of number of workers employed, but, in terms of total output and value-added, they are not statistically different from only exporters (XJ), and are even *smaller* than only importers (MJ). This suggests that the size premia of two-way traders relative to one-way traders, which is a common finding reported in previous studies, does not necessarily hold for two-way traders specializing in processing trade. Second, two-way mixed traders are clearly the largest in terms of all three size indicators; they are almost twice as large as one-way exporters or importers ($\exp(0.678)-1=0.96$) in terms of employment, and nearly 40% larger than two-way ordinary traders in terms of all three size indicators. Third, two-way ordinary traders are the second largest, and their advantage over one-way importers is between 25-36% depending on the size measure.

Next we turn to results on other firm characteristics shown in columns (4)-(8). Panel A reports the estimation results without controlling for firm size, whilst in Panel B we include log employment as an additional control to check whether the results are solely driven by differences in firm size. First, we investigate the link between firms' trading status and productivity performances – in terms of TFP or value-added per worker. The results are shown in columns (4) and (5). When we compare firms' TFP without controlling for size differences, as shown in column (4) in Table 4's Panel A, the productivity hierarchy reported in most previous studies still hold. Two-way traders as a whole have higher TFP than one-way importers which are in turn more productive than only exporters. Further, two-way mixed traders exhibit the highest TFP, followed by two-way ordinary traders, whilst two-way pure processing traders are the least productive. However, such clear pattern of TFP hierarchy disappears when we control for size differences, as shown in column (4) in Panel B; the productivity differences between two-way ordinary and mixed traders and one-way importers is not statistically significant any more, although all of them are more productive than only exporters. Further, two-way pure processing traders are even less productive than only exporters by nearly 10%. As a result, two-way traders as a whole have slightly *lower* TFP than only importers, although the difference is not statistically significant. To see whether such ambiguity exists when we look at labour productivity rather than TFP, in column (5) we report the results using value-added per worker as dependent variable. A quite different pattern emerges – it turns out that now only importers have the highest labour productivity, followed by two-way ordinary and then two-way mixed traders, all of which are more productive than one-way exporters, whilst two-

¹⁷ The gap between two-way traders as a whole and one-way exporters is 64% ($\exp(0.495)-1$) in terms of employment, and 78% and 84% in terms of total output and value added, respectively. These magnitudes are comparable to those found in previous studies - Muûls and Pisu (2009), for example, shows that the gap for Belgium between two-way traders and one-way exporters is 59% in terms of employment (calculated from Muûls and Pisu (2009, Table 12)).

way pure processing traders exhibit the lowest labour productivity. This pattern is robust to controls of size. Similar patterns are found when we look at differences in firms' capital/skill intensity as reported in column (6) and (7). Clearly, in terms of capital intensity, one-way importers are the most capital intensive, followed by two-way ordinary or mixed traders, then one-way exporters, with the two-way processing traders being the least capital intensive. This suggests that the superior labour productivity of only importers relative to two-way traders might be attributed to their differences in capital intensity. Further, only importers are also shown to be more skill intensive than two-way traders as a whole, although the difference is insignificant when size of employment is controlled. Finally, when we compare firms' wage per worker across their trading statuses in column (8), it is interesting that only-importers' superiority in labour productivity and capital/skill intensity does not carry over to their (per worker) wage payment. Controlling for size differences, firms involved in two-way ordinary trade and two-way mixed trade pay higher wage than only importers, followed by only exporters, whilst pure processing traders pay the lowest.

[Insert Table 4 here]

In summary, our OLS regression results reported in Table 4 revealed substantial heterogeneity among Chinese exporters-importers across different trading statuses. More importantly, we discovered significant heterogeneity *within* two-way traders depending on their engagement in processing trade. Several important patterns stand out from our results. First, whilst two-way traders as a whole are larger than only importers or only exporters, they exhibit *lower* capital-labour intensity, lower labour productivity, and similar TFP level relative to one-way importers, once differences in firm size, industry, location and ownership are controlled for. The latter finding contrasts with those found in previous studies that two-way traders as a whole are typically more productive and capital intensive than one-way traders. These results may look surprising at the first sight, but they are actually consistent with the notion that China has comparative advantage in labour intensive tasks/activities even within a narrowly defined industry. As was pointed out in Bernard et al. (2007), the findings reported in previous studies that even in developing countries exporters are more capital intensive are hard to be reconciled with the old trade theory of comparative advantage. What we have shown here, however, is that once we properly control for firms' import status, the capital/skill intensity advantage of exporters versus non-exporters may be significantly reduced or even reversed in developing countries, especially those with a vast comparative advantage in labour intensive activities such as China. In other words, the puzzle pointed out by Bernard et al. (2007) may be reconciled, if data allows us to control for firms' importing status and take into account firms' engagement in processing trade. Secondly, we find that two-way pure processing traders, which only conduct assembly and processing activities, are the least productive, least capital/skill intensive, and pay lowest wage among all trading firms,

although they employ larger number of workers than one-way exporters. This finding is consistent with the prior that processing activities are highly unskilled-labour intensive, heavily reliant on imports of intermediate inputs, and generate relatively low value added (per bundle of input) to the production of final goods. Finally, relative to two-way ordinary traders, two-way mixed traders are much larger in all three size indicators, but exhibit lower skill intensity and lower wage payment. Again, this might be attributed to the latter's processing activities that churn out large sales/output with large number of workers with relatively low skill requirement. Together, our findings suggest that in developing countries such as China and Mexico, where potentially a significant portion of exporters can undertake labour-intensive processing tasks for multinationals from developed countries, ignoring firms' engagement in processing trade might generate significant biases in the observed linkage between firms' key economic performances and their trading behaviours.

4. Trading Partners and Performances of China's exporters and Importers

In this section, we turn to explore the relation between firms' performances and the characteristics of their trade partners. Our main interest is whether our findings are broadly consistent with the existing heterogeneous firm trade models especially when we consider both exports and imports, and make a distinction between ordinary and processing trade.

A main result from the Melitz-style trade models is that firms' export market entry decisions are mainly driven by self-selection in terms of firm-level productivity. Based on the key assumption that entering into a different market requires substantial sunk cost, the existing theory predicts that high productivity firms are selected into "tougher" markets. This is because only the most productive firms are able to generate sufficiently high profits to cover the fixed cost of entry, especially in countries with "tougher" market conditions such as long distances. In a multi-country Melitz model with asymmetric markets, this implies a "market hierarchy hypothesis" (MHH), namely, both the "intensity" and "toughness" of a firm's export markets should increase with its productivity and size. In other words, the larger or the more productive a firm, the greater number of export markets it should penetrate, as well as the simple average of the "toughness" of these markets. It is worth noting, however, that the definition of "toughness" of an export market is not always clear cut. Whilst it is clear that the markets with higher trade costs, such as longer distances or higher tariffs, are "tougher" ones, the theory is ambiguous on whether larger markets are "tougher" than smaller ones or not. Extending the Melitz model to asymmetric countries with endogenous factor prices, Baldwin and Harrigan (2011) show that selection is weaker in larger export markets even allowing free entry, for the productivity threshold required for survival is lower in larger countries. In other words, "toughness" of a market is decreasing in its size. By contrast, Melitz and Ottaviano (2008) show that, by allowing endogenous markups under monopolistic competition, selection is stronger in larger markets. This is because markets with greater number of

consumers attract a larger number of entrants, which decrease firm level markups. As a result, survival is more difficult in larger markets, and therefore, “toughness” of a market increases with its size. Although a strict test of alternative HFT models is beyond the scope of this paper, in what follows we do examine whether there exists a monotonic relation between productivity/size and the “toughness” of their export markets (proxied by distance, GDP and GDP per capita per market), as predicted by the MHH discussed above. More interestingly, we extend the findings in the existing literature further by also linking other firm characteristics such as factor intensities to trade partner characteristics, as well as comparing between exports and imports, and between ordinary and processing trade.

a. Descriptive Analysis

As a starting point, Table 5 presents summary information on various characteristics of the trade partners of the firms, including the simple averages of the numbers of trade partners, value of trade per country, GDP and income per capita per country, and distance per country, by different size groups. Consistent with the MHH, as is shown in Panel A, larger firms tend to export to a larger number of markets which are on average “tougher” for their longer distances and smaller market sizes (in terms of both GDP and GDP per capita). On average the largest firms export to almost 3.5 times as many markets (16.72) as the smallest firms (4.84). Remarkably, exactly the same pattern is found for imports as shown in Panel B. This indicates that the selection mechanism not only works at the export side but also may be operating for firms’ import decisions; importing from a particular source country may also incur substantial fixed costs such as those associated with searching for or matching with an appropriate supplier, so only the largest firms can afford such costs and import from a larger number of source countries with longer distances.

[Insert Table 5 here]

To examine whether firms’ trade partner intensity are also linked to other firm-level characteristics, in Table 6 we compare across firms in different trade partner intensity categories for year 2004, which is the only year we have data on skill intensity. Clearly, exporters/importers with greater trade partner intensity have higher productivity in terms of both TFP and value added per worker, which is in line with previous findings in the literature such as Lawless (2009). There is also some evidence suggesting that, for both exports and imports, firms with greater trade partner intensity have higher capital/skill intensity and pay higher wages per worker, although such relationship is not strictly monotonic for exports.

[Insert Table 6 here]

b. Regression Analysis

Of course, the summary statistics above does not take into account the vast differences in firms' location, industry, ownership, and trade regime, so a regression analysis similar to Lawless (2009) is needed to control for these effects, and test whether the market hierarchy hypothesis holds for both ordinary and processing trade. Specifically, we employ the following OLS regression:

$$\ln P_{it} = \alpha + \delta \ln X_{it} + \theta \vec{Z}_{it} + \epsilon_{it}, \quad (3)$$

where $\ln P_{it}$ is the log of firm i 's performance measures at time t , $\ln X_{it}$ is the log of firms' trade partner intensity, or, alternatively, the logs of firms' value of trade per trade partner, or average GDP or GDP per capita per trade partner, or average distance per country; the vector \vec{Z}_{it} contains a complete sets of ownership, location and industry dummies as before. We first run the regression for all exports and imports, respectively, as reported in Panel A and Panel B in Table 7, and then do so separately for ordinary trade and processing trade as in Table 8a and 8b, respectively.

[Insert Table 7 here]

[Insert Table 8a-8b here]

Consistent with the summary statistics reported in Table 5, the regression results regarding the relation between productivity and distance/size strongly support the MHH. As can be seen from the first three columns of Table 7, larger and more productive firms trade with a larger number of countries, which are, on average, more distant and smaller in terms of GDP or GDP per capita, and also trade more values per country. Remarkably, such pattern holds not only for exports, but also for imports as shown in Panel B. However, one straightforward explanation for such strong symmetric pattern across exports and imports is that firms import from the same country where they export to, which is quite likely if firms conducting processing trade import materials from their parent companies and re-export back to the same market. To look into such possibility, we further break down trade into ordinary trade and processing trade, and re-estimate regression (3) to check whether our results are driven mainly by processing trade. As is shown in the first 3 columns of Tables 8a-8b, in terms of size and productivity, the results are quite similar to those reported in Table 7, especially for ordinary trade.¹⁸ These results are thus broadly consistent with the market

¹⁸ The only exception is the link between average GDP per trade partner and productivity becomes insignificant for processing imports, indicating that more productive firms may not necessarily import processing materials from sources with smaller market size.

hierarchy hypothesis based on HFT models for both exports and imports, as well as ordinary and processing trade, especially when country size is used as an inverse measure of market “toughness”.

Next we discuss how other firm-level characteristics, such as factor intensity, are linked to the characteristics of their trade partners based on the results reported in the last three columns of Table 7. Note that, however, unlike the previous regressions focusing on firm size and productivity, now we do not have strong priors regarding the relation between firms’ capital/skill intensity and the average size and distance of their trade partners. This is because the heterogeneous firm trade theories so far mostly focus on firms’ productivity differences, rather than their heterogeneity in factor intensity within industry.¹⁹ Hence, the evidence provided above should be viewed as suggestive for future development in theory rather than evaluations for existing models. Nonetheless, the following interesting results are worth noting.

Firstly, we find some strong evidence that controlling for firm size, firms with higher capital/skill intensity and higher wages trade with a larger number of countries, as well as greater values of trade per country. This pattern is quite robust when we further break down trade into ordinary and processing trade as shown in Table 8a-b. Again, this result is consistent with the notion that “good” firms in general are more diversified in terms of exporting to more markets and importing from a larger number of sources, where “good performance” is not only reflected in their size and productivity, but also in higher capital/skill intensity and higher wage.

Secondly, in terms of exports, we observe that firms with higher capital/skill intensity and higher wages on average sell in markets with lower GDP and lower income per capita, as can be seen from the last three columns of Panel A in Table 7. Note that this pattern also holds in general for ordinary and processing exports.

Thirdly, as far as imports are concerned, firms with higher capital/skill intensity and higher wage on average purchase from trade partners with longer distance, and this pattern holds for both ordinary and processing imports. Again, this may be simply because “good” firm with higher capital and skill intensities and wages can afford to source their inputs and machineries from a larger number of foreign countries with higher trade costs.

Finally, the relationship between importers’ factor intensity and the size/income of their trade partners is more ambiguous, for most of the coefficients are statistically insignificant. There is, however, one important exception. As shown in Panel B of Table 8a, for ordinary imports, the correlation between firms’ capital intensity and their GDP per capita per source is positive and statistically significant at 1%. This may reflect the fact that more capital intensive firms source their high quality equipments or inputs from high income countries with more advanced technology.

¹⁹ A few exceptions in the literature, notably Bustos (2011), do allow intra-industry skill intensity differences across firms. But none of these studies consider multi-market firms and the implications for the link between factor intensity and selection into multiple foreign markets.

Note that such correlation is negative and insignificant for processing imports, which explains the insignificant coefficient of GDP per capita in the capital intensity regression for *total* imports as shown in Panel B of Table 7.

5. Traded Products and Performances of China's Exporters and Importers

Now we turn to investigate the relation between firms' characteristics and their traded products. Manova and Zhang (2009b) show the existence of tremendous variation in Chinese traders' product intensity at the 8-digit HS level for both exports and imports. We use the same level of goods classification here, and examine whether such variation could be systematically linked to various firm-level characteristics, such as size, productivity, factor intensity, etc. One novelty of our analysis is that we generate a firm-level "product complexity" index based on the updated version of Nunn (2007)'s measure of contract intensity for both exports and imports, as was mentioned in section 2. Construction of this index can be shown as follows:

$$Complexity_{it}^k = \sum_j \omega_{itj}^k Nunn_j, \quad k = EX, IM,$$

where $\omega_{ijt}^{EX} \equiv \frac{EX_{ijt}}{\sum_j EX_{ijt}}$ and $\omega_{ijt}^{IM} \equiv \frac{IM_{ijt}}{\sum_j IM_{ijt}}$ are, respectively, the shares of good j in firm i 's exports (imports) at time t , and $Nunn_j$ is the Nunn's measure of product complexity of good j (updated to HS2002) as mentioned in section 2.²⁰ We then link this constructed firm-level product complexity measure $Complexity_{it}^k$ to firm size, productivity, capital intensity etc., to see, for example, whether larger firms export/import more complex products or not. Finally, we pay special attention to the distinction between ordinary and processing trade when the above firm-level product-performance linkages are considered.

a. Descriptive Analysis

We first provide some summary statistics regarding the link between firm size and product intensity and complexity. As can be seen in Table 9, where we use the number of employees as the proxy for firm size, it is clear that on average larger firms export and import a larger number of products than smaller firms. More interestingly, we find that in all firm size categories, (i) exporters on average trade fewer products than importers, and (ii) such product intensity gaps (between exports and imports) increase with firm size. The first finding is consistent with the results reported in Manova and Zhang (2009b) for the universe of Chinese traders in the year 2005, while the

²⁰ All the results reported in this paper adopt our updated Nunn's measure using the proportion of differentiated inputs classified according to the Rauch method. We obtain qualitatively very similar results if we use Nunn's measure by non-homogeneous good. The results are available from the authors upon request.

second finding is new. Overall, an average exporter exports 6.7 products, which is only about one third of the number of products traded by an average importer (19.5). This comparison, however, masks substantial differences across firms with different sizes. For the smallest firm size category (1-49), the product intensity of an average exporter (4.46) is about 40% of that of an average importer (10.41), and this ratio is much lower ($13.06/55.75=24\%$) for the largest size category (2000+). This pattern could be interpreted by at least three alternative possibilities. The first explanation is that this is driven by the correlation between firm size- in terms of number of employees- and their engagement in processing trade. Compared to ordinary traders (mostly domestic firms), processing traders (mostly foreign firms) import a larger number of inputs to be assembled into relatively small number of specially specified products which are then re-exported to foreign destinations; and meanwhile, processing traders are typically larger than ordinary traders, especially in number of employees, as is shown in Section 3.

Another possibility is that larger firms produce higher-quality products which rely more heavily on high-quality imported inputs, implying a larger number of imported varieties per exported product. Note that the first explanations is related to the compositional effects of industry, ownership or trade regime, which can be simply controlled for by adding corresponding dummies in a regression framework. However, the second mechanism could work at the level of firm heterogeneity within the sector-ownership-regime composition. So if the export-import gap of product intensity can be found to vary systematically with firm size when the composition effects are controlled for, it would be suggestive evidence that the quality story is a plausible mechanism at work for Chinese firms.

Another observation from Table 9 is that on average the per product value of trade increases with firm size, and this value is higher for exports than for imports. This is consistent with the notion that multi-product firms expand in the foreign markets in both extensive and intensive margins, and at both export and import sides. Finally, the last row of Table 9 shows that on average the product complexity of exports (0.55) is higher than that of imports (about 0.45), and this pattern holds for all firms size categories. One possible interpretation is that imports are dominated by relatively homogeneous inputs, such as steel, while the exports are mostly differentiated final goods, such as automobiles and computers. Also note that there is a tendency that larger firms export and import more complex products, although this relation is not strictly monotonic.

[Insert Table 9 here]

In the above analysis we only focus on one firm characteristic, namely firm size. In Table 10, we follow Bernard et al. (2009) to report the mean value of various firm characteristics, such as productivity, factor intensity and wage, by the number of products firms export or import. Not very surprisingly, average output, employment, total factor productivity and wage increase with the

number of products exported or imported. Multi-product firms that export (import) 50 products or above are on average 15 (7) times larger - in terms of total output - and 3 (2) times more productive - in terms of TFP- than single-product exporters (importers). Regarding factor intensity, both capital per worker and skill intensity appear to increase with the number of imported products, reflecting complementarity between imported varieties and human/physical capital intensity at the firm level. What is somehow unexpected is that, at the export side, however, there is a non-monotonic relationship between capital/skill intensity and product intensity. Firms exporting one or two products have more capital/skill per worker than those exporting 3-49 products, whilst firms export the largest number of products (50+) have the highest skill intensity and relatively high capital intensity. One possible explanation for this ambiguity, again, is the composition effect mentioned above: the number of products exported is highly correlated with industry characteristics such as capital intensity, and industries producing relatively small number of products, such as steel industry, may have relatively high capital intensity.

[Insert Table 10 here]

b. Regression Analysis

To formally control for the substantial differences in firms' location, industry, ownership, etc., we run firm-level OLS regressions similar to Equation (3) where various firm level characteristics considered in Table 10 are regressed, separately, on the log of the number of products traded, the log of the value of trade per product, and the product complexity measure, controlling for industry, location, ownership dummies as well as firm size.

The results are reported in Table 11. It is clear that both the intra-firm extensive margin of trade (number of products) and the intensive margin (mean value of traded product) are positively correlated with firm size, productivity, capital intensity, skill intensity, and wage per worker. All the correlations are statistically significant at 1% level, and this pattern holds for both exports and imports. For example, as shown in Panel A of Table 11, the correlation between the number of exported products and TFP is 0.107, which is comparable to that reported in Bernard et al. (forthcoming) where they find the correlation is about 0.071 for US firms.

Interestingly, comparing the coefficients across exports and imports (Panel A and Panel B), we find the correlation between capital intensity and product intensity to be much higher for imports (0.20) than that of exports (0.04). Similar patterns are also found for wage per worker and skill intensity, where in the import regressions the coefficients are almost twice as large as those in the export regressions. In other words, the number of products traded is more responsive to firms' capital/skill intensity and wage per worker in imports than in exports. This is consistent with the notion that firms focusing on the production of higher quality products use more capital/skill

intensive technology, pay higher wage per worker, and at the same time source more varieties of high quality inputs from abroad.

Finally, the last rows of Panel A and Panel B in Table 11 show how firms' various characteristics are correlated with the product complexity measure in exports and imports, respectively. Interestingly, there is a positive correlation between firm size and product complexity in both exports and imports, indicating that larger firms export and import more complex products than smaller firms.²¹ Also note that the size-complexity coefficient is much larger for exports (0.546) than imports (0.095), indicating a greater gap between the complexity of products exported and imported when firm sizes become larger.

Furthermore, the last row of Panel B also shows that the complexity of products imported by firms is higher, the more productive and more capital/skill intensive the firms are and the higher wages are paid per worker. Again, this may simply reflect that fact that high ability firms with superior firm characteristics are more likely to import and use more complex machinery and equipments, such as whole production lines, rather than just sourcing relatively simple raw materials, such as leather, steel etc., from overseas. What may look a bit surprising is that more productive and capital/skill intensive firms export *less* complex products, as indicated in the last row of Panel A. One possible explanation is that foreign multinational firms producing more complex products, such as iPod, are more likely to outsource the labour-intensive segments of the value chain, such as simple accessories or assembly tasks, to Chinese firms. So, Chinese suppliers specializing in such activities use more labour-intensive technology and exhibit lower labour productivity as well as pay lower wage per worker. In contrast, within the same industry, Chinese firms producing less complex products, such as TV sets, undertake less outsourcing (labour-intensive) activities, and therefore, are more capital/skill intensive and exhibit higher labour productivity.

[Insert Table 11 here]

c. Ordinary versus Processing Trade

Next we proceed to examine whether the above pattern holds when we distinguish between ordinary and processing trade. The results are shown in Table 12. Several interesting points are worth noting. First, the coefficients of product intensity and value per product traded are all positive and significant in both ordinary trade and processing trade. This is consistent with the pattern presented in Table 11. Note, however, that as shown in Panel A.1-A.2, the correlation between the number of products and TFP is much smaller for processing exports (0.045) than for ordinary

²¹ In Table 11 we only use the number of employees as a proxy for firm size, the results are very similar when we use total output, total value added as alternative size measures.

exports (0.12). This is consistent with the notion that processing exports specialise in narrower range of products assigned by foreign multinationals, and concentrate in assembly tasks that produce low value-added per worker or per bundle of inputs. Second, consistent with the pattern observed in Table 11, the correlation between capital intensity/skill intensity/wage and the number of products is higher for imports than that of exports in both ordinary and processing trade. However, the differences are much larger between ordinary exports and imports than those between processing exports and imports. For example, under ordinary trade, in terms of capital intensity, the coefficient of the number of products is 0.19 for imports, as opposed to 0.034 for exports, while under processing trade, the coefficient is 0.078 and 0.049 for imports and exports, respectively. Similar comparisons can be observed for wage per worker and skill intensity. Such pattern provides some supporting evidence to our interpretation above that more capable Chinese firms producing higher quality products employ more capital/skill intensity technology and at the same time complementarily import greater varieties of imported inputs and machineries. If this interpretation is correct, then the above pattern would be stronger for ordinary traders than for processing traders, because the technology-imports complementarity hypothesis is presumably weaker for processing trade that relies heavily on labour-intensive technology. This is exactly what we find.

[Insert Table 12 here]

Finally, the signs of the product complexity coefficients are again quite consistent with those reported in Table 11. The only exception is the negative correlation (-0.477) between complexity and capital intensity in processing imports, as shown in the last row of Panel B.2. Combined with the positive correlation between capital intensity and the number of processing products imported (0.078), this simply suggests that more capital intensive firms import a larger number of processing inputs that are relatively simple. Also note that the negative correlation between skill intensity/wage and product complexity is significant only for processing exports, but insignificant for ordinary exports. This is, again, supportive to our hypothesis that multinational firms source unskilled-intensive assembly tasks in more complex products to Chinese suppliers; and therefore, the more complex the final products exported in processing trade, the more unskilled intensive the Chinese firms are and the lower wage they pay.

6. Conclusions

By linking a comprehensive data on Chinese firms' international transactions to a census of Chinese enterprises with production and accounting data, in this paper we document some new patterns on the linkages between firms' key performance indicators and their engagements in international trade in terms of importing, exporting, and processing trade. First, there exists

substantial heterogeneity among two way traders when we account for firms' participation in export processing. Pure processing two-way traders are less productive, less capital/skill intensive, and pay lower wages than one way exporters or importers, possibly reflecting the fact that assembly and processing activities are highly unskilled-labour intensive, heavily reliant on imports of intermediate inputs, and thus, generate relatively low value added per bundle of input. Second, among firms that import, exporting firms are less capital and skill intensive than non-exporters (independent of whether they are engaged in processing trade or not). This is consistent with the notion that China has comparative advantage in labour intensive tasks/activities even within a narrowly defined industry. Third, larger and more productive firms trade with a larger number of trade partners with loner average distance and smaller market size; and this pattern is highly symmetric between exports and imports, as well as ordinary and processing trade. Fourth, more capital intensive firms import inputs with greater complexity from countries with higher income per capita, but this pattern holds only for ordinary imports, not imports for export processing. Overall, these results suggest that ignoring firms' participation in processing trade, especially in developing countries, may lead to a serious bias on estimating the relation between firms' performances and their international trade activities.

The data constructed in this paper can be used to analyse a number of interesting issues on firms' engagement in international transactions. Being able to combine detailed export-import data and production-accounting information at firm level, we could explore questions like how does firm level characteristics affect firms' export/import responses to exchange rate fluctuations, the causal effect of falling import barriers on firm performances via their impacts on imported inputs, and the causes and consequences of developing country firms' participation in global value chain in the form of export processing, and many others.

Table 1
Statistics of Exports and Imports in the CASIF-CCTS Matched Data

Year	No. Firms in Matched CASIF-CCTS Sample	No. Matched Firms as a Share (%) in CCTS Data	No. Matched Firms as a Share (%) in CASIF Data	Exports			Imports		
				No. Firms Matched	Value % Share in CCTS	No. Firms % Share in CCTS	No. Firms Matched	Value % Share in CCTS	No. Firms % Share in CCTS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2002	31,481	30.2	19.2	27,385	43.2	34.8	23,334	38.9	30.2
2003	37,419	30.1	20.9	32,999	45.1	34.5	26,591	39.1	30.2
2004	54,077	35.2	21.3	47,843	49.8	39.7	36,938	41.8	36.1
2005	55,224	30.7	22.1	49,929	48.1	34.7	36,275	39.8	32.0
2006	59,917	28.7	21.6	54,485	46.6	31.8	38,198	38.5	31.4
<i>Total</i>	<i>238,118</i>	<i>30.9</i>	<i>21.0</i>	<i>212,641</i>	<i>47.0</i>	<i>34.9</i>	<i>161,336</i>	<i>39.6</i>	<i>32.1</i>

Notes:

Authors' calculation.

Source: CASIF-CCTS matched database.

Table 2
Exporters, Importers and Processing Traders by Ownership Type, 2002-2006

Ownership		Trade Status						Total
		Export Only (XJ) (1)	Import Only (MJ) (2)	Two-Way Traders (XM) (3)	Two-Way Ordinary (XMO) (4)	Two-Way Processing (XMP) (5)	Two-Way Mixed (XMOP) (6)	
Domestic	No. Firms	48,670	7,253	31,347	16,074	799	14,474	87,270
	Share %	55.77	8.31	35.92	18.42	0.92	16.59	36.60
HMT	No. Firms	14,531	8,736	48,342	8,275	9,556	30,511	71,609
	Share %	20.29	12.2	67.51	11.56	13.34	42.61	30.06
Foreign	No. Firms	13,581	9,488	56,170	14,006	2,570	39,594	79,239
	Share %	17.14	11.97	70.89	17.68	3.24	49.97	33.34
<i>All Firms</i>	<i>No. Firms</i>	<i>76,782</i>	<i>25,477</i>	<i>135,859</i>	<i>38,355</i>	<i>12,925</i>	<i>84,579</i>	<i>238,118</i>
	<i>Share %</i>	<i>32.25</i>	<i>10.7</i>	<i>57.06</i>	<i>16.11</i>	<i>5.43</i>	<i>35.52</i>	<i>100</i>

Notes:

Authors' calculation. Firms are divided into three ownership types, domestic ownership, Hong Kong, Macao and Taiwan owned (HMT), and foreign owned, as well as six trading status including: export only, import only, two-way trade, two-way ordinary trade only, two-way processing trade only, and two-way mixed trade. Note that the last three trading status (columns 4-6) are sub-groups of the two-way traders (column 3). Numbers in the rows labeled "No. Firms" show the number of firms in each group according to their export-import status and ownership. Numbers in the rows labeled "Share %" show the fractions of firms in each group as a share of these firms within the same ownership type as indicated at the left. In column (7) the fractions represent the each ownership type's share of all trading firms. Percentages in columns (1)-(3) sum up to 100%, and the sum of the percentages in column (4)-(6) equals that in column (3).

Source: CASIF-CCTS matched database.

Table 3
Summary Statistics on Trading Status and Firm Level Characteristics, 2004

Trade Status	Firm Performances								
	No. Firms	No. Employees	Output	Value-Added	TFP	Value-Added per Worker	Capital Intensity	Skill Intensity	Wage per Worker
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
One-Way Exporters (XJ)	31.7%	264.2 (537.2)	56.76 (197.56)	14.46 (53.33)	6.18 (1.67)	67.4 (136.0)	59.6 (196.9)	0.432 (0.522)	12.7 (40.8)
One-Way Importers (MJ)	11.5%	341.3 (1407.6)	172.75 (871.77)	42.72 (203.69)	6.38 (1.89)	171.5 (601.3)	216.7 (609.1)	0.650 (0.612)	21.3 (22.9)
Two-Way Traders (XM)	56.8%	497.3 (1203.7)	189.19 (1144.98)	46.87 (344.96)	6.53 (1.69)	96.7 (361.2)	106.6 (311.5)	0.507 (0.540)	17.8 (26.9)
Two-Way Ordinary (XMO)	16.2%	451.1 (1299.989)	208.69 (1208.25)	59.15 (471.07)	6.70 (1.75)	127.2 (267.7)	142.1 (317.8)	0.594 (0.359)	20.6 (18.8)
Two-Way Processing (XMP)	5.5%	310.2 (435.294)	38.12 (76.61)	8.21 (19.42)	5.76 (1.71)	38.2 (91.4)	36.6 (71.0)	0.369 (0.284)	12.5 (9.1)
Two-Way Mixed (XMOP)	35.1%	547.7 (1234.788)	203.69 (1200.61)	47.22 (299.39)	6.57 (1.62)	91.7 (419.0)	101.1 (328.8)	0.488 (0.627)	17.3 (31.4)
<i>Total</i>	<i>100%</i> <i>54,077</i>	<i>405.4</i> <i>(1074.3)</i>	<i>145.32</i> <i>(920.86)</i>	<i>36.12</i> <i>(271.05)</i>	<i>6.40</i> <i>(1.71)</i>	<i>96.0</i> <i>(350.0)</i>	<i>104.4</i> <i>(335.0)</i>	<i>0.500</i> <i>(0.547)</i>	<i>16.6</i> <i>(31.7)</i>

Notes:

Authors' calculation. Column (1) shows the shares of each trading category in total number of firms. Column (2)-(9) provides the mean values and standard deviations (in parentheses) of corresponding firm-level characteristics (as indicated at the first row) for each trading status group (as indicated at the left). TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Output and value-added are in millions of Chinese yuan. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan.

Source: CASIF-CCTS matched database.

Table 4
Trading Status and Firm-level Characteristics, Pooled OLS Regressions, 2002-2006

Dependent Variables	Log Employment	Log Output	Log Value-Added	TFP	Log Value- Added per Worker	Log Capital Intensity	Log Skill Intensity	Log Wage per Worker
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A. Estimation Results Controlling for Year, Ownership and Industry-Location Effects</i>								
One-way Importers (β_1)	-0.004 ^d	0.186	0.257	0.134	0.260	0.349	0.163	0.071
Two-way Traders (β_2)	0.495	0.576	0.608	0.372	0.107	0.247	0.096	0.067
Two-way Ordinary (β_3)	0.309	0.427	0.473	0.297	0.161	0.248	0.165	0.086
Two-way Processing (β_4)	0.165	0.011 ^d	0.020 ^d	-0.014 ^d	-0.158	-0.082	-0.097	-0.036
Two-way Mixed (β_5)	0.678	0.751	0.775	0.472	0.091	0.281	0.073	0.063
<i>Panel B. Estimation Results Controlling for Year, Ownership and Industry-Location Effects and Log Employment</i>								
One-way Importers (β_1)	-	-	-	0.134	0.260	0.348	0.163	0.075
Two-way Traders (β_2)	-	-	-	0.127	0.177	0.299	0.156	0.084
Two-way Ordinary (β_3)	-	-	-	0.145	0.208	0.284	0.204	0.097
Two-way Processing (β_4)	-	-	-	-0.098	-0.137	-0.063	-0.077	-0.029
Two-way Mixed (β_5)	-	-	-	0.140	0.192	0.361	0.156	0.089
No. Observations	238,118	238,118	231,514	231,142	231,142	238,083	54,077	238,118
No. Clusters (county-industry level)	52,657	52,657	51,096	51,029	51,029	52,630	25658	52,657

Notes:
 Authors' calculation. This table reports coefficients for the trading status dummy variables in the OLS regression as specified in equation (1) and (2), with dependent variables indicated at the first row. In Panel A, each regression includes time dummies, ownership dummies, and county-industry fixed effects as control variables. In Panel B, log employment is included as an additional control. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Output and value-added are in millions of Chinese yuan. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. All coefficients are significant at 1% level, except those with superscript d indicating insignificant at 10% level.

Source: CASIF-CCTS matched database.

Table 5
Firm Size and Trade Partner Characteristics, Average 2002-2006

	Firm Employment Category							All Firms
	1 to 49	50 to 99	100-199	200-499	500-1000	1000-1999	2000+	
<i>Panel A. Exports</i>								
No. Firms	19,173	36,525	51,541	61,180	25,385	11,497	7,340	212,641
Share of No. Firms	9.0%	17.2%	24.2%	28.8%	11.9%	5.4%	3.5%	100%
Average No. Markets	4.84	5.64	6.83	8.61	11.47	14.04	16.72	8.24
Average Value of Exports per Market	400	412	551	867	1,593	3,106	7,642	1,111
Average Real GDP per Market	2,052	1,969	1,926	1,863	1,692	1,535	1,447	1,861
Average Real GDP PC per Market	21,526	21,267	21,240	20,966	20,045	18,977	17,809	20,808
Average Distance per Market	5,430	5,704	5,895	6,124	6,315	6,488	6,403	5,986
<i>Panel B. Imports</i>								
No. Firms	14,683	25,478	36,229	46,363	21,197	10,306	7,080	161,336
Share of No. Firms	9.1%	15.8%	22.5%	28.7%	13.1%	6.4%	4.4%	100%
Average No. Sources	2.69	2.9	3.36	4.14	5.48	7.3	9.59	4.26
Average Value of Imports per Source	377	426	513	675	1,016	1,634	3,615	808
Average Real GDP per Source	2,597	2,407	2,246	2,189	2,146	2,139	2,091	2,260
Average GDP PC per Source	2,4192	2,3854	2,3391	23,149	22,798	22,464	21,714	23,257
Average Distance per Source	4,812	4,604	4,619	4,666	4,999	5,523	6,210	4,825

Notes:

Authors' calculation. This table provides summary statistics on the characteristics of firms' trade partners by different size group. "Average No. Markets/Sources" and "Average Value of Exports/Imports per Market/Source" represent the mean of the numbers of countries traded and the value of trade per country, respectively, of the Chinese trading firms in each size category. The trade values are in thousands of USD. "Average Real GDP/GDP PC/Distance per Market/Source" represents the mean real GDP, GDP per capita and distance per country of the trade partners with which Chinese firms trade with, where distance is measure by kilometres.

Source: CASIF-CCTS matched database.

Table 6
Firm Characteristics and Trade Partner Intensity, 2004

No. Trade Partners	No. Firms	Employment	Output	TFP	Value-Added per Worker	Capital Intensity	Skill Intensity	Wage per Worker	Average Sales/Purchase per Market
<i>Panel A. Exports</i>									
1	11,062	281	74.91	6.14	81.07	91.15	0.48	15.90	1,842.59
2	6,908	308	92.38	6.23	78.67	88.05	0.47	15.57	1,586.92
3-4	7,784	343	100.18	6.29	83.57	90.18	0.49	15.49	817.54
5-9	9,468	393	131.89	6.45	87.72	93.11	0.48	15.93	658.11
10-49	12,240	607	229.19	6.73	94.65	86.47	0.47	16.54	653.93
50+	381	1,954	1,262.60	7.66	117.90	96.58	0.51	18.41	1,512.19
<i>All firms</i>	<i>47,843</i>	<i>414</i>	<i>141.75</i>	<i>6.40</i>	<i>86.21</i>	<i>89.78</i>	<i>0.48</i>	<i>15.98</i>	<i>1,097.76</i>
<i>Panel B. Imports</i>									
1	11,419	283	71.56	6.23	83.40	90.84	0.50	15.84	490.02
2	6,828	323	88.17	6.34	85.29	105.54	0.51	16.59	618.10
3-4	7,710	403	111.04	6.42	94.35	111.46	0.52	17.61	646.23
5-9	7,299	559	201.26	6.71	135.54	162.21	0.56	20.36	909.54
10-49	3,678	1,276	830.28	7.44	213.72	223.79	0.63	27.40	2,056.70
50+	4	19,702	21,906.57	9.06	282.13	88.78	0.74	25.83	31,226.57
<i>All Firms</i>	<i>36938</i>	<i>471</i>	<i>186.00</i>	<i>6.51</i>	<i>109.33</i>	<i>125.20</i>	<i>0.53</i>	<i>18.39</i>	<i>788.52</i>

Notes:

Authors' calculation. This table provides the mean values of various firm characteristics by the numbers of firms' trade partners. Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Output and value-added are in millions of Chinese yuan. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. "Average Sales/Purchases per Market" is in thousands of USD.

Source: CASIF-CCTS matched database.

Table 7
Trade Partner Characteristics and Firm Characteristics:
Pooled Regression Results, 2002-2006

Dependent Variable	Log Employment	TFP	Log Value-Added per Worker	Log Capital Intensity	Log Skill Intensity	Log Wage per Worker
<i>Panel A. Exports</i>						
Log No. of Markets	0.322	0.123	0.119	0.068	0.018	0.033
Log Value of Exports per Market	0.199	0.091	0.084	0.048	0.002 ^d	0.028
Log Real GDP per Market	-0.058	-0.052	-0.055	-0.031	-0.005	-0.008
Log Real GDP PC per Market	-0.084	-0.064	-0.069	-0.037	-0.006	-0.010
Log Distance per Market	0.163	0.050	0.036	-0.025	0.007	-0.003 ^d
No. Observations	21,2641	206,899	206,899	212,608	47,843	212,641
<i>Panel B. Imports</i>						
Log No. of Sources	0.514	0.214	0.263	0.290	0.038	0.101
Log Value of Imports per Source	0.136	0.069	0.089	0.095	0.007	0.027
Log Real GDP per Source	-0.064	-0.021	-0.017	0.005 ^d	0.001 ^d	0.000 ^d
Log Real GDP PC per Source	-0.110	-0.041	-0.041	-0.009 ^d	0.004 ^d	-0.006
Log Distance per Source	0.210	0.119	0.158	0.158	0.029	0.056
No. Observations	161,336	156,076	156,073	161,309	36,938	161,332

Notes:

Authors' calculation. Each cell reports the coefficient of the variables listed at the far left as regressors from an individual OLS regression, with dependent variable listed at the first row. Control variables include county-industry fixed effects, year dummy and ownership dummies, as well as log employment (except the first column). Panel A and Panel B reports results of all exports and imports, respectively. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. All coefficients are clustered at county-industry level, and are significant at 1% level, except those with superscript d indicating insignificant at 10%. Source: CASIF-CCTS matched database.

Table 8a
Trade Partner Characteristics and Firm Characteristics:
Pooled Regression Results for Ordinary Trade, 2002-2006

	Log Employment	TFP	Log Value-Added per Worker	Log Capital Intensity	Log Skill Intensity	Log Wage per Worker
<i>Panel A. Ordinary Exports</i>						
Log No. of Markets	0.266	0.124	0.118	0.057	0.018	0.034
Log Value of Exports per Market	0.076	0.068	0.055	0.0028 ^d	0.000 ^d	0.015
Log Real GDP per Market	-0.044	-0.041	-0.044	-0.020	-0.004	-0.005
Log Real GDP PC per Market	-0.048	-0.046	-0.049	-0.023	-0.003 ^d	-0.006
Log Distance per Market	0.096	0.045	0.030	-0.023	0.005 ^d	-0.004 ^d
No. Observations	181,820	177,280	177,280	181,790	40,720	181,820
<i>Panel B. Ordinary Imports</i>						
Log No. of Sources	0.414	0.254	0.32	0.269	0.046	0.120
Log Value of Imports per Source	0.062	0.068	0.094	0.082	0.009	0.029
Log Real GDP per Source	-0.030	-0.021	-0.018	0.0016 ^d	-0.002 ^d	-0.001 ^d
Log Real GDP PC per Source	-0.0148	-0.015	-0.006 ^d	0.0211	0.001 ^d	0.002 ^d
Log Distance per Source	0.063	0.0488	0.0716	0.0694	0.017	0.027
No. Observations	107,664	104,048	104,048	107,647	24,428	107,510

Notes:

Authors' calculation. Each cell reports the coefficient of the variables listed at the far left as regressors from an individual OLS regression, with dependent variable listed at the first row. Control variables include county-industry fixed effects, year dummy and ownership dummies, as well as log employment (except the first column). Panel A and Panel B reports results of ordinary exports and imports, respectively. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. All coefficients are clustered at county-industry level, and are significant at 1% level, except those with superscript d indicating insignificant at 10% level.

Source: CASIF-CCTS matched database.

Table 8b
Trade Partner Characteristics and Firm Characteristics:
Pooled Regression Results for Processing Trade, 2002-2006

	Log Employment	TFP	Log Value-Added per worker	Log Capital Intensity	Log Skill Intensity	Log Wage per Worker
<i>Panel A. Processing Exports</i>						
Log No. of Markets	0.337	0.097	0.100	0.075	0.0122	0.030
Log Value of Exports per Market	0.223	0.087	0.096	0.077	0.0052	0.038
Log Real GDP per Market	-0.055	-0.046	-0.055	-0.053	-0.003 ^d	-0.013
Log Real GDP PC per Market	-0.156	-0.085	-0.105	-0.081	-0.010	-0.018
Log Distance per Market	0.273	0.055	0.050	-0.011 ^d	0.002 ^d	-0.003 ^d
No. Observations	96,330	93,294	93,294	96,324	21,559	96,330
<i>Panel B. Processing Imports</i>						
Log No. of Sources	0.511	0.175	0.201	0.204	0.022	0.075
Log Value of Imports per Source	0.192	0.1005	0.114	0.100	0.0069	0.033
Log Real GDP per Source	-0.041	-0.008 ^d	0.0029 ^d	0.023	0.001 ^d	0.010
Log Real GDP PC per Source	-0.050	-0.025	-0.022	-0.008 ^d	0.001 ^d	-0.000 ^d
Log Distance per Source	0.160	0.077	0.093	0.095	0.010	0.038
No. Observations	98,914	95,857	95,857	98,908	22,451	98,914

Notes:

Authors' calculation. Each cell reports the coefficient of the variables listed at the far left as regressors from an individual OLS regression, with dependent variable listed at the first row. Control variables include county-industry fixed effects, year dummy and ownership dummies, as well as log employment (except the first column). Panel A and Panel B reports results of processing exports and imports, respectively. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. All coefficients are clustered at county-industry level, and are significant at 1% level, except those with superscript d indicating insignificant at 10% level.

Source: CASIF-CCTS matched database.

Table 9
Firm Size and Traded Products, 2002-2006

	Employment Category							All Firms
	1 to 49	50 to 99	100-199	200-499	500-1000	1000-1999	2000+	
<i>Panel A. Exports</i>								
No. Firms	19,173	36,525	51,541	61,180	25,385	11,497	7,340	21,2641
Share	9.0%	17.2%	24.2%	28.8%	11.9%	5.4%	3.5%	100.0%
No. Products	4.46	4.79	5.73	7.22	8.43	10.12	13.06	6.7
Average Value of Exports per Product	411	449	619	984	1967	4014	8479	1292
Nunn's Product Complexity Measure	0.504	0.529	0.546	0.564	0.571	0.567	0.541	0.548
<i>Panel B. Imports</i>								
No. Firms	14,683	25,478	36,229	46,363	21,197	10,306	7,080	161,336
Share	9.1%	15.8%	22.5%	28.7%	13.1%	6.4%	4.4%	100%
No. Products	10.41	11.37	14.17	18.68	26.12	36.88	55.75	19.53
Average Value of Imports per Product	205	214	256	311	449	529	1,244	347
Nunn's Product Complexity Measure	0.457	0.451	0.445	0.443	0.455	0.473	0.483	0.451

Notes:

Authors' calculation. Table reports the number of trading firms, average number of products traded per firm, average nominal value per traded product traded per firm (thousands of USD), and average product complexity per firm (by updated Nunn's measure) for exports or imports by firm size in terms of employment during 2002-2006.

Source: CASIF-CCTS matched database.

Table 10
Distribution of Firm Characteristics by Number of Products Exported or Imported per Firm, 2004

No. Traded Products	No. Firms	Employment	Output	TFP	Value-Added per Worker	Capital Intensity	Wage per Worker	Skill Intensity	Average Value per Product
<i>Panel A. Exports</i>									
1	10,843	282.9	86.5	6.15	91.4	113.2	15.4	0.49	1,662.8
2	7,653	320.6	93.2	6.25	86	94.4	15.2	0.49	1,292.8
3-4	9,634	376.1	113.5	6.35	80.7	91.5	15.8	0.48	1,172.9
5-9	10,762	442.6	136.0	6.49	85.9	79.3	16	0.47	890.2
10-49	8,637	615.5	248.8	6.74	84.1	66.8	17	0.44	785
50+	314	1,820.3	1,334.1	7.55	142.8	97.6	21.9	0.62	1,281.8
<i>All firms</i>	<i>47,843</i>	<i>413.7</i>	<i>141.7</i>	<i>6.40</i>	<i>86.2</i>	<i>89.7</i>	<i>15.9</i>	<i>0.48</i>	<i>1,170.3</i>
<i>Panel B. Imports</i>									
1	6,267	342.1	96.9	6.29	88.7	91.6	14.5	0.49	615.3
2	3,743	338.3	96.0	6.31	97.2	106.8	15.5	0.49	481.1
3-4	4,539	325.9	96.8	6.28	87.0	105.1	16.0	0.50	366.7
5-9	6,070	374.0	108.0	6.35	95.9	108.8	16.9	0.52	245.2
10-49	12,634	490.7	156.6	6.54	107.4	124.5	19.6	0.52	184.7
50+	3,685	1,095.0	770.0	7.45	212.9	255.2	29.1	0.69	304.9
<i>All Firms</i>	<i>36,938</i>	<i>470.9</i>	<i>186.0</i>	<i>6.50</i>	<i>109.3</i>	<i>125.2</i>	<i>18.4</i>	<i>0.53</i>	<i>332.1</i>

Notes:

Authors' calculation. This table reports mean values of various firm characteristics according to the number of their exported or imported product in year 2004. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Output and value-added are in millions of Chinese yuan. Value-added per worker, capital intensity, wage per worker, and average value per product are all in thousands of Chinese yuan.

Source: CASIF-CCTS matched database.

Table 11
Firm Characteristics and the Extensive and Intensive Margins of Traded Products:
Pooled Regression Results, 2002-2006

	Log Employment	TFP	Log Value- Added per Worker	Log Capital Intensity	Log Wage per Worker	Log Skill Intensity
<i>Panel A. Exports</i>						
Log No. Products	0.302	0.107	0.093	0.040	0.034	0.013
Log Value of Exports per Product	0.204	0.098	0.095	0.058	0.029	0.005
Nunn's Product Complexity Measure	0.546	-0.156	-0.367	-0.755	-0.048	-0.016 ^d
No. Observations	212,638	206,899	206,899	212,608	212,638	47,842
<i>Panel B. Imports</i>						
Log No. Products	0.338	0.106	0.148	0.205	0.072	0.025
Log Value of Imports per Product	0.120	0.078	0.094	0.087	0.023	0.007
Nunn's Product Complexity Measure	0.095	0.092	0.095	0.293	0.058	0.067
No. Observations	161,332	156,073	156,073	161,309	161,332	36,937

Notes:

Authors' calculation. Each cell reports the coefficient of the variables listed at the far left as regressors with dependent variable listed at the first row from an individual OLS regression. Control variables include county-industry fixed effects, year dummy and ownership dummies, as well as log employment (except the first column). Panel A and Panel B reports results of processing exports and imports, respectively. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. All coefficients are clustered at county-industry level, and are significant at 1% level, except those with superscript d indicating insignificant at 10% level.

Source: CASIF-CCTS matched database.

Table 12
Traded Products and Firm Characteristics: Ordinary Trade versus Processing Trade,
Pooled Regression Results, 2002-2006

	Log Employment	TFP	Log Value-Added per Worker	Log Capital Intensity	Log Wage per Worker	Log Skill Intensity
<i>Panel A. Exports</i>						
<i>Panel A.1 Ordinary Exports</i>						
Log No. Products	0.237	0.121	0.102	0.034	0.032	0.014
Log Value of Exports per Product	0.087	0.067	0.058	0.011	0.015	0.003
Product Complexity	0.148	-0.125	-0.301	-0.750	-0.033 ^d	-0.018 ^d
No. Observations	181,820	177,280	177,280	181,790	181,820	40,720
<i>Panel A.2 Processing Exports</i>						
Log No. Products	0.380	0.045	0.045	0.049	0.029	0.006 ^d
Log Value of Exports per Product	0.238	0.109	0.119	0.091	0.041	0.008
Product Complexity	0.906	-0.069	-0.314	-0.699	-0.058	-0.011
No. Observations	96,330	93,294	93,294	96,324	96,330	21,559
<i>Panel B. Imports</i>						
<i>Panel B.1 Ordinary Imports</i>						
Log No. Products	0.249	0.133	0.182	0.191	0.080	0.030
Log Value of Imports per Product	0.050	0.071	0.094	0.073	0.025	0.008
Product Complexity	0.246	0.096	0.082	0.123	0.072	0.044
No. Observations	107,510	104,048	104,048	107,493	107,664	24,457
<i>Panel B.2 Processing Imports</i>						
Log No. Products	0.376	0.058	0.063	0.078	0.039	0.010
Log Value of Imports per Product	0.179	0.122	0.140	0.121	0.037	0.008
Product Complexity	0.350	0.347	0.195	-0.477	0.082	0.012 ^d
No. Observations	98,559	95,816	95,816	98,908	98,914	22,445

Notes:

Authors' calculation. Each cell reports the coefficient of the variables listed at the far left as regressors with dependent variable listed at the first row from an individual OLS regression. Control variables include county-industry fixed effects, year dummy and ownership dummies, as well as log employment (except the first column). Panel A.1 and A.2 reports results for ordinary and processing exports, respectively, and Panel B.1 and B.2 reports results for ordinary and processing imports, respectively. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan. All coefficients are clustered at county-industry level, and are significant at 1% level, except those with superscript d indicating insignificant at 10% level.

Source: CASIF-CCTS matched database.

Appendix A

A.1 Matching between the Firm-level (CASIF) and the Transaction-Level (CCTS) Datasets

Our matching strategy is to make use of firm names as the main common variable linking firms in the CASIF to those in the CCTS. In both datasets, a field of company name is included, which is in principle and generally unique to each firm. We therefore construct a concordance matching the firm identifiers across these two datasets (we use “FIRMID” to refer to the firm identifier code in the CASIF and “FIRMCODE” to refer to those in the CCTS) by matching their corresponding names. As a robustness check, we also compare other common variables included in both datasets such as their province code. Details of the matching procedure are elaborated as below.

a. The Matching Method

The most straightforward matching method is to match a FIRMID-year observation in the CASIF with a FIRMCODE-year observation in CCTS as long as they have strictly the identical firm name for the same year. After the matching, if a FIRMID corresponds to multiple FIRMCODEs within the same year, the corresponding matching will be excluded from the sample. Analogously, matches where a FIRMCODE is matched to different FIRMIDs will also be dropped. This method leaves us a strictly one-to-one matching between the FIRMID-year pair in the CASIF data and the FIRMCODE-year pair in the CCTS data. We call this approach the “conservative” matching method.

The main issue with the above matching method is that the same firm appearing in both datasets may not be included in the concordance if it happened to have different names in the two datasets. This could take place when, for example, firms registered or reported to the Chinese Customs with a slightly different name from that in the CASIF due to a typo or other reasons, or vice versa. To improve the success rate of the matching, in this paper we adopt an alternative method, which we call the “liberal” matching method described as follows.

The basic idea is that we do the matching by using all the different names ever used by a firm in the datasets. More concretely, a CASIF FIRMID will be matched to a CCTS FIRMCODE, as long as one of the names ever used by the FIRMID in the CASIF data can be matched to one of the names ever pertaining to the FIRMCODE in the CCTS data. For example, if in a given year there exists a FIRMID in the CASIF which has six different names in the whole sample period, and meanwhile a FIRMCODE in the CCTS data has five different names, we then exhaust all of the thirty possible combination of the names across the two datasets ($5 \times 6 = 30$) to see if any of these names is identical to a name in the other data set. Figure A1 illustrates this matching strategy.

Clearly, compared to the “conservative” method, this matching method allows the largest flexibility in variations of firm names and minimizes the possibility of failure to identify matched firms simply due to changes in their names for whatever reasons. Under this “liberal” matching method, a firm in the CASIF can always be linked to its corresponding transaction-level information in the CCTS as long it used a common name for at least once in both data sets. Following this procedure, we obtained 239,502 firm-year matches during 2002-2006.

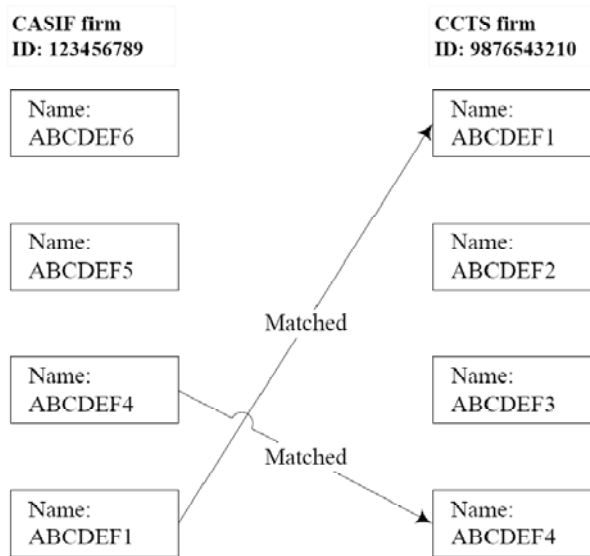


FIGURE A1
The Matching Method

b. Further Robustness Checks and Cleaning

After the above matching procedure, we conduct a number of checks to assess the quality of the matching. Firstly, we check if there are “duplicates” in the matched sample, in the sense that within a given year, more than one CASIF FIRMID is matched to one CCTS FIRMCODE. It turns out that such duplicates do exist but only constitutes a negligible proportion of the sample - 1,303 matches have duplicate FIRMIDs corresponding to one FIRMCODE, which are excluded from the concordance. Secondly, we check if there are multiple CCTS FIRMCODEs matched to one CASIF FIRMID. There are 4% matches from the cleaned sample (9,524) where multiple FIRMCODE are matched to one FIRMID for the same year. After checking these multiple correspondences very carefully in the original CCTS data, we found that this is due to the that firms changed their CCTS code during the same year in different months whilst keeping their names unchanged (recall that the unit of time variation in the CCTS data is by month rather than by year). In other words, these multiple FIRMCODEs actually correspond to the same firm, but reported their transaction information in different FIRMCODEs in different months. We therefore choose to include these duplicates and aggregate their transaction information by year during our main analysis. Third, we check the location of the CASIF FIRMID and the CCTS FIRMCODE for each matched pair, and exclude matches with inconsistent location (province) indicators. More concretely, we compared the first two digits of the FIRMCODEs in the CCTS against the first two digits of the FIRMIDs in the CASIF. Only a negligibly small proportion of the matches (81) has inconsistent province codes and is therefore dropped from the concordance. The final result is 238,118 firm-year observations as shown in Table 1.

A.2 Updating the Nunn Measure to HS2002

Nunn (2007) constructed a measure of contract intensity using Rauch measure (Rauch, 1999) of product differentiation and US input-output table 1997. If we apply this measure to an international trade data since 2002, we need to convert the Nunn’s measure by 1997 US IO industry code to 2002. To do so, we will need a concordance between US IO code 2002 and US IO code 1997, or HS 2002 code and US IO code 1997. However, direct concordances between the above industry classifications does not exist, so one needs to construct them using other HS concordances to convert the 1997 version to 2002 version, assuming the input-output relation remains constant over this period. Nevertheless, given all these possibilities, one would prefer to use the Nunn’s

measure upgraded to 2002 using US IO table 2002 to avoid these complications. This is the purpose of this work. Using Stata codes kindly provided by Nunn, the 2002 measure is constructed strictly following the method by Nunn (2007), which takes two steps. The first is to aggregate the Rauch classification to IO 2002, so one can measure whether an intermediate input is relation-specific or not. As in Nunn (2007), this is achieved by matching the IO 2002 commodity codes to 4-digit SITC rev2 using the following two concordances: the first is from US IO 2002 to 10-digit HS2002 published on the US Bureau of Economic Analysis website, the second is from 6-digit HS 2002 to 5-digit SITC rev2. from World Integrated Trade Solution (WITS) maintained by the World Bank. The aggregated Rauch measure by IO 2002 code thus includes 303 intermediate inputs with fractions of each inputs sold in organized exchange (homogenous), referenced price or neither (differentiated). The second step is to construct the Nunn’s contract intensity measure by each IO product using the aggregated Rauch measure by inputs. Again, the method strictly follows Nunn (2007), so that the contract intensity measure equals the fraction of the inputs that are relation-specific/ differentiated or not. The final measure includes 369 industries by US IO code 2002. Compared with the 1997 measure, 233 out of the 369 IO 2002 codes can be directly matched with the 1997 IO codes. For these products whose IO codes are unchanged during this time period, the average fraction of differentiated inputs (neither category of the Rauch measure) is 0.548 for 2002 and 0.494 for 1997. Table A1 summarises the correlation between the 2002 and 1997 measures, all coefficients significant at 0.1% level.

Table A1
Correlations between Nunn’s Contract Intensity Measures 1997 and 2002

Measure	Simple Correlation	Spearman Rank Test
Fraction Differentiated	0.9056	0.9034
Fraction Non-Homogeneous	0.9075	0.8316
No. Observations	233	233

Notes:

Author’s calculation.

Source: CASIF-CCTS matched database.

As expected, the measures are highly correlated, with the coefficient of the rank test of the non homogeneous measure less than the others. The source for the imperfect correlation or differences between the 1997 and 2002 version may come from two aspects. First, there could be changes in the structure of the inputs used by each industry/product over this time period, e.g. changes in the number of inputs or the fractions each input used in the production. The second source is the changes in concordance, which may have nothing to do with the “true” changes in relation-specificity of the industry. This is because the 1997 measure is created using concordance between IO 1997 and HS 1997, and that between HS 1997 to SITC rev2, whereas the 2002 measure is created using IO 2002 to HS 2002, and HS2002 to SITC rev2. This may cause changes in the aggregation of the Rauch measure in 2002 relative to that in 1997, due to differences between the input’s matching to the HS 2002 and HS 1997 classification. Another possible distortion is the changes in the US IO classification over time. For example, an input that is defined separately in 1997 may be regrouped with other inputs, leading to a reduction of the number of inputs, although the “true” types of inputs used in the production remains unchanged over time. Hence, overall, it might be difficult to make sense of the changes in the Nunn’s measure over time. The main marginal value-added of this upgrading exercise is to make it easier to apply the Nunn’s measure to make cross-industry comparisons of their contract-intensity using trade/industry data with more recent time periods.

Appendix B

Table B1
Test Results of the Differences in Coefficients in Table 4

P-values from F-Test (Prob > F)		Log Employment	TFP	Log Value-Added per Worker	Log Capital Intensity	Log Skill Intensity	Log Wage per Worker
<i>Panel A. Estimation Results Controlling for Year, Ownership and Industry-Location Effects</i>							
MJ=XM	($\beta_1=\beta_2$)	0.000	0.000	0.000	0.000	0.0030	0.237
MJ=XMO	($\beta_1=\beta_3$)	0.000	0.000	0.000	0.000	0.4678	0.040
MJ=XMOP	($\beta_1=\beta_5$)	0.000	0.000	0.000	0.000	0.0101	0.239
XMO=XMOP	($\beta_3=\beta_5$)	0.000	0.000	0.000	0.013	0.0001	0.000
<i>Panel B. Estimation Results Controlling for Year, Ownership and Industry-Location Effects and Log Employment</i>							
MJ=XM	($\beta_1=\beta_2$)	-	0.6579	0.0000	0.0006	0.120	0.1523
MJ=XMO	($\beta_1=\beta_3$)	-	0.2986	0.0071	0.000	0.0868	0.000
MJ=XMOP	($\beta_1=\beta_5$)	-	0.4359	0.0004	0.499	0.796	0.014
XMO=XMOP	($\beta_3=\beta_5$)	-	0.7063	0.1923	0.000	0.0106	0.077

Notes:

Author's calculation. This table presents the F-test results of the differences in coefficients between various traders groups in Table 4. TFP is the total factor productivity calculated using the Levinson-Petrin method (Levinson and Petrin, 2003). Capital intensity is capital per worker, and skill intensity is measured by the ratio of skilled worker to total number of workers, whereas workers with degree equivalent or above high-school are classified as skilled workers. Value-added per worker, capital intensity and wage per worker are all in thousands of Chinese yuan.

Source: CASIF-CCTS matched database.

REFERENCES

- Bustos P. (2011), 'Trade Liberalization, Exports and Technology Upgrading: Evidence on the impact of MERCOSUR on Argentinean Firms', *American Economic Review*, **101**, 1, 304-340.
- Baldwin, R. and J. Harrigan, (2011), 'Zeros, Quality and Space: Trade Theory and Trade Evidence', *American Economic Journal: Microeconomics*, **3**, 2, 60-88.
- Bernard, A., J. B. Jensen, S. Redding and P. Schott, (2007), 'Firms in International Trade', *Journal of Economic Perspectives*, **31**, 3, 105-130.
- Bernard, A., J. B. Jensen and P. Schott (2009), 'Importers, Exporters, and Multinationals: A Portrait of Firms in the U.S. that Trade Goods' in T. Dunne, J. B. Jensen and M. J. Roberts (eds.), *Producer dynamics: New Evidence from Micro Data* (Chicago, IL: University of Chicago Press).
- Bernard, A. and B. Jensen (1999), 'Exceptional Exporter Performance: Cause, Effect, or Both?', *Journal of International Economics*, **47**, 1, 1-25.
- Bernard, A, S. Redding and P. Schott (forthcoming), 'Multi-Product Firms and Trade Liberalization', *Quarterly Journal of Economics*.
- Boyenge, S. (2007), 'ILO Database on Export Processing Zones', Working Paper, International Labour Office.
- Cai, H. and Q. Liu (2009), 'Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms', *Economic Journal*, **119**, 537, 764-795.
- Castellani, D., F. Serti and C. Tomasi (2010), 'Firms in International Trade: Importers' and Exporters' Heterogeneity in Italian Manufacturing Industry', *The World Economy*, **33**, 3, 424-457.
- Fernandes, A. and H. Tang (2011), 'Trade Dynamics of Export Processing Plants: Evidence from China', mimeo. University of Sussex.
- Girma, S., Y. Gong, H. Görg and Y. Zhihong (2009), 'Can Production Subsidies Explain China's Export Performance? Evidence from Firm-level Data', *Scandinavian Journal of Economics*, **111**, 4, 863-891.
- Haller, S. (2010), 'Exporting, Importing, Intra-Firm Trade and Firm Performance', Working Paper, Economic and Social Research Institute, Ireland.
- Heid, B., M. Larch and A. Riaño (2011), 'The Rise of the Maquiladoras: Labor Market Consequences of Offshoring in Developing Countries', Working Paper, CESifo.
- Hsieh, C.-T. and P. Klenow (2009), 'Misallocation and Manufacturing TFP in China and India', *Quarterly Journal of Economics*, **124**, 4, 1403-1448.
- Kasahara, H. and B. Lapham (2008), 'Productivity and the Decision to Import and Export: Theory and Evidence', Working Paper, University of Western Ontario.
- Kasahara, H. and B. Lapham (2006), 'Import Protection as Export Destruction', Working Paper, University of Western Ontario.

- Koopman, R., Z. Wang and S.-J. Wei (2008), 'How Much of Chinese Exports is Really Made in China? Assessing Domestic Value-Added When Processing Trade is Pervasive', NBER Working Paper 14109.
- Lawless, M. (2009), 'Firm Export Dynamics and the Geography of Trade', *Journal of International Economics*, **77**, 2, 245-254.
- Levinsohn, J. and A. Petrin (2003), 'Estimating Production Functions Using Inputs to Control for Unobservables', *Review of Economic Studies*, **70**, 2, 317-341.
- Lu, J., Y. Lu and Z. Tao (2010), 'Exporting Behavior of Foreign Affiliates: Theory and Evidence', *Journal of International Economics*, **81**, 2, 197-205.
- Melitz, M. (2003), 'The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity', *Econometrica*, **71**, 6, 1695-1725.
- Melitz, M. and G. I. P. Ottaviano (2008), 'Market Size, Trade, and Productivity', *Review of Economic Studies*, **75**, 1, 295-316.
- Manova, K. and Z. Zhang (2009a), 'Export Prices across Firms and Destinations', NBER Working Paper 15342.
- (2009b), 'China's Exporters and Importers: Firms, Products, and Trade Partners', NBER Working Paper 15249.
- Muûls, M. and M. Pisu (2009), 'Imports and Exports at the Level of the Firm: Evidence from Belgium', *The World Economy*, **32**, 5, 692-734.
- Nunn, N. (2007), 'Relationship-Specificity, Incomplete Contracts and the Pattern of Trade', *Quarterly Journal of Economics*, **122**, 2, 569-600.
- Rauch, J. (1999), 'Networks versus Markets in International Trade', *Journal of International Economics*, **48**, 1, 7-35.
- Upward, R., Z. Wang and J. Zheng (2010), 'Weighing China's Export Basket: An Account of the Chinese Export Boom, 2000-2007', Working Paper, University of Nottingham.
- Vogel, A. and J. Wagner (2009), 'Higher Productivity in Importing German Manufacturing Firms: Self-Selection, Learning from Importing, or Both?', *Review of World Economics*, **145**, 4, 641-665.
- Yu, M. (2011), 'Processing Trade, Firm Productivity, and Tariff Reductions: Evidence from Chinese Products', Working Paper, Peking University.