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FACTOR INTENSITY, PRODUCT SWITCHING, AND PRODUCTIVITY: EVIDENCE FROM CHINESE EXPORTERS

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Factor Intensity, Product Switching, and Productivity: Evidence from Chinese Exporters*

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Abstract

Using Chinese manufacturing firm data over the period of 1998-2007, we find that firms become less capital-intensive after exporting, compared to similar non-exporting firms. To rationalize this finding that contrasts with existing evidence for most countries, we develop a variant of the multi-product model of Bernard, Redding, and Schott (2010) to consider products with varying capital intensity. In the model, firms in a labor-abundant country specialize in their core competency by allocating more resources to produce labor-intensive products after exporting. Consistent with the model predictions, we find evidence that the ex-ante more productive firms experience a smaller decline in capital intensity after exporting, but firms that experience a sharper decline in capital intensity after exporting have a larger increase in measured total factor productivity. Using transaction-level data, we confirm that Chinese exporters add new products that are less capital-intensive than their existing product portfolios and

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drop those that are more capital-intensive over time.

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1. Introduction

A growing body of research has documented the superior performance of exporters relative to non-exporters. Exporters are found to be larger, more capital-intensive, more technologically advanced, and pay higher wages (e.g. Bernard and Jensen, 1999). Theories suggest that at least three mechanisms can explain the correlation between exporting and firm performance. The first relates to self-selection (e.g., Clerides, Lach, and Tybout, 1998; Bernard, Eaton, Jensen, and Kortum, 2003; Melitz, 2003): only the best firms engage in international trade. The second explanation is "learning-by-exporting" (e.g., Van Biesebroeck, 2005; De Loecker, 2007): after firms enter the export markets, they gain new knowledge and expertise that helps to improve their productivity. The third explanation relates to exporters' optimizing their product scope to specialize in their core competency (Feenstra and Ma, 2008; Nocke and Yeaple, 2008; Carsten and Neary, 2010; Bernard, Jensen, and Schott, 2011). Whereas various empirical studies have confirmed the self-selection theory, existing findings are mixed for the "learning by exporting" phenomenon, and are relatively silent about the "core competency" hypothesis.

In this paper, we provide empirical evidence for all three channels, with an emphasis on the "core competency" hypothesis that has received relatively little attention in the empirical literature. In particular, we empirically examine an unexplored channel through which changes in factor intensity, due to within-firm reallocation of resources across products, can contribute to an increase in a firm’s measured productivity after trade. To this end, we use a large panel data set on China's manufacturing firms over the 1998-2007 period, and employ the matched sampling techniques from the program evaluation literature for identification (Heckman, Ichimura, and Todd, 1997, among others). Using these techniques, we can construct a counterfactual control sample of non-exportering firms which allows us to evaluate the impact of exporting on firm factor intensity and productivity.

Using matching estimators, we find that export participation increases a domestic firm's measured total factor productivity (TFP) in the year that it starts exporting. Compared to non-exporting firms, those that export increase their total factor productivity (TFP) by 8.5 percent. But we also find that more productive firms are more likely to start exporting. These results support the literature which finds a positive correlation between firm TFP and export participation.

Importantly, we find that *within a narrow industry*, for both domestic firms and foreign invested enterprises (FIEs), exporters are *less* capital-intensive than non-exporters in China, contrasting with most existing findings (Bernard and Jensen, 1999; Bernard, Jensen, and Schott, 2007; De Loecker, 2007; Van Biesebroeck, 2005, Bustos, 2011; among others). Using matching estimators, we find that exporting reduces an exporter's capital intensity compared to the matched non-exporters. These patterns are observed for both domestic and foreign firms. Specifically, capital intensity drops by about 6 percent relative to the matched non-exporters in the first year of exporting, with further declines in subsequent years. We conduct a host of robustness checks, employ different matching techniques, and use several measures of capital intensity to confirm these results. Our results suggest that exporters exploit the comparative advantage of China's labor abundance more efficiently than non-exporters, and specialize more in their core competency after exporting. Figure 1 shows the evolution of average capital intensity of exporters and non-exporters in our data between 1998 and 2007. From 2000 onwards, exporters are persistently less capital-intensive than non-exporters. To circumvent the potential biases due to firm entry and exit, we plot the average capital intensity using a balanced panel of firms in Figure 2. As is shown, capital intensity increases for both types of firms over time, but exporters are still less capital-intensive than non-exporters by the last year of the sample period. Figure 3 plots the distribution of capital intensity for both exporters and non-exporters in 2007 and shows a consistent pattern across firms.

It is noteworthy that, although our results appear to contradict the existing literature at first sight, they provide "mirror image" evidence to support the work of Bernard, Jensen, and Schott (2006). They find that US manufacturing firms become more capital-intensive in sectors facing more import competition from low-wage countries. We find that firms in China, a large low-wage country, exhibit the opposite pattern in capital intensity when they start exporting. Our results are consistent with Bernard, Redding, and Schott (2007) in the sense that exporters exploit China's comparative advantage of labor abundance by reducing the cost share of capital over time. These findings have important implications for understanding the impact of trade on factor markets in China and its trading partners. For example, one important question in the trade literature is whether Chinese exporters increase the capital content of their exports to compete with firms in developed countries. Our findings show that this trend is not obvious up to 2007, the last year in our sample.

To rationalize the findings that Chinese firms become increasingly labor-intensive after exporting, we develop a variant of the multi-product model of Bernard, Redding, and Schott (2010) (BRS) to consider both capital and labor as factors of production. In the model, heterogeneous firms can potentially produce a continuum of products, which differ in their capital intensity. In addition to firm heterogeneity in productivity ("ability") as in Melitz (2003), a firm's profitability from selling its product in a foreign market depends on a random draw of a firm-product-specific "consumer taste" attribute. On top of the country-specific fixed export cost, for each product produced an exporter needs to incur extra fixed costs (e.g. R&D expenditure to produce a blue print or overhead costs to manage a product-specific sales force). A firm would export a product only if its "consumer taste" attribute is above the corresponding zero-profit threshold. Thus, when a shock to fixed exporting costs trigger a firm to start exporting to a capital-abundant country, the firm would specialize in its core competency -- the labor-intensive products, which are associated with relatively lower zero-profit thresholds due to China's labor abundance. As such, a firm would become more labor-intensive after exporting either by expanding its sales of existing labor-intensive products (the intensive margin) or adding more labor-intensive products (the extensive margin). Given short-run adjustment costs, exporters would become more labor-intensive over time before the optimal product portfolio is attained.

Our model sheds light on how changes in a firm's product scope affects its measured TFP. In particular, firms that have a larger reallocation of resources from capital-intensive to labor-intensive products after exporting have a bigger increase in measured TFP. The reason is that given fixed export costs and firm intrinsic productivity, an increase in sales of labor-intensive products implies a larger scope of increasing returns, relative to capital-intensive products. Furthermore, our model predicts that the ex-ante more productive exporters experience a smaller decline in capital intensity after exporting. We find evidence supporting these theoretical predictions. These findings provide a new angle to interpret the effect from export participation on a firm's productivity.

To test the proposed mechanism through which trade increases exporters' labor intensity in a developing country, we use transaction-level data that cover the universe of Chinese exporters. We find evidence that products added by exporters in subsequent years after export participation are on average more labor-intensive than previously exported products, while those products which are dropped are less labor-intensive.

The rest of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes our data source. Section 4 explores the basic patterns of export participation, technology, and capital intensity. Section 5 examines the impact of exporting on new exporters, with a focus on capital intensity. Section 6 presents a theoretical model to rationalize our findings. Sections 7 and 8 examine the specific theoretical predictions using transaction-level trade data. The last section concludes.

2. Related Literature

As we discussed at the beginning of the introduction, the existing literature has focused on three causal channels through which a firm's productivity and export participation may be related: 1) self-selection, 2) "learning by exporting" , and 3) product scope (re)optimization. The self-selection theory stresses the significance of sunk entry costs. The seminal work by Bernard, Eaton, Jensen, and Kortum (2003) and Melitz (2003) show how trade barriers deter the less productive firms from selling abroad, leaving only the most productive firms to serve foreign markets. The learning-by-exporting theory postulates that exporters, especially in less-developed economies, are able to learn from foreign buyers about product design and production technology (World Bank, 1993; De Loecker, 2007).

Firm-level empirical studies find strong evidence for self-selection, but mixed results for learning-by-exporting. Clerides, Lach, and Tybout (1998) and Bernard and Jensen (1999) were one of the first studies to try to distinguish between the two channels empirically. They find evidence that exporters have higher productivity than non-exporters before exporting but not after.[1] Recent studies, on the

[1] Clerides, Lach, and Tybout (1998) use firm-level from Colombia, Mexico, and Morocco for their study; while Bernard and Jensen (1999) use firm-level data from the U.S. Aw, Chung, and Roberts (2000) and Delgado, Farinas, and Ruano (2002) come to the same conclusions for Taiwan, Korea, and Spain.

other hand, find supporting evidence for the learning-by-exporting theory.[2] Among others, Lileeva and Trefler (2010) use the elimination of the U.S. tariffs as an instrument to predict Canadian firms' entry into the U.S. market, and show that access to foreign markets enhances labor productivity and technology adoption for the less productive firms. Specific to China, Kraay (1999) finds that exporters are more productive than non-exporters based on survey data over 2000 firms. Park et al. (2007) use exposure to the 1997 Asian financial crisis as an instrument and find that exports causally raise the productivity of Chinese firms that export to developed countries.

Recent theoretical work has utilised a multi-product firm framework to examine how specialization in core competency can enhance firm productivity after exporting. These models commonly postulate that diversification across products is costly, and access to foreign markets provides an opportunity for firms to specialize in a narrower product scope. In this literature, Feenstra and Ma (2008) study how trade liberalization reduces firms' product scope due to the presence of cannibalization effects. Nocke and Yeaple (2008) study the implications when a firm's marginal cost of production rises in product scope due to managers' limited span of control as in Lucas (1978). Eckel and Neary (2010) examine theoretically how exports can enhance firm productivity when multi-product firms specialize in their core competency, taking advantage of the larger market size. In their model, each firm has a core-competence product that is associated with the lowest marginal cost. Producing a product farther away from the firm's core competency is more costly. Based on a multi-product extension of Melitz (2003), Bernard, Jensen, and Schott (2011) show theoretically that trade liberalization would result in both within and across-firm reallocation of resources, leading to growth in both firm and aggregate productivity. The added multi-product dimension permits firms to drop products that are less appealing to the consumers and add those that are more appealing upon trade liberalization. Product churning thus results in higher firm productivity. To the best of our knowledge, we are one of the first to provide empirical evidence on how product specialization by a multi-product firm can enhance firm productivity. Moreover, we extend the existing multi-product framework that largely focuses on a single factor of production to consider both capital and labor as inputs, and postulate how specialization in labor-intensive products (core competency for developing countries' firms) can explain the observed productivity gain from trade.[3]

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2 These studies include Wagner (2002) for Germany; Girma, Greenway, and Kneller (2003) for the United Kingdom; Alvarez and Lopez (2005) for Chile; Van Biesebroeck (2005) for sub-Saharan African countries; and De Loecker (2007) for Slovenia. A more recent study by a group of economists (International Study Group on Exports and Productivity, 2008) uses comparable firm panel data for 14 countries and an identical method to investigate the relationship between exports and productivity. They find strong evidence for self-selection but no evidence for learning-by-exporting.

3 In the appendix of Bernard, Redding, and Schott (2010), the authors extend the baseline model to consider two factors of production. They further show how endogenous product choices upon export participation affect firm measured productivity. They did not, however explicitly solve for how relative factor endowment of the exporting country can serve as a source of within-firm comparative advatange. Our later discussion on specialization in core comptetence and productivity gains are developed on their argument.

3. Data

The firm-level data for our analysis are from the annual survey of industrial firms conducted by China's National Bureau of Statistics (NBS) for the 1998-2007 period. The survey covers all state-owned firms and all non-state-owned firms with sales above 5 million yuan.[4] The industry section in China's Statistical Yearbooks is compiled based on this data set. The data set provides detailed information on about 100 variables, including firm ID, address, ownership, output, value added, four-digit industry code (about 480 categories), six-digit geographic code, exports, employment, original value of fixed asset, and intermediate inputs. The firms in our sample account for 57% of total industrial value added in 1998 and 94% in 2007. Since we focus on manufacturing, mining and utility industries are excluded from our sample. Moreover, we delete observations with missing values for key variables and those that fail to satisfy some basic error checks.[5] The cleaned data set provides an unbalanced panel of firms that increases in coverage from 148,685 firms in 1998 to 313,048 in 2007.

We use unique numerical IDs to link firms in the sample over time. Firms occasionally receive a new ID as a result of restructuring, merger, or acquisition. Where possible, we aim to track firms as their boundaries or ownership structures change, using information on the firm's name, industry, address, etc., to link them.[6] These other matches are important as one-sixth of all firms that are observed for more than one year experience a change in their official ID over the period of analysis.

In the later part of the paper, we also use transaction-level trade data from China Customs that cover the universe of all Chinese exporters and importers over 2000-2006 for analysis. The trade dataset provides information on import and export values, quantities, and prices between China and over 200 destination countries at the HS 6-digit level for each trading firm, by ownership of enterprise (out of 9 types, e.g. state owned, foreign invested, Sino-foreign joint ventures), and customs regime (ordinary trade and processing trade).[7] Online[8] Appendix Table A6 shows an example of HS 6-digit products within the industry of "footware, gaiters, & the like" (HS2 = 64). The use of this data set allows us to study product churning and within-firm dynamics after a firm starts exporting. To identify new exporters in the trade data set, we merge the NBS firm data with the transaction-level trade data

4 The unit of analysis is a firm, and not the plant, but other information in the survey suggests that more than 95% of all observations in our sample are single-plant firms.

5 Some firms have missing observations for variables needed to calculate productivity. This arises either because the information was not originally reported, or because of negative values for variables such as the real capital stock or value added. Following Jefferson, Rawski and Zhang (2008), we drop all firms with less than 8 employees as they fell under a different legal regime. As a result, 17% of firms in the the original data set are dropped from the sample in 1998, but the fraction drops to 6% in each year after 2001.

6 The fraction of firms in a year that can be linked to a firm in the previous year increases over time from 84.5% in the first two years (1998-1999) to 92.2% in the final two years (2006-2007). Overall, 95.9% of all year-to-year matches are constructed using firm IDs, and 4.1% using other information on the firm.

7 The data also report quantity, quantity units, customs offices (ports) where the transaction was processed (97 in total), and transportation modes.

8 Online Appendix available on www.hwtang.com

based on firm names.[9] Statistics about the merging are reported in online Appendix Table A5. We use the merged data set to compute measures of capital intensity at the product level (HS 6-digit). To the best of our knowledge, we are the first to do this for China.[10] Details about the steps to compute the product-level capital intensities are provided in online Appendix A.3.

A firm's real output and value added are deflated by a sector-specific ex-factory price index.[11] Real wages are calculated using the consumer price index.[12] A firm's capital intensity is defined as the real value of capital stock per worker.

Since capital intensity is the focus of this paper, it is critical to measure capital and labor accurately. Firms do not report fixed investment. For capital stock, the NBS data only report the original value of fixed asset (OVFS) and net value of fixed asset (NVFS). OVFS is the total capital stock at original purchase prices, and NVFS is equal to OVFS less accumulated depreciation. Thus, OVFS and NVFS are the sum of nominal values of different years. To deal with this problem, we follow the recent estimation method in Brandt, Van Biesebroeck, and Zhang (2011). The idea is to use information from the founding year of a firm to estimate the firm's initial capital stock. Then we apply a perpetual inventory method and calculate firm real capital stock in each year. In this procedure, we assume a depreciation rate of 9% and deflate nominal fixed investment using the deflators constructed in Perkins and Rawski (2008).[13] Firm's nominal fixed investment is the observed change in OVFS. To test the robustness of our results, we also use the NVFS deflated by industry-specific investment price index as an alternative measure of real capital stock.

To try to adjust for the quality of the workers, we could use total wage bill data instead of employment to compute an alternative measure of labor. The problem with wage bill data, however, is that it is likely to underestimate the total employee compensation which also includes employee supplementary benefits. In our data, labor's share of value added is only 34 percent, which is much lower than 55 to 60 percent suggested by national income accounting. The magnitude of such underestimation may vary across different ownership, region and year. Therefore, we decide to use employment as our primary measure for labor and reserve the wage bill data for robustness checks.

To deal with the biases arising from endogenous input choices (Griliches and Mairesse, 1998), we adopt the Levinsohn and Petrin (2003) procedure that uses intermediate inputs as a proxy for

9 Depending on the year, 37-48% of export value in the trade data set is successfully merged to the NBS firm data set. 70% of exporters in NBS is merged.

10 Bernard et al. (2010) compute the measures of factor intensity at the SIC 5-digit level for the US, and find substantial within-sector (2-digit) heterogeneity in capital and skill intensity.

11 Ex-factory price refers to the price at the factory, and does not include any other charges, such as delivery or subsequent taxes.

12 The price indices are from China Statistical Yearbook, various issues.

13 Please see the appendix of Brandt, Van Biesebroeck and Zhang (2011) for more details.

unobservable productivity shocks.[14] For reasons that will become clear below, exporters and non-exporters can have different factor intensity of production within a disaggregated sector. We thus assume different sector-specific production functions for exporters and non-exporters respectively to estimate firm productivity.[15]

In this paper, a non-exporter is a firm that never exported up to and including the reporting year. New exporters are firms that did not export in the previous years but started exporting in the year of analysis. Their pre-export characteristics can therefore be matched with those of the non-exporting firms (see section 5 for details about the matching approach). Existing exporters are firms that have export records in previous years, or firms that start exporting already in their first year of entry (since matching this group of firms with pre-export characteristics is not possible, it is excluded from our analysis).

4. Basic Patterns

Table 1 reports the key statistics of exporters and non-exporters for odd years in our sample. In particular, it reports the distribution of new exporters, continuing exporters, and non-exporters for domestic and foreign firms, respectively. Among domestic firms, the fraction of exporters fluctuates between 16 and 24 percent (continuing exporters and new exporters combined), which is similar to the U.S. where roughly 20 percent of plants exported in 1992 (Bernard, Eaton, Jensen, and Kortum, 2003). Notice that for China, there is a significant difference between domestic firms and FIEs in terms of the prevalence of exporters. Foreign firms overwhelmingly engage in exporting, with the fraction of exporters ranging between 63 percent (in 1999) and 72 percent (in 2004). Table 1 also presents the pattern of export intensity of new exporters, the focus of this study. Similar to the U.S. firms, over 80 percent of domestic new exporters also sell domestically in China; and about half of the domestic new exporters sell less than 10 percent of their products abroad.

Before discussing our main empirical strategy and results, we explore some basic patterns about exporters and non-exporters. To this end, we estimate the following specification:

$$\ln S_i = \beta E_i + \gamma_0 + F_{Ind} + F_{Prov} + F_{year} + \varepsilon_i \quad (1)$$

where S_i can be firm i's TFP or capital intensity. E_i is a dummy variable indicating the firm's export status. We control for industry (F_{Ind}), province (F_{Prov}), and year (F_{Year}) fixed effects; γ_0 is a

14 The Levinsohn-Petrin procedure is implemented in this paper using the Stata module "levpet" developed by Petrin, Levinsohn and Poi (2004).

15 In the early version of the paper, we extend the Levinsohn-Petrin procedure by incorporating the firm's export decision into the productivity estimation procedure to control for the export endogeneity problem (Van Biesebroeck, 2005; De Loecker, 2007), instead of estimating productivity using separate production functions for exporters and non-exporters, respectively. The results obtained were qualitatively similar.

constant and ε_i is the error term. The percentage differential in S_i between new exporters and non-exporting firms can be calculated from the estimated coefficient as $100\times(\exp(\beta)-1)$.

Panel A in Table 2 shows the estimates of equation (1), with ln(TFP) as the dependent variable. Column (1) includes E_i but no additional controls, while column (2) adds industry, year, and province fixed effects. We find that exporters (new exporters and continuing exporters combined) are on average more productive than non-exporters. These results on the productivity gap for domestic firms are generally consistent with findings in the existing literature.

In columns (3) and (4), we find that the productivity premium of exporters is mostly determined by the productivity variation among domestic private firms. Foreign exporters do not appear to be more productive than foreign non-exporters. In column (4), we show that even among state-owned enterprises (SOEs), for which soft-budget constraints and measurement errors may mask the true measures of productivity and other characteristics, exporters appear to be more productive. By splitting the sample into the pre-WTO period (1999-2001) and the post-WTO period (2002-2007), column (6) and (7) show that the TFP premium of exporters is larger before China's accession to the WTO than after (decreased from 0.13 to 0.07 log points).

Our findings that foreign exporters exhibit no superior productivity echo those by Baldwin and Gu (2003), who also find no productivity premium among foreign exporters in Canada. These results lend support to the productivity-sorting prediction by Helpman, Melitz, and Yeaple (2004), who show theoretically that only the most productive firms engage in foreign direct investment. Another explanation is that foreign firms come with experience and knowledge in serving foreign markets. The potential to learn by exporting is limited.

Next, we present results on the gap in capital intensity between exporters and non-exporters. Existing studies consistently find that exporters are more capital-intensive (e.g., Bernard and Wagner (1997) for Germany, Isgut (2001) for Columbia, Bernard and Jensen (2004) for the US, Van Biesebroeck (2005) for Sub-Saharan Africa, and De Loecker (2007) for Slovenia.). In sharp contrast, we find that exporters in China are *less* capital-intensive than non-exporters, as is shown in Table 2. Specifically, in Panel B when capital intensity is measured as the ratio of real capital stock to employment (our preferred measure that is computed based on the perpetual inventory method proposed by Brandt, Van Biesebroeck, and Zhang, 2011), we find in column (2) that exporters are about 4 percent *less* capital-intensive than non-exporters within a four-digit industry (>400 industries). Notice that this difference in capital intensity is larger among domestic private firms than among foreign firms (columns (3) and (4)).

When a firm's real capital stock is measured as the average net value of fixed assets deflated by the industry-specific investment price index (Panel C), or when capital intensity is measured using a firm's total wage bill instead of employment as the denominator (Panel D), exporters still appear to be less capital-intensive than non-exporters. The capital intensity gap is significantly larger when the latter measure is used. A possible reason is that using total wage bill to compute capital intensity partially adjusts for the quality of the firm's workforce. To the extent that exporters employ workers who are more skilled than non-exporters and thus pay higher wages, as evidenced by the existing literature, capital intensity will be even lower for exporters when it is measured by effective labor units. To conserve space, we focus on the results based on capital intensity measured by the perpetual inventory method (i.e., the Panel B measure) below. Since using the wage-bill-based capital intensity measure tends to give us a wider capital intensity gap between exporters and non-exporters, the results below can be considered as a lower bound of the capital intensity change after exporting.

The results in column (5) suggest that the capital intensity gap between exporters and non-exporters is not driven by a potentially different accounting standard to measure capital by state-owned enterprises (SOEs). Columns (6) and (7) show that the capital intensity disparity is widened after China's accession to the WTO. Online Appendix Table A1 shows that the strong pattern is observed in each sample year. It seems that the capital intensity gap between exporters and non-exporters has increased over time.

Given China's comparative advantage in labor-intensive goods, it may not seem surprising that exporters in China are less capital-intensive than non-exporters at first sight. However, since this pattern is found within disaggregated industries at the 4-digit level (about 480 industries), the standard factor-proportions theory of trade that emphasizes between-sector reallocation of resources cannot be used to explain within-industry heterogeneity in factor intensity. Given the novelty of these findings, we will devote relatively more attention to explaining this pattern in the rest of the paper. We will also discuss the implications on interpreting the impact of exporting on measured productivity. A theoretical model will be developed in Section 6 to rationalize the findings.

The findings reported in Table 2 say little about whether exporting improves firms' performance or lowers their capital intensity. An alternative hypothesis is that the more productive or more labor-intensive firms self-select into exporting. In online Appendix Table A2, we estimate the probability of exporting as a function of ex-ante firm performance, labor intensity, and other firm attributes commonly examined in the literature.[16] We find that the more productive and more labor-intensive domestic firms are more likely to start exporting. Among foreign-invested firms, ex-ante firm productivity or labor intensity once again does not appear to determine export participation.

5. Impact of Exporting on New Exporters

To identify the causal impact of exporting on exporters' outcomes, we apply a matching estimator developed by Rosenbaum and Rubin (1984) and applied by Heckman, Ichimura, and Todd (1997),

[16] To examine the empirical validity of this hypothesis, we focus on firms that do not export initially, which we categorize into two groups: those that start exporting in the following year, and those that stay as non-exporters. Existing exporters are excluded from the sample.

among others, in the "program evaluation" literature (see online Appendix A.1 for details). The goal, as in a typical program evaluation, is to examine the average treatment effect on the treated. Here, exporting is a treatment. We separate the sample into two groups, with one group containing observations of firms that never export in the sample (the untreated group), and another group containing observations of all export starters (the treated group). To ensure that we are comparing new exporters and non-exporters in the same industry, we first divide firms into individual cells according to their reporting year and industries. Within each cell, we estimate the propensity score of each firm by a Probit model conditional on a vector of pre-export firm characteristics, which include TFP, wage, capital intensity, firm age, sales, and province dummies. Then local linear regression weights are constructed to match new exporters and never-exporters in each cell. Differences in TFP or capital intensity after exporting between the treated group and the matched comparison group can be attributed to the effect of exporting. See online Appendix A.1 for the detailed procedures of implementing the difference-in-difference (DID) matching estimator. Previous studies have used the matching approach to search for causal effects of exporting on productivity, such as Wagner (2002), Girma, Greenaway, and Kneller (2003), Alvarez and Lopez (2005), Konings and Vandenbussche (2005), and De Locker (2007).

Since the productivity effects of exporting have been well studied, we focus on the causal impact of exporting on capital intensity instead. To our understanding, we are the first to examine such a causal impact using the matching techniques.

5.1 Impact of Exporting on Firm Productivity

In Table 3, we present the estimation results to examine the "learning by exporting" effects, using three different matching estimators. Using the DID matching estimator in Panel A, we find a positive and significant effect of exporting on the firm's TFP in the first year of exporting for the full sample (column (1)). In particular, export participation leads to about a 7-percent increase in productivity in the first year of exporting. Similar to the correlation results reported in Table 2, we find that the productivity differential is driven by the differences among domestic firms (private or SOEs), but not among foreign firms. As is discussed in the previous section, with foreign experience and know-how, there can be little room for foreign exporters to “learn by exporting”.

In Panel B, we report estimation results based on the local linear regression matching estimator without differencing the variables, while in Panel C, we use the nearest neighbor matching. In both panels, we continue to observe the same pattern. Notice that the productivity effect is particularly significant for domestic private firms. Columns (5) and (6) show no systematic difference in the exporting effects on TFP after China's accession to the WTO.

5.2 Impact of Exporting on Capital Intensity

Table 4 reports the estimation results which test for a causal channel of exporting on capital intensity. DID estimator shows that new exporters become less capital-intensive after exporting. In particular, new exporters are 0.061 log-point less capital-intensive compared to the matched firms that never export in our sample (column (1)). These exporting effects are quantitatively similar for both domestic and foreign firms, though statistically less significant for the latter (columns (2) and (3)). A similar pattern is found among state-owned enterprises. The quantitative impact is similar before and after China's accession to the WTO (columns (5) and (6)). The results remain robust when we measure capital stock by the net real value of fixed assets (column (7)), and become quantitatively more significant when firms' wage bills are used to calculate firm capital intensity (column (8)). The estimates from Panel B and Panel C remain quantitatively similar and statistically significant for most cases. In sum, regardless of matching methods, ownership types, sample periods, and measures of capital intensity, we find that export participation lowers capital intensity of the firm, relative to the non-exporters that share similar ex-ante firm attributes. Online Appendix Table A3 shows the DID matching estimation results for each year in our sample.

These estimation results so far compare only the average capital intensity of new exporters with that of non-exporters. Next, we compare the entire distribution of capital intensity of the two groups of firms by conducting the Kolmogorov-Smirnov stochastic dominance test. The null hypothesis is that new exporters and non-exporters have the same capital intensity. The alternative hypothesis is that one group of firms are stochastically more capital-intensive. The testing procedure is discussed in detail in Delgado, Farinas, and Ruano (2002) and Gibbons and Chakraborti (2003, p.244). As is reported in online Appendix Table A4, the capital intensity of new exporters is stochastically dominated by that of non-exporters, for both domestic and foreign firms*.* These results remain significant (at the 1% level) in each sample year and in the pooled sample.

One may wonder whether the exporting effects on an exporter's capital intensity are long-lasting. It is possible that Chinese exporters test the foreign market by exporting labor-intensive products, but subsequently export more capital-intensive products that they have been selling at home. To analyze whether there are lasting effects on an exporter's capital intensity, we use the DID matching estimator to compare the capital intensity of exporters and the matched non-exporters n years after exporting, where $1 \leq n \leq 8$. Results are reported in Table 5*.* As is shown, almost all estimates are negative and statistically significant, suggesting that the decrease in capital intensity of exporters in China is long lasting. Compared to non-exporters in the year of matching, new exporters (started exporting in the year right after matching) continue to be less capital-intensive n years later. For instance, the new exporters in 1999 (who did not export in 1998) were less capital-intensive than the matched non-exporters (matched in 1998) in every year between 2000 and 2007. There is also a downward trend of capital intensity for exporters relative to non-exporters over time. For instance, the capital intensity gap between the new exporters in 1999 and the matched non-exporters (matched in 1998) is 0.09 log points in 1999. The gap between the same pair of firms increases to 0.18 in 2007.

Notice that the initial non-exporters in 1999 can exit from the sample in any year between 2000 and 2007 (the last sample year). Suppose we conduct a more complicated analysis by using a balanced panel of non-exporters as our control group for matching, what would happen to the estimates? If exiters are more labor-intensive, the balanced panel of non-exporters will be on average more capital-intensive than the unbalanced panel we use. As such, the actual difference in capital intensity over time is likely to be larger if we use a balanced panel of non-exporters as the control group. Then our estimate can serve as a lower bound of the actual capital intensity change after exporting. On the other hand, if exiters are more capital-intensive, our estimates are biased upward. This is a counter-intuitive assumption though since existing research has shown that exiters tend to be smaller and less capital-intensive.

All matching methods have their short-comings. The ultimate goal of estimating the exporting effects on firm outcomes using matching techniques is to ensure that new exporters' ex-ante observable firm characteristics are as close to those of non-exporters as possible. Table 6 shows the balancing test results, where we compare the means of each of the observable characteristics used for matching. Our matching procedure has passed the *t*-tests for equality of the means that are reported in the last two columns. Before matching, there was a statistically significant difference in all matching variables between new exporters and non-exporters. But for the matched firms, we cannot reject the null hypothesis that these variables are identical for new exporters and non-exporters, before the former start exporting (p-values are always significantly higher than 15 percent). Table 6 also shows the standardized bias and the percentage of the reduction of such bias due to matching. The likelihood ratio test shows that the differences in the mean of those five variables between the treated and the untreated are jointly insignificant.

6. Theoretical Explanation

To summarize, the most surprising empirical finding in this paper is that a Chinese firm becomes less capital-intensive after exporting, more so in subsequent years. To rationalize these findings that appear to contrast with the exiting literature, we construct a variant of the model by Bernard, Redding, and Schott (2010) (BRS hereafter). In BRS, heterogeneous firms can potentially produce a continuum of multiple products. We first briefly discuss the set-up of the BRS model, and elaborate our extension in greater detail. Readers are referred to BRS (2010) for details.

Consumers consume a continuum of products with identical preferences: $U = \left[\int_0^1 C_s^{\nu} ds\right]^{\frac{1}{\nu}}$, where $\kappa \equiv 1/(1-\nu) > 1$ is the elasticity of substitution between products. Within a product, firms produce horizontally differentiated varieties, facing their own demand. The consumption index for product s, C_s, takes the following form:

$$C_s = \left[\int_{\omega \in \Omega_S} \left(\lambda_s(\omega) c_s(\omega) \right)^{\rho} d\omega \right]^{\frac{1}{\rho}}, 0 < \rho < 1,$$

where $\sigma \equiv 1/(1-\rho) > 1$ is the elasticity of substitution between varieties within a product. Following BRS, we assume that the elasticity of substitution between varieties within a product is larger than that between products ($\sigma > \kappa > 1$).

With firm heterogeneity in productivity ("ability") and fixed exporting costs as in Melitz (2003), the BRS model delivers the standard productivity-sorting results -- the least productive firms exit, the intermediate-productive firms serve the domestic market, and the most productive firms serve both the domestic and foreign markets. In addition to firm heterogeneous productivity, profitability of selling a product in a foreign market depends on an exogenous firm-product-specific attribute, called "consumer taste." In addition to the country-specific fixed export costs, a multi-product exporter also needs to incur product-specific fixed costs, f_s, for each product s produced.[17] Firms experience exogenous changes in consumer tastes and may add and drop products over time. When the consumer-taste shock for a product drops below the firm-product-specific zero-profit cutoff, the firm would drop the product from its portfolio to avoid a loss. On the other hand, if the shock is above the cutoff, the firm keeps the existing product or adds a new product to its portfolio. BRS predict that the more productive exporters have a wider product scope, all else equal, as higher firm-specific labor productivity lowers the "consumer taste" zero-profit cutoffs for all products.[18]

To rationalize our empirical results and derive a few more testable predictions regarding exporters' capital intensity, we modify the one-factor BRS model to consider two factors of production -- capital and labor. Formally, firms have the following total cost function:

$$TC_s = \left[f_s + \frac{q_s}{\varphi} \right] w^{1-\beta(s)} r^{\beta(s)}, \tag{2}$$

where w and r are the wage rate and the rental rate, respectively. We choose the wage as the numeraire (i.e., $w = 1$). Notice that the fixed cost to produce a product is assumed to have the same factor shares as the variable costs. $\beta(s)$ represents capital intensity for product s. φ is the firm-specific productivity term, which is identical for all products. Without loss of generality, we rank product index $s \in [0,1]$ so that $\beta(0) = 0$, $\beta(1) = 1$, and $\beta'(s) > 0$ (i.e., capital intensity is increasing

17 Think of f_s as R&D expenditure required to produce a blue print for the product or the overhead costs to manage the product-specific sales force.

18 Bernard, Redding, and Schott (2011, BRS2 hereafter) show theoretically and empirically that trade liberalization leads to surviving exporters to reduce the product scope and specialize in their core competence.

in product index s). Firm profit maximization implies the standard optimal price of a variety exported to country j as

$$p_{sj} = \frac{\sigma\tau_j}{\sigma - 1}\frac{r^{\beta(s)}}{\varphi},$$

where τ_j is the iceberg trade cost to country j. For simplicity, we assume that τ_j is identical for all products.

Consider two countries: China and destination country j. Country j (for example, the U.S.) is assumed to be relatively more capital-abundant than China. With trade frictions, factor prices would not be equalized across countries, and the wage-rental ratio in country j will be higher than that in labor-abundant China in equilibrium (i.e., $w_j/r_j > 1/r$). It can then be readily shown that the relative price of product s between country j and China, $\tilde{P}_j(s) = P_j(s)/P(s)$, is *decreasing* in capital intensity (i.e., $\tilde{P}_j'(s) < 0$) (see online Appendix A.2 for details).[19]

Given that $\tilde{P}_j(s)$ varies across products, an exporter has a different export portfolio to country j compared to the domestic market. This is true even when the set of "consumer tastes" (λ_s) is identical for different destinations.[20] Consider a firm with total factor productivity φ that exceeds the export threshold, the consumer taste cutoff $\lambda_s^*(\varphi)$ for product s, above which the firm produces s for domestic sales, is pinned down by the following zero-profit condition:

$$\pi_s(\varphi, \lambda_s^*(\varphi)) = \frac{R_s}{\sigma}(\rho P(s)\varphi\lambda_s^*(\varphi))^{\sigma-1} - f_s r^{\beta(s)} = 0, \tag{3}$$

19 A similar point has been made by Lu (2011) to rationalize why Chinese exporters are less productive than domestic producers in labor-intensive sectors.

20 A firm decides to become a new exporter after experiencing a positive productivity shock. In BRS, there is a Poisson probability for the firm to draw firm-specific productivity term, and another Poisson probability that the firm draws a new consumer taste for a product. It is theoretically possible that a firm gets hit by a positive productivity shock and decides to export, while its product-specific consumer taste shocks do not change. Moreover, we follow BRS to assume that the distribution of abilities and consumer taste attributes are independent of one another.

where $\pi_s(\varphi, \lambda_s^*(\varphi))$ represents the firm's profit by selling a variety of product i domestically; R_s stands for domestic expenditure spent on product s. $P(s)$ is the ideal price index for product s.[21] Solving (3) gives us the firm-product specific consumer taste cutoff $\lambda_s^*(\varphi)$. Similarly, we can solve the zero-profit condition for export sales to country j and obtain the consumer taste cutoff for market j and product s, denoted as $\lambda_{sj}^*(\varphi)$.

Importantly, the ratio of the firm's export participation cutoff to domestic sales cutoff $\tilde{\lambda}(s) = \dfrac{\lambda_{sj}^*(\varphi, P_j(s))}{\lambda_s^*(\varphi, P_j(s))}$ can be solved as

$$\tilde{\lambda}(s) = \left(\frac{P_j(s)}{P(s)}\right)^{-\gamma} \left(\frac{f_{sj}}{f_s}\right)^{\frac{1}{\sigma-1}} \Lambda_j, \tag{4}$$

where $\Lambda_j = \tau_j \left(\dfrac{\hat{P}_j}{\hat{P}} \dfrac{R}{R_j}\right)^{\frac{1}{\sigma-1}}$ is a country-specific "resistance" for exports, independent of a product's characteristics. Given a draw of λ, a higher $\tilde{\lambda}(s)$ implies a lower likelihood of exporting, conditional on positive domestic sales.

Λ_j is increasing in both variable (τ_j) and fixed export costs (f_{sj}), as well as the relative aggregate price index of country j, $\dfrac{\hat{P}_j}{\hat{P}}$. The reason is that a higher aggregate price index in country j lowers the purchasing power of the foreign customers, which in turn reduces the market size for product s. For the same reason, Λ_j is decreasing in total expenditure in country j, R_j. Existing studies usually assume symmetry of economies (i.e., $\hat{P}_j = \hat{P}$ and $R = R_j$), higher fixed costs for export sales than domestic sales ($f_{sj} > f_s$), and an iceberg trade cost $\tau_j > 1$. Under these assumptions,

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21 Specifically, consumers' utility maximization yields $R_s = \left[P(s)^{\frac{-\nu}{1-\nu}} / \int_0^1 P(k)^{\frac{-\nu}{1-\nu}} dk\right] R$, where R is total expenditure of the economy; $P(s) = \left[\int_{\omega\in\Omega_s} p(s,\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$.

$\Lambda_j > 1$. Deviating from these assumptions, Bernard, Redding, and Schott (2009) and Lu (2011) postulate the possibility of having $\Lambda_j < 1$ and study the resulting implications.[22]

If country j is relatively more capital-abundant than China, $\frac{P_j(s)}{P(s)}$ is decreasing in s. Given the assumption that $\sigma > \kappa > 1$, $\tilde{\lambda}(s)$ is thus increasing in capital intensity. That is, $\frac{\partial \tilde{\lambda}(s)}{\partial s} > 0$. In words, all else being equal, the "consumer taste" draw that guarantees profitable domestic sales is less likely to generate profitable export sales to j, the higher is the capital intensity of the product.

For a firm with productivity φ, denote capital intensity (i.e., capital cost share) for product s by $\theta_s = \frac{rk_s}{rk_s + wl_s}$, where k_s and l_s are the total amounts (including fixed cost of production) of capital and labor used to produce s.[23] Capital intensity of a firm with productivity φ serving only the domestic market is

$$\Theta_d(\varphi) = \int_0^1 \frac{R_s(\varphi, \lambda_s)}{R(\varphi)} \theta_s I_s\left(\lambda_s \geq \lambda_s^*(\varphi)\right) ds,$$

where subscript d denotes "domestic" ; $I_s\left(\lambda_s \geq \lambda_s^*(\varphi)\right)$ is an indicator function, which equals 1 if $\lambda_s \geq \lambda_s^*(\varphi)$, $R_s(\varphi)$ represents the firm's product s domestic sales, whereas $R(\varphi)$ is its total domestic sales.

Condition on export participation in market j, we can derive the firm's capital intensity of the basket of goods exported to j as

$$\Theta_j(\varphi) = \int_0^1 \frac{R_{sj}(\varphi, \lambda_s)}{R_j(\varphi)} \theta_s I_s\left(\lambda_s \geq \Phi_j(s) \lambda_s^*(\varphi)\right) ds,$$

22 In particular, Lu (2011) finds that in labor-intensive sectors, Chinese exporters are on average less productive than non-exporters. Based on an extension of Bernard el al. (2007), she rationalizes the findings by postulating that if the domestic is more competitive than the foreign market, the domestic production cutoff can be lower than the export participation cutoff.

23 e.g. $rk_s = rk_s^p + rk_s^f$, where k_s^p stands for the level of capital used for producing goods, while k_s^f is the corresponding amount to cover the fixed cost of production, such as developing a blue print of the product.

where $\Phi_j(s) \equiv \tilde{P}(s)^{\frac{1-\sigma(1-\nu)}{(\sigma-1)(1-\nu)}} \Lambda_j$ is increasing in s; $R_{sj}(\varphi)$ is the firm's product s export sales in j, and $R_j(\varphi)$ is its total sales there. We assume that θ_s is identical for product s across different markets. A firm selling both at home and country j thus has the following capital intensity:

$$\Theta_{d+j}(\varphi) = d_j(\varphi)\Theta_d(\varphi) + (1 - d_j(\varphi))\Theta_j(\varphi), \tag{5}$$

where $d_j(\varphi) = \dfrac{R(\varphi)}{R(\varphi) + R_j(\varphi)}$.

As in BRS (2010), given a continuum of products, the law of large numbers implies that a firm's exporting status is entirely determined by firm productivity, φ, and an overall fixed cost for exporting to country j, f_j. Given φ, $\lambda_s^*(\varphi)$, and f_e, firm expected profits from serving a given market is

$$\pi(\varphi) = \int_0^1 \left[\int_{\lambda_s^*(\varphi)}^{\bar{\lambda}} \pi_s(\varphi, \lambda_s) g(\lambda_s) d\lambda_s \right] ds - f_j$$

where $g(\lambda_s)$ is the stationary distribution for consumer tastes, which is discussed in detail in BRS (2010). f_j is measured in labor in BRS, but is measured in Home's consumption bundle here.

Consider a firm that receives a shock that lowers its fixed exporting cost, f_j, so that it switches from non-exporting to exporting to country j at t.[24] For the moment, consider sufficiently high trade costs so that all "consumer taste" cutoffs for foreign sales are higher than the corresponding ones for domestic sales, $\Phi_j(s) > 1$ or $\lambda_{sj}^*(\varphi) > \lambda_s^*(\varphi)$ $\forall s$.[25] Since $\dfrac{\partial \tilde{\lambda}(s)}{\partial s} > 0$, the firm is more likely to draw a λ_s that is higher than both λ_s^* and λ_{sj}^* for labor-intensive (low-s) products. In other words, the firm is less likely to have λ_s that justifies capital-intensive exports (high s), even though the firm could be selling the same good at home. Given a continuum of products, the average capital intensity of the domestic product portfolio, $\Theta_d(\varphi)$, would be more labor-intensive than that of the export bundle, $\Theta_j(\varphi)$. As such, we have the following proposition:

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24 A firm can also switches from non-exporting to exporting after receiving a favorable shock to productivity, φ. With a few mild assumptions, our main theoretical results will go through. Since our empirical analysis has focued on comparing exporters and non-exported with similar ex-ante characteristics, including productivity, we choose to focus on the case of fixed-cost shocks to more closely link our theory to the empirical results.

25 Bernard et al. (2007) make a similar assumption -- the productivity cutoffs to export are higher in both capital- and labor-intensive sectors.

Proposition 1

A firm's capital intensity $\Theta(\varphi)$ after exporting to a capital-abundant country at period $t+1$ satisfies the following inequality:

$$\Theta_{j,t+1}(\varphi) < \Theta_{t+1}(\varphi) < \Theta_{d,t+1}(\varphi) < \Theta_{t}(\varphi),$$

where $\Theta_t(\varphi)$ is the capital intensity of the firm before exporting; $\Theta_{d,t+1}(\varphi)$ and $\Theta_{j,t+1}(\varphi)$ are the capital intensities of the domestic and foreign baskets of products after exporting.

This theoretical prediction is consistent with our empirical findings that firms become less capital-intensive after exporting to a capital-abundant country. Notice that Proposition 1 does not depend on the assumption that $\lambda^*_{sj}(\varphi) > \lambda^*_s(\varphi)\ \forall s$. For Proposition 1 to hold, what we need is $\frac{\partial \tilde{\lambda}(s)}{\partial s} > 0$. In fact, we can follow Lu (2011) to assume that there exists $\bar{s}(\varphi) < 1$ such that $\lambda^*_{sj}(\varphi) \le \lambda^*_s(\varphi)$ $\forall s \le \bar{s}(\varphi)$, and $\lambda^*_{sj}(\varphi) > \lambda^*_s(\varphi)$ otherwise. In online Appendix A.3, we show that as long as there are some s with $\lambda^*_{sj}(\varphi) > \lambda^*_s(\varphi)$, $\frac{\partial \tilde{\lambda}(s)}{\partial s} > 0$ suffices to guarantee a decline in capital intensity of a new exporter serving j.

According to our model, new exporters in labor-abundant countries exporting to capital-abundant countries will experience at least one of the following changes. First, it will experience a larger sales increase in labor-intensive (low-s) products after exporting (the intensive margin). Second, the firm will add products that it does not produce for domestic sales if the corresponding "customer taste" cutoff is higher for domestic sales than for exporting (i.e., $\lambda^*_s(\varphi) > \lambda_s > \lambda^*_{sj}(\varphi)$).[26] This situation is more likely to happen for labor-intensive (low s) products as $\frac{\partial \tilde{\lambda}(s)}{\partial s} > 0$. Regardless, either of the two changes will lower the overall capital intensity of production for firms that start exporting to capital-abundant countries.

Notice that without more structure about export dynamics, little can be said about the evolution of an exporter's factor intensity. Table 5 shows a widening gap in capital intensity years after matching. To rationalize these findings, one needs to consider significant adjustment costs to change product scope, or that there are option values for waiting for the realization of consumer tastes, which can be both

[26] Notice that unlike Bernard, Redding, and Schott (forthcoming), an exogenous productivity shock would not result in product dropping. Product dropping would happen in general equilibrium if trade liberalization happens across the board, which raises the competitiveness of the foreign market and thus the real wage rate.

country and product-specific. Under either of these considerations, exporters may not attain the optimal product portfolio immediately in the year of exporting. It will adjust the product scope for exports over time towards a more labor-intensive portfolio. We will provide evidence below to show that exporters' evolution of capital intensity is indeed determined by the change in the product portfolio, on both the intensive margin (through expansion in labor-intensive product sales) and the extensive margin (through product churning).

Though our model focuses mostly on how a firm can become more labor-intensive after exporting, it can be used to understand how a more labor-intensive firm is also more likely to start exporting, as our findings suggest. According to our model, conditional on productivity, a firm is more labor-intensive because it has more favorable "consumer taste" draws for labor-intensive products. Since the "consumer taste" cutoffs for exporting labor-intensive products to a capital-abundant country are lower for all firms, a labor-intensive firm is more likely to start exporting.

Our model also predicts that the more productive firms have a larger product scope, as $\lambda_s^*(\varphi)$ is decreasing in φ for all s. Therefore, all else equal, the shrinkage of the product scope is smaller for the ex-ante more productive firms. As such, the firm's capital intensity after exporting would also decline less if the firm is more productive (or if the productivity shock that triggers exporting is larger).

Proposition 2

An ex-ante more productive firm experiences a smaller decline in capital intensity $\Theta_{t+1}(\varphi)$ after exporting. Formally,

$$\frac{\Theta_{t+1}(\varphi)}{\Theta_t(\varphi)} < \frac{\Theta_{t+1}(\varphi')}{\Theta_t(\varphi')} < 1 \text{ if} \varphi' > \varphi.$$

6.1 A Note about the Revenue-based Productivity Estimates

Our empirical results show that domestic firms become more productive after they start exporting. It is important to understand how changes in product scope after exporting, conditional on φ, can contribute to the observed productivity gain. To this end, we derive the revenue-based productivity measure associated with domestic sales of product s as:

$$\mu_s = \frac{R_s(\varphi, \lambda_s)}{x(\varphi, \lambda_s)}, \tag{6}$$

where $x(\varphi,\lambda_s)=\Gamma_s l(\varphi,\lambda_s)^{1-\beta(s)}k(\varphi,\lambda_s)^{1-\beta(s)}$ is the associated input bundle, and Γ_s is a sector-specific constant that delivers a cost function equal to equation (2). By expressing the quantity produced as $q_s(\varphi,\lambda_s)=\varphi(x_s(\varphi,\lambda_s)-f_s)$, we can rewrite (6) as:

$$\mu_s=\frac{r^{\beta(s)}}{\rho}\left(1-\frac{f_s}{x_s(\varphi,\lambda_s)}\right).$$

Since $x_s(\varphi,\lambda_s)$ is increasing in λ_s and φ, μ_s is increasing in λ_s and φ as well. The intuition is that a firm with a better "consumer taste" cutoff and/ or firm productivity produces more and can spread the fixed cost of production (or exporting) over a larger volume of production.

Similarly, the product-specific measured productivity corresponding to sales in country j is

$$\mu_{sj}=\frac{\tau_j r^{\beta(s)}}{\rho}\left(1-\frac{f_{sj}}{x_{sj}(\varphi,\lambda_s)}\right).$$

Notice that $\mu_{sj}>\mu_s$ if τ_j or resources allocated to production of exported goods, $x_j(\varphi,\lambda_s)$, are sufficiently high. On the other hand, higher fixed export costs, f_{sj}, would make $\mu_{sj}<\mu_s$ more likely.

The measured revenue-based productivity of an exporter (selling to country j) then becomes

$$\hat{TFP}_j(\varphi)=d_j(\varphi)\int_0^1\mu_s\frac{R_s(\varphi,\lambda_s)}{R(\varphi)}ds+(1-d_j(\varphi))\int_0^1\mu_{sj}\frac{R_{sj}(\varphi,\lambda_s)}{R_j(\varphi)}ds, \tag{7}$$

where $d_j(\varphi)=\dfrac{R(\varphi)}{R(\varphi)+R_j(\varphi)}$, as defined for equation (5) above. Denote the measured TFP before exporting by $\hat{TFP}(\varphi)$. According to (7), when we observe $\hat{TFP}_j(\varphi^{'})>\hat{TFP}(\varphi)$, it can be partly due to $\varphi^{'}>\varphi$, a shock that triggers exporting, and partly due to product switching and thus reallocation of resources toward the higher "consumer taste" products, conditional on φ.

In an open-economy model with symmetric countries (identical country size and factor endowment) and no iceberg trade cost, because of higher fixed costs for exporting than domestic sales, it can be readily shown that μ_{sj} is always smaller than μ_s $\forall s$. In this situation, given φ, product-switching is associated with a lower measured TFP in the absence of general equilibrium effects.

However, when we consider asymmetric country size and factor endowment, the contribution of product switching becomes less clear. In particular, we can show that for a given product s, $\mu_{sj} > \mu_s$ if and only if $\tau_j\left(1-\frac{f_{sj}}{x_{sj}(\varphi,\lambda_s)}\right) > \left(1-\frac{f_s}{x_s(\varphi,\lambda_s)}\right)$. For simplicity, suppose $\tau_j = 1$, this inequality is reduced to[27]

$$\frac{f_{sj}}{f_s} < \left(\frac{P_j(s)}{P(s)}\right)^{\gamma}\Psi_j,$$

where $\Psi_j = \frac{R_j/\hat{P}_j}{R/\hat{P}}$, which is constant across s.[28] Suppose $\frac{f_{sj}}{f_s}$ is the same for all products, since $\tilde{P}'(s) < 0$ and $\gamma \equiv \frac{\sigma(1-\nu)-1}{(\sigma-1)(1-\nu)} > 0,$ the right hand side of the inequality is decreasing in s. That is, the inequality is *less likely* to hold for capital-intensive products, all else being equal. In other words, the more the exporters specialize in labor-intensive products (with relatively higher μ), the higher the measured productivity gain is relative to the actual TFP gain, $\Delta\varphi$, after exporting. That said, it is possible that $\mu_{sj} < \mu_s$ even for the most labor-intensive products exported to capital-abundant countries. This would be the case if f_{sj} is significantly higher than f_s, or the destination country is sufficiently small (low R_j) or remote (high $\hat{P}_j$). In that case, the actual increase in TFP after exporting is always higher than the measured one. Specialization in labor-intensive exports is then associated with a *relative* gain, instead of an absolute gain, in measured productivity.

7. Evidence on Heterogeneous Changes in Capital Intensity

We already provide robust firm-level evidence that supports Proposition 1. Proposition 2 postulates that firms hit by a stronger productivity shock that triggers exporting would experience a smaller decline in capital intensity. We test this prediction by estimating the following specification:

$$\Theta_{i,d}^{matched}(\varphi) - \Theta_{i,d+j}(\varphi) = \mathbf{X}_i\boldsymbol{\gamma} + F_{Ind} + F_{Prov} + F_{year} + \varepsilon_i, \tag{8}$$

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27 $\frac{f_{sj}}{f_s} < \frac{x_j(\varphi,\lambda_s)}{x(\varphi,\lambda_s)} \Leftrightarrow \frac{f_{sj}}{f_s} < \frac{r_{sj}(\varphi,\lambda_s)}{r_s(\varphi,\lambda_s)} = \frac{R_{sj}}{R_s}\left(\frac{P_j(s)}{P(s)}\right)^{\sigma-1} = \left(\frac{P_j(s)}{P(s)}\right)^{\gamma}\Psi_j,$

28 Suppose $\tau_j > 1$, $\mu_{sj} > \mu_s$ if and only if $\tau_j - 1 + \frac{f_s}{\kappa_s(\varphi,\lambda_s)} > \frac{\tau_j f_{sj}}{\kappa_{sj}(\varphi,\lambda_s)}$.

where $\Theta_{d+j}(\varphi)$ is firm $i's$ capital intensity, and $\Theta_{d}^{matched}(\varphi)$ is the average measure of capital intensity of the matched "untreated" group of firms. The main idea is to examine how an exporter is different in capital intensity from a non-exporter that shares very similar pre-export characteristics, such as ownership types. X_i is a vector of firm i's previous year characteristics, including TFP and other key attributes. F_{Ind}, F_{Prov}, and F_{year} stand for industry, province, and year fixed effects, respectively.

The results for estimating (8) are reported in Table 7. In column (1), ln(TFP) is negatively and significantly correlated with the gap in capital intensity between exporters and non-exporters, supporting Proposition 2. To the extent that more productive firm pay higher wages, the negative and significant coefficient on ln(wage rate) is also consistent with Proposition 2. However, when sales is used as a proxy for productivity, the positive coefficient on ln(sales) is inconsistent with our theoretical prediction.

Beyond the model predictions, we also find that older firms experience a smaller decline in capital intensity after exporting. While our model assumes exogenous firm productivity and product appeal, one can argue that firms' experience in sales can enhance the level of the "consumer taste" attributes. Based on this rationale, expertise in production would imply a higher chance of selling a product in a foreign market. Finally, a positive correlation between initial capital intensity and the decline in capital intensity is consistent with our findings that more labor-intensive firms are more likely to start exporting (see online Appendix Table A2). The rationale is that an ex-ante more capital-intensive firm has more room to adjust its product scope to exploit the comparative advantage of low labor costs in China, resulting in a larger drop in capital intensity.

From columns (2) through (5), we find strong evidence confirming the baseline results using different sub-samples of firms. Regardless of firms' ownership types or sample periods, the results about the firm heterogeneous changes in capital intensity after exporting remain robust.

Next, we explore the relation between the increase in labor intensity in the first year of exporting and the gain in measured productivity to shed light on the "core competency" hypothesis. According to our model predictions, new exporters that have a larger increase in labor intensity should have a *relatively* larger increase in measured productivity gain. As is shown in Table 8, we find a positive coefficient on *labor intensity increase*, controlling for industry, ownership, year fixed effects, and a number of key firm attributes. This positive correlation remains robust for both domestic and foreign exporters, and are particularly significant after China's accession to the WTO. There results are consistent with our theoretical prediction that firms' specialization in core competency enhances measured TFP. However, notice that in light of the results reported in Table 7, there can be unresolved endogeneity issues in the results reported in Table 8. In particular, if productive firms grow slower than unproductive firms, who experience a larger increase in labor intensity as supported by the findings in Table 7, the positive correlation between labor intensity increase and TFP gain reported in Table 8 can arise from reverse causality.

8. Evidence on Within-Firm Product Switching

Since our model emphasizes the multi-product aspect of firms, in the remainder of the empirical analysis, we use transaction-level (firm-product-year) trade data to verify the theoretical results above. We first merge the NBS firm data with the trade data as discussed in Section 3. We use various methods to merge the two data sets, including merging by firm name, address, and manager names. The summary statistics of the merged data set are reported in online Appendix Table A5. About one-third of the exporters in the trade data set can be merged with the NBS data set. These merged firms account for 37% to 49% (depending on the year) of the values of aggregate Chinese exports. A conservative estimate shows that over 20% of Chinese exports were intermediated by trading companies (Ahn et al., 2011; Tang and Zhang, 2011). It is worth noting that trading companies are considered service providers, which are included in the trade data set but not in the NBS industrial firm data set. A large fraction of the unmerged firms in our sample are thus trading companies.

Using the merged data set, we compute capital intensity for each HS 6-digit product. The computation procedures, which are similar to the method used by Bernard et al. (2010), are discussed in online Appendix A.3. Table 9 reports the measured capital intensity by broad industries (approximately at the level of HS 2-digit). Similar to the findings by Bernard et al. (2010) for the U.S., there exists a wide variation in capital intensity within industries. For instance, the mean capital intensity of the "textiles and textile articles" industry is about 68 thousands yuan per worker, with standard deviation across HS6 products equal to about 55 thousands. The number of HS6 product categories ranges from 9 (Works of art) to 818 (Textile and textile articles), suggesting that firms have a wide range of products with vastly different capital intensity to choose from within the same industry. In fact, based on the transaction-level data, Table 10 shows that exporters actively add and drop products over time. New exporters in year t (those who did not export in $t-1$ according to the NBS data set) on average added about 10 products, dropped 6 products, and continued only 5 products per year between 2002 and 2006. This active within-firm extensive margin of trade can play an important role in affecting factor intensity and measured productivity after export participation.

Using the merged data set and capital intensity measures at the HS 6-digit level, we compare the (average) capital intensity of the newly added products, dropped products, and products that were continued from the previous year. To this end, we first record all products exported in the first year and subsequent years for each new exporter. In each subsequent year, we keep track of the new, dropped, and continued products. Then for each exporter-year, we compute the sales-weighted averages of capital intensity for each of the following product portfolios: the newly added products, the continued products, and the dropped products. With this panel data set in hand, we estimate the following specification:

$$\ln(K/L)_{ik} = \alpha + \beta\left(new\_product_{ik}\right) + \delta\left(dropped\_product_{ik}\right) + e_i, \tag{9}$$

where $\ln(K/L)_{ik}$ is the sales-weighted average of capital intensity for firm i and basket $k \in \{new\_products, contining\_products, dropped\_products\}$. α is a constant and e_i the error term. Our model predicts that newly added products are less capital-intensive than the basket of continued products, while dropped products are more capital-intensive (i.e., $\beta < 0$ and $\delta > 0$).

As Table 11 shows, the estimated coefficient on the new-product dummy is negative and significant using the pooled sample, while the dropped product dummy is positive and significant. More specifically, the new products are about 5 percent less capital-intensive than the continuously exported products, while the dropped products are about 2 percent more capital-intensive. Importantly, these results hold for both ordinary exporters and processing exporters who assemble imported intermediate inputs solely for foreign sales. These findings address the concern that our results are driven by the predominance of export-processing plants in China.

9. Concluding Remarks

This paper analyzes the causal relations between firms' productivity, factor intensity, and export participation. In particular, we provide empirical evidence on how firms' specialization in core competency after exporting can contribute to higher measured productivity. Using panel data for China's manufacturing firms over the period of 1998-2007, and the matched sampling techniques from the program evaluation literature for identification, we find that exporting increases domestic firms' measured productivity. Depending on the matching methods, export participation increases new exporters' measured productivity by 5.5 to 7.4 percent. We also find that the more productive domestic firms self-select into exporting. However, once we take out domestic firms from the sample, foreign exporters do not appear to be more productive than foreign non-exporters, both ex ante and ex post.

These results are broadly consistent with the idea that increasing access to export markets boosts productivity for domestic firms in developing countries. From an industrial policy perspective, there are reasons to promote foreign sales over domestic sales because firms improve once they participate in export markets. Our results also highlight the importance of evaluating the effects of export-promotion policies separately for different ownership types of firms.

Importantly, in sharp contrast to the existing literature, we find that both domestic and foreign firms become *less* capital-intensive in their first year of exporting relative to the matched non-exporters within a narrow industry. This gap in capital intensity between exporters and the matched non-exporters is not shrinking before 2007, the last year in our sample. To rationalize these results, we develop a variant of the multi-product model of Bernard, Redding, and Schott (2010) to consider varying capital intensity across products. The model predicts that exporters in labor-abundant countries choose to specialize in their core competency -- labor-intensive exports to capital-abundant countries. It also discusses how the within-firm reallocation of resources from capital-intensive to labor-intensive products can contribute to higher measured productivity after exporting. Using transaction-level export data, we find evidence that Chinese exporters add new products that are more labor-intensive than the existing exported products, and drop products that are less labor-intensive over time. New exporters with a larger increase in labor intensity after exporting also experience a bigger measured productivity gain, as predicted by the model.

References

Ahn, J., A. Khandelwal and S. J. Wei (2011), "The Role of Intermediaries in Facilitating Trade," *Journal of International Economics*, 84: 73-85.

Alvarez, R. and R. Lopez (2005), "Exporting and Performance: Evidence from Chilean Plants," *Canadian Journal of Economics*, 38: 1384-400.

Aw, B., S. Chung and M. Roberts (2000), "Productivity and Turnover in the Export Market: Micro-level Evidence from the Republic of Korea and Taiwan (China)," *World Bank Economic Review*, 14: 65-90.

Baldwin, J. and W. Gu (2003), "Export-Market Participation and Productivity Performance in Canadian Manufacturing," *Canadian Journal of Economics*, 36: 634-57.

Becker, S. and A. Ichino (2002), "Estimation of Average Treatment Effects Based on Propensity Scores," *Stata Journal*.

Bernard, A. and B. Jensen (1999), "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics*, 47: 1-25.

Bernard, A. and J. Jensen (2004), "Why Some Firms Export," *Review of Economics and Statistics*, 86: 561-8.

Bernard, A., J. Jensen, S. Redding and P. K. Schott (2007), "Firms in International Trade," *Journal of Economic Perspectives*, 21: 105-30.

Bernard, A., J. Jensen, and P. K. Schott (2006), "Survival of the Best Fit: Exposure to Low Wage Countries and The (Uneven) Growth of US Manufacturing Plants," *Journal of International Economics*, 68: 219-37.

Bernard, A. B., S. Redding and P. K. Schott (2007), "Comparative Advantage and Heterogeneous Firms," *Review of Economic Studies*, 74: 31-66.

Bernard, A., J. Eaton, B. Jensen and S. Kortum (2003), "Plants and Productivity in International Trade," *American Economic Review*, 93: 1268-90.

Bernard, A., S. Redding and P. Schott (2010), "Multiple-Product Firms and Product Switching," *American Economic Review*, 100: 70-97.

Bernard, A., S. Redding and P. Schott (2011), "Multi-Product Firms and Trade Liberalization," *Quarterly Journal of Economics,* 126: 1271-318.

Bernard, A. and J. Wagner (1997), "Exports and Success in German Manufacturing," *Weltwirtschaftliches Archiv*, 133: 134-57.

Brandt, L., J. Van Biesebroeck and Y. Zhang (2011), "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics,* forthcoming.

Bustos, P. (2011), "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms," *American Economic Review*, 101: 304-40.

Clerides, S., S. Lach and J. Tybout (1998), "Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia Mexico, and Morocco," *Quarterly Journal of Economics*, 113: 903-47.

De Loecker, J. (2007), "Do Exports Generate Higher Productivity? Evidence from Slovenia," *Journal of International Economics*, 73: 69-98.

Delgado, M., J. Farinas and S. Ruano (2002), "Firm Productivity and Export markets: A Nonparametric Approach," *Journal of International Economics*, 57: 397-422.

Eckel, C., and J. P. Neary (2010), "Multi-Product Firms and Flexible Manufacturing in the Global Economy," *Review of Economic Studies*, 77: 188-217.

Fan, J. (1993), "Local Linear Regression Smoothers and their Minimax Efficiencies," *Annals of Statistics*, 21: 196-216.

Feenstra, R. and H. Ma (2008), "Optimal Choice of Product Scope for Multiproduct Firms under Monopolistic Competition," in E. Helpman, D. Marin and T. Verdier, eds., *The Organization of Firms in a Global Economy*, Harvard University Press.

Feenstra, R. and G. Hanson (2005), "Ownership and Control in Outsourcing to China: Estimating the Property-Rights Theory of the Firm," *Quarterly Journal of Economics,* 120: 729-61.

Gibbons, J. D. and S. Chakraborti (2003), *Nonparametric Statistical Inference*, New York: Marcel Dekker.

Girma, S., D. Greenaway and R. Kneller (2003), "Export Markets Exit and Performance Dynamics: A Causality Analysis of Matched Firms," *Economics Letters*, 80: 181-7.

Griliches, Z. and J. Mairesse (1998), "Production Functions: The Search for Identification," in S. Strom, ed., *Essays in Honour of Ragnar Frisch*, Econometric Society Monograph Series, Cambridge University Press

Heckman, J., H. Ichimura and P. Todd (1997), "Matching as an Econometric Evaluation Estimator," *Review of Economic Studies*, 65: 261-94.

Helpman, E., M. Melitz and S. Yeaple (2004), "Export vs. FDI with Heterogeneous Firms," *American Economic Review*, 94: 300-16.

International Study Group on Exports and Productivity (2008), "Exports and Productivity -- Comparable Evidence for 14 Countries," *Review of World Economics,* 144: 636-59.

Isgut, A. (2001), "What's Different about Exporters? Evidence from Colombian Manufacturing," *Journal of Development Studies*, 37: 57-82.

Jefferson, G, T. Rawski and Y. Zhang (2008), "Productivity Growth and Convergence across China's Industrial Economy," *Journal of Chinese Economic and Business Studies*, 6: 120-41.

Konings, J. and H. Vandenbussche (2005), "Heterogeneous Responses of Firms to Trade Protection," *Journal of International Economics*, 76: 371-83.

Lucas, R. (1978), "On the Size Distribution of Business Firms," *Bell Journal of Economics*, 9: 508-23.

Nocke, V. and S. Yeaple (2008), "Globalization and the Size Distribution of Multiproduct Firms," NBER Working Paper No.12322.

Kraay, A. (1999), "Exports and Economic Performance: Evidence from a Panel of Chinese Enterprises," *Revue d'Economie du Development*, 1-2: 183-207.

Leuven, E. and B. Sianesi (2003), "PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing," http://ideas.repec.org/c/boc/bocode/s432001.html.

Levinsohn, J. and A. Petrin (2003), "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economics Studies*, 70: 317-42.

Lileeva, A. and D. Trefler (2010), "Improved Access to Foreign Markets Raises Plant-Level Productivity... for Some Plants," *Quarterly Journal of Economics,* 125: 1051-99.

Lu, D. (2010), "Exceptional Exporter Performance? Evidence from Chinese Manufacturing Firms," Working Paper, University of Chicago.

Melitz, M. (2003), "The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71: 1695-725.

Park, A., D. Yang, X. Shi and Y. Jiang (2007), "Exporting and Firm Performance: Chinese Exporters and the Asian Financial Crisis," working paper, University of Michigan.

Perkins, D. H. and T. G. Rawski (2008), "Forecasting China's Economic Growth," in L. Brandt and T. G. Rawski, eds., *China's Great Economic Transformation*, Cambridge University Press.

Petrin, A., B. Poi and J. Levinsohn (2004), "Production Function Estimation in Stata Using Inputs to Control for Unobservables," *Stata Journal*, 4: 113-23.

Rosenbaum, P. R. and D. B. Rubin (1984), "Reducing Bias in Observational Studies using Subclassification on the Propensity Score," *Journal of the American Statistical Association,* 79: 516-24.

Tang, H. and Y. Zhang (2011), "Quality Differentiation and Trade Intermediation," Tufts University Working Paper.

Van Biesebroeck, J. (2005), "Exporting Raises Productivity in Sub-Saharan African Manufacturing Firms," *Journal of International Economics*, 67: 373-91.

Wagner, J. (2002), "The Causal Effect of Exports on Firm Size and Labor Productivity: First Evidence from a Matching Approach," *Economics Letters*, 77: 287-92.

World Bank (1993), *The East Asian Miracle: Economic Growth and Public Policy*, New York: Oxford University Press.

Table 1. New Exporter Information 1999-2007 (Odd years only)

	1999		2001		2003		2005		2007	
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Total no. of firms	118,251	25,272	121,896	29,332	140,107	36,192	195,902	55,597	246,558	78,801
%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Non-exporters	97,079	9,209	96,944	9,534	107,578	10,954	156,325	20,786	208,027	26,220
%	82%	36%	80%	33%	77%	30%	80%	37%	84%	33%
Continuing exporters	18,394	14,742	23,383	18,442	30,128	23,616	31,088	32,759	33,504	49,773
%	16%	58%	19%	63%	22%	65%	16%	59%	14%	63%
New exporters	2,778	1,321	1,569	1356	2,401	1622	8,489	2,052	5,027	2,808
%	2.3%	5.2%	1.3%	4.6%	1.7%	4.5%	4.3%	3.7%	2.0%	3.6%
Export intensity of new exporters (%)										
0 to 10	35.9	25.2	41.1	35.1	38.9	33.8	58.1	36.0	46.2	36.1
10 to 20	11.1	7.7	11.9	9.7	11.6	9.9	20.3	12.5	11.6	10.5
20 to 30	7.2	5.1	6.6	9.2	7.8	5.3	3.8	6.2	5.8	5.9
30 to 40	6.0	4.1	5.2	4.6	6.1	4.3	2.5	4.2	4.5	4.2
40 to 50	6.2	6.0	3.9	2.8	5.1	4.0	2.1	4.0	3.5	3.9
50 to 60	4.4	4.2	4.2	3.0	4.8	4.0	1.2	3.7	2.4	3.2
60 to 70	5.3	4.7	3.3	2.4	4.3	4.2	1.2	3.1	2.3	2.9
70 to 80	4.2	6.8	3.5	4.2	4.0	4.7	1.4	3.4	2.2	3.1
80 to 90	5.7	7.6	5.3	4.9	3.7	4.9	1.4	2.8	2.2	3.5
90 to 100	14.2	28.7	15.1	24.1	13.8	24.9	8.1	24.1	19.3	26.7
Sum	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: China's National Bureau of Statistics industrial (above-scale) firm survey data.

Table 2. Comparing Productivity and Capital Intensity of Exporters and Non-Exporters

	(1) All Firms	(2) All Firms	(3) Private Firms	(4) Foreign Firms	(5) SOEs	(6) Before WTO	(7) After WTO
Panel A: Dependent variable ln(TFP)							
Exporter	0.137	0.087	0.101	0.003	0.091	0.132	0.074
	[0.000]***	[0.000]***	[0.001]***	[0.439]	[0.021]**	[0.000]***	[0.000]***
N	1,916,347	1,916,347	1,104,987	421,232	390,128	543,921	1,372,426
Panel B: Dependent variable ln(K/L)							
Exporter	-0.191	-0.062	-0.082	-0.031	-0.041	-0.021	-0.075
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
N	1,976,637	1,976,637	1,163,419	421,561	391,657	568,127	1,431,350
Panel C: Dependent variable ln(K/L), alternative measure of K							
Exporter	-0.171	-0.024	-0.025	-0.017	-0.026	0.002	-0.025
	[0.000]***	[0.000]***	[0.000]***	[0.078]*	[0.046]**	[0.564]	[0.000]***
N	1,982,457	1,982,457	1,170,348	421,678	390,431	568,725	1,413,365
Panel D: Dependent variable ln(K/L), alternative measure of L							
Exporter	-0.311	-0.143	-0.178	-0.078	-0.154	-0.124	-0.158
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
N	1,976,637	1,976,637	1,163,419	421,463	391,347	568,121	1,431,480
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (4-digit) FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	No	Yes	No	No	No	Yes	Yes

Notes: This table reports estimation results for equation (1) in the text. The Exporter dummy equals 1 if a firm is either a new exporter or a continuing exporter. Column (2) includes four-digit (about 480) industry, ownership and province fixed effects. In Panel A, ln(TFP) is measured using the Levinsohn-Petrin (2003) method. In Panel B, real capital stock (K) is measured using the perpetual inventory method specified in Brandt et al. (2011), while labor is the firm's total employment. In Panel C, capital stock is the net value of fixed assets deflated by the sector-specific capital-good deflator, while labor is the firm's total employment. In Panel D, capital stock is measured using the perpetual inventory method specified in Brandt et al. (2011), while labor is the firm's total wage bill. Columns (1) and (2) compare exporters and non-exporters using all firms in the sample; column (3) includes only domestic private firms; column (4) includes only foreign-invested enterprises (FIEs); column (5) includes only state-owned enterprises (SOEs); column (6) and (7) split the sample into that before 2002 when China was accessed to the WTO; and that after and including 2002.

Numbers reported in brackets are p-values corrected for industry-ownership clustering. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3. New Exporters' Productivity ln(TFP) - Propensity Score Matching Results

	(1) All New Exporters	(2) Private New Exporters only	(3) SOE New Exporters only	(4) Foreign New Exporters only	(5) Before WTO	(6) After WTO
Panel A: DID Matching						
	0.071	0.082	0.065	0.004	0.068	0.071
	[0.003]***	[0.003]***	[0.010]**	[0.491]	[0.005]***	[0.004]***
Panel B: Local Linear Regression Matching						
	0.069	0.071	0.062	0.002	0.063	0.072
	[0.004]***	[0.006]***	[0.084]*	[0.674]	[0.005]**	[0.005]**
Panel C: Nearest Neighbor Matching						
	0.054	0.056	0.051	-0.005	0.067	0.043
	[0.002]***	[0.005]***	[0.011]**	[0.418]	[0.002]***	[0.003]***

Notes: This table reports the estimation results of the impact of exporting on ln(TFP) , using three different propensity score matching methods. Firms are matched based on estimated propensity scores estimated using the independent variables as listed in Table A2. ln(TFP) is measured using the Levinsohn-Petrin (2003) method. Panel A reports DID estimation results described in online Appendix A1. Panel B reports the estimation results based on local linear regression matching. Panel C reports estimation results based on nearest neighbor matching. P-values, based on bootstrapped standard errors are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4. New Exporters' Capital Intensity ln(K/L) - Propensity Score Matching Results

	(1) All New Exporters ln(K/L)	(2) Private New Exporters only	(3) Foreign New Exporters only	(4) SOE New Exporters only	(5) Before WTO	(6) After WTO	(7) All New Exporters ln(K/L), alternative K	(8) All New Exporters ln(K/L), alternative L
Panel A: DID Matching								
	-0.061	-0.063	-0.051	-0.052	-0.066	-0.061	-0.036	-0.093
	[0.018]**	[0.038]**	[0.063]*	[0.064]*	[0.045]**	[0.029]**	[0.010]**	[0.000]**
Panel B: Local Linear Regression Matching								
	-0.048	-0.047	-0.042	-0.039	-0.050	-0.047	-0.021	-0.081
	[0.015]**	[0.028]**	[0.037]**	[0.094]*	[0.024]**	[0.013]**	[0.010]***	[0.007]***
Panel C: Nearest Neighbor Matching								
	-0.062	-0.075	-0.040	-0.059	-0.07	-0.059	-0.066	-0.103
	[0.016]**	[0.020]**	[0.025]**	[0.062]*	[0.020]**	[0.008]***	[0.014]**	[0.014]**

Notes: This table reports the estimation results of the impact of exporting on ln(K/L) , using three different propensity score matching methods. Panel A reports DID estimation results described in online appendix A.1. Panel B reports the estimation results based on local linear regression matching. Panel C reports estimation results based on nearest neighbor matching. Firms are matched based on estimated propensity scores estimated using the independent variables as listed in Table A2. In columns (1)-(6), real capital intensity ln(K/L) is measured by the perpetual inventory method specified in Brandt et al. (2011), while labor is the firm's total employment. In column (7), capital stock is the net value of fixed assets deflated by the industry's investment deflator, while labor is the firm's employment. In column (8), capital stock is measured as in column (1), while labor is the firm's total wage bill. P-values, based on bootstrapped standard errors are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Over-time Exporting Effects on ln(K/L) – Propensity Score Matching Results

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9
1999	-0.086	-0.132	-0.149	-0.171	-0.178	-0.181	-0.184	-0.185	-0.184
	[0.053]*	[0.028]**	[0.034]**	[0.041]**	[0.048]**	[0.052]*	[0.047]**	[0.141]	[0.079]*
2000	-0.054	-0.081	-0.082	-0.121	-0.131	-0.129	-0.142	-0.143	
	[0.048]**	[0.027]**	[0.031]**	[0.034]**	[0.043]**	[0.045]**	[0.054]*	[0.059]*	
2001	-0.051	-0.104	-0.131	-0.142	-0.148	-0.156	-0.152		
	[0.024]**	[0.019]**	[0.017]***	[0.042]**	[0.049]**	[0.342]	[0.458]		
2002	-0.017	-0.064	-0.077	-0.093	-0.089	-0.094			
	[0.152]	[0.041]**	[0.034]**	[0.037]**	[0.052]*	[0.063]*			
2003	-0.055	-0.085	-0.096	-0.106	-0.115				
	[0.020]**	[0.022]**	[0.026]**	[0.034]**	[0.037]**				
2004	-0.077	-0.084	-0.101	-0.112					
	[0.024]**	[0.031]**	[0.036]**	[0.037]**					
2005	-0.051	-0.081	-0.098						
	[0.031]**	[0.027]**	[0.036]**						
2006	-0.061	-0.081							
	[0.009]***	[0.061]*							
2007	-0.071								
	[0.005]***								
Pooled	-0.061	-0.090	-0.107	-0.122	-0.133	-0.141	-0.157	-0.165	-0.184
	[0.023]**	[0.020]**	[0.033]**	[0.027]**	[0.035]**	[0.042]**	[0.051]*	[0.095]*	[0.079]*

Notes: This table reports estimation results of the impact of exporting on capital intensity, using the DID matching estimator discussed in online Appendix A.1. Firms are matched based on estimated propensity scores estimated using the independent variables before the first year of exporting. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. P-values based on bootstrapped standard errors are reported in brackets.

Table 6. Propensity Score Matching Balancing Test

		Mean		Bias		*t*-test	
		Treated	Control	%bias	% reduction of |bias|	*t*	p-value
ln(TFP)	Unmatched	-1.1267	-1.2696	13.1	97.2	8.35	0.000
	Matched	-1.1267	-1.1308	0.4		0.19	0.853
ln(wage rate)	Unmatched	1.9804	1.7199	34.9	94.1	21.3	0.000
	Matched	1.9804	1.9651	2.0		0.93	0.354
ln(sales)	Unmatched	10.101	9.5056	45.2	98.1	29.69	0.000
	Matched	10.101	10.112	-0.9		0.25	0.802
ln(age)	Unmatched	2.0858	2.3672	-29.3	96.8	-17.67	0.000
	Matched	2.0858	2.0767	0.9		0.44	0.660
ln(K/L)	Unmatched	3.7688	3.7146	4.5	62.7	1.86	0.063
	Matched	3.7688	3.789	-1.7		-1.09	0.278
LR test (Chi-sq)	Unmatched			2413.7	[0.000]***		
	Matched			4.32	[0.431]		

Notes: This table reports balancing test for propensity score matching with first year of exporting. For each year, we report p-value of t-tests for equality of means in the treated and the non-treated groups, both before and after matching. "% of bias" is the standardized bias before and after matching. We also report the chi-sq statistics and the corresponding p-values of the likelihood-ratio test of the joint insignificance of all the regressors before and after matching.

Table 7. Determinants of Capital Intensity Effects

	Dependent Variable = Reduction in ln(K/L) relative to the matched (counterfactual) group				
	(1) All New Exporters	(2) Domestic New Exporters only	(3) Foreign New Exporters only	(4) Before WTO	(5) After WTO
ln(TFP)	-0.059	-0.052	-0.081	-0.080	-0.056
	[0.003]***	[0.005]***	[0.008]***	[0.013]***	[0.005]***
ln(wage rate)	-0.145	-0.155	-0.131	-0.190	-0.087
	[0.000]***	[0.000]***	[0.034]**	[0.000]***	[0.013]***
ln(sales)	0.110	0.139	0.141	0.104	0.110
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
ln(age)	-0.056	-0.020	-0.006	-0.049	-0.042
	[0.017]**	[0.052]*	[0.341]	[0.094]*	[0.018]**
ln(K/L)	0.765	0.829	0.714	0.784	0.767
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Ownership FE	Yes	No	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
N	50,231	33,645	16,586	10,074	40,157

Notes: All regressors are lagged by one year. P-values based on standard errors clustered at the four-digit industry are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Exporters and their matched non-exporters are matched using the DID matching techniques discussed in online Appendix A.1.

Table 8. Determinants of the TFP Effects

	Dependent Variable: △ln(TFP) from year t-1 (not exporting) to t (exporting)				
	(1)	(2)	(3)	(4)	(5)
	All New Exporters	Domestic New Exporters only	Foreign New Exporters only	Before WTO	After WTO
labor intensity increase	0.071	0.071	0.067	0.078	0.064
	[0.000]***	[0.000]***	[0.002]***	[0.002]***	[0.000]***
ln(wage rate)	0.154	0.184	0.169	0.091	0.164
	[0.000]***	[0.001]***	[0.002]***	[0.003]***	[0.002]***
ln(sales)	0.141	0.121	0.158	0.157	0.141
	[0.000]***	[0.000]***	[0.000]***	[0.003]***	[0.000]***
ln(age)	-0.089	-0.094	-0.084	-0.073	-0.112
	[0.009]***	[0.011]**	[0.038]**	[0.077]*	[0.016]**
Industry FE	Yes	Yes	Yes	Yes	Yes
Onwership FE	Yes	No	No	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
N	50,245	33,645	16,600	10,076	40,169

Notes: All regressors are lagged by one year, besides labor intensity increase, which is defined as the first difference in labor intensity from year t-1 to t. Only new exporters are included in the regressions. P-values, based on standard errors clustered at the four-digit industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Capital Intensity by Sector (2001)

Sector	HS 2-digit codes	Num. of HS-6 products	Capital Intensity (mean)	Capital Intensity (St Dev)
Animals & Animal Products	01-05	174	70.9	56.9
Vegetable Products	06-14	254	71.8	61.1
Animal Or Vegetable Fats	15	35	64.9	63.3
Prepared Foodstuffs	16-24	173	94.6	69.0
Mineral Products	25-27	134	90.1	70.9
Chemical Products	28-38	764	111.6	66.5
Plastics & Rubber	39-40	198	79.6	65.2
Hides & Skins	41-43	62	45.5	47.0
Wood & Wood Products	44-46	75	62.3	56.5
Wood Pulp Products	47-49	147	93.7	66.8
Textiles & Textile Articles	50-63	818	68.1	54.9
Footwear, Headgear	64-67	55	27.8	43.0
Articles Of Stone, Plaster, Cement, Asbestos	68-70	147	72.2	64.9
Pearls, Precious Or Semi-Precious Stones, Metals	71	41	32.1	59.5
Base Metals & Articles Thereof	72-83	563	93.9	63.5
Machinery & Mechanical Appliances	84-85	792	99.2	63.9
Transportation Equipment	86-89	121	107.2	66.8
Instruments - Measuring, Musical	90-92	235	99.6	62.8
Arms & Ammunition	93	10	152.4	69.9
Miscellaneous	94-96	130	47.8	51.5
Works Of Art	97-99	9	30.7	53.2

Notes: The unit is throusand yuan (RMB) per worker. We estimate the capital intensity of HS6 products using the merged data set. This table shows the summary statistics of capital intensity by broad sectors. See online Appendix A.3 for the procedure to compute capital intensity at the HS 6-digit level.

Table 10. Product Switching of New Exporters (Customs Transaction-level Data)

	Number of new exporters	Number of new exporters that survived to next year	Total (average) number of products added next year	Total (average) number of products dropped next year	Total number of continuing products
2000					
2001	15,928	13,187	134059 (10.17)	56389 (4.28)	63929 (4.85)
2002	21,383	18,410	176066 (9.56)	82096 (4.46)	98364 (5.34)
2003	27,107	22,941	229762 (10.02)	127959 (5.58)	125753 (5.48)
2004	37,646	31,583	322921 (10.22)	207112 (6.56)	161901 (5.13)
2005	40,024	33,552	311839 (9.29)	265860 (7.92)	166894 (4.97)
2006	46,400				
Average	31,415	23,935	9.85	5.76	5.15

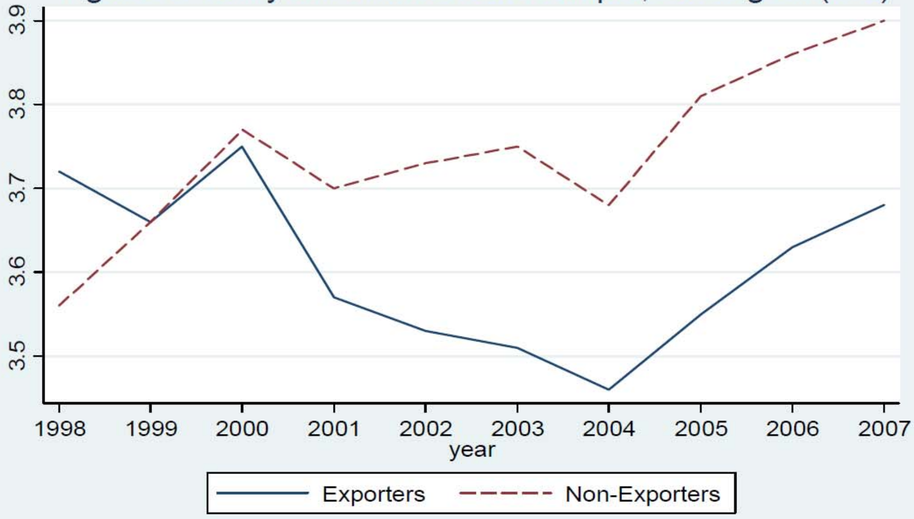
Source: Transaction-level trade data from China Customs (2000-2006)
Notes: A product is defined as a HS 6-digit category. There are over 5000 HS-6 categories.

Table 11. Capital Intensity of New Products and Dropped Products of Exporters that Started Exporting in 2001

	Dependent Variable: ln(K/L)		
	All New Exporters	Ordinary Trade New Exporters only	Processing Trade New Exporters only
New Product Portfolio Dummy	-0.049	-0.050	-0.048
	[0.000]***	[0.000]***	[0.000]***
Dropped Product Portfolio Dummy	0.021	0.024	0.013
	[0.000]***	[0.000]***	[0.005]***
Year Fixed Effects	Yes	Yes	Yes
N	343,062	257,295	85,767

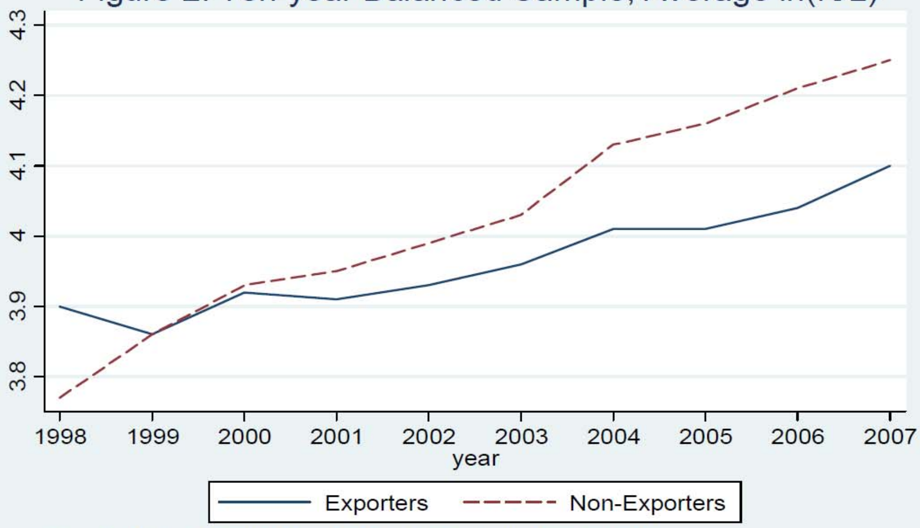
Notes: This table reports the results of regressions of capital intensity on the new product portfolio dummy and the dropped product portfolio dummy. The omitted group is the continuing product portfolio. P-values, based on robust standard errors, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Ten-year Unbalanced Sample, Average ln(K/L)



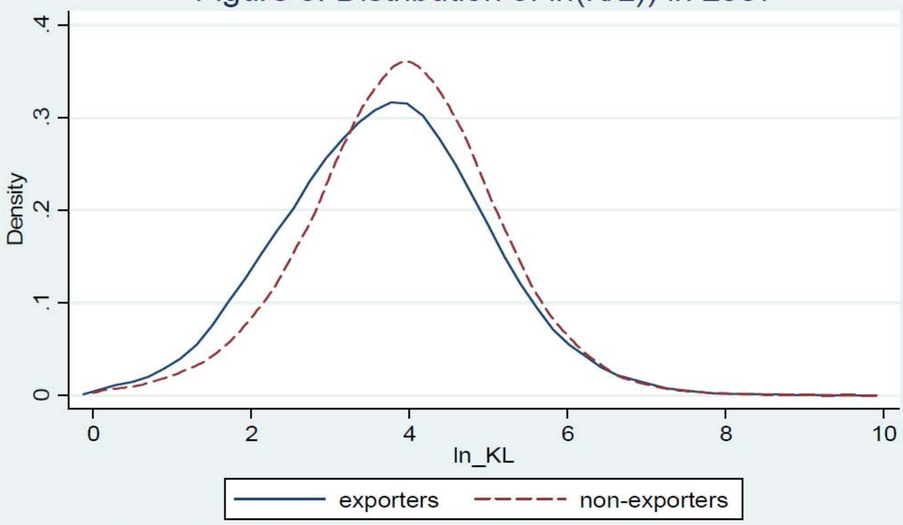
Average ln(K/L) is calculated using China's NBS Industrial Survey Data

Figure 2: Ten-year Balanced Sample, Average ln(K/L)



Average ln(K/L) is calculated using China's NBS Industrial Survey Data

Figure 3: Distribution of ln(K/L)) in 2007



ln(K/L) are measured relative to the ownership and industry (4-digit) means