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Factor Intensity, product switching, and productivity: Evidence from Chinese exporters[☆]

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ABSTRACT

This paper analyzes how a firm's specialization in its core products after exporting affects its factor intensity and productivity. Using Chinese manufacturing firm data for the 1998–2007 period, we find that firms become less capital-intensive but more productive after exporting, compared to non-exporters that share similar ex ante characteristics. To rationalize these findings that contrast with existing studies, we develop a variant of the model by Bernard, Redding, and Schott (2010, 2011) to consider firms producing multiple products with varying capital intensity. The model predicts that when a firm in a labor-abundant country starts exporting, it specializes in its core competencies by allocating more resources to produce more labor-intensive products. Firm ex ante productivity is associated with a smaller decline in capital intensity after exporting. A sharper post-export decline in capital intensity is associated with a larger increase in measured total factor productivity. We find firm-level evidence supporting these predictions. Using transaction-level data for the 2000–2006 period, we show that Chinese new exporters add products that are less capital-intensive than their existing products and drop those that are more capital-intensive in subsequent years.

1. Introduction

A rich body of research documents the superior performance of exporters compared to non-exporters. Exporters are larger, more productive, more capital-intensive, and more skill-intensive (e.g., Bernard and Jensen, 1999). Existing explanations for exporters' superior performance can be categorized into three broad themes: self-selection (e.g., Clerides et al., 1998; Bernard et al., 2003; Melitz, 2003), learning by exporting (e.g., Aw et al., 2000; Van Biesebroeck, 2005; De Loecker, 2007), and firms' investment in preparation for export (e.g., Bernard and Jensen, 1997; Yeaple, 2005; Lileeva and Trefler, 2010; Bustos, 2011; Aw et al., 2011; Iacovone and Javorcik, 2012).

This paper studies a lesser known effect of exporting on firm performance: how a firm's specialization in its core products after exporting affects its factor intensity and thus productivity. Using a large panel data set of China's manufacturing firms for the 1998–2007 period, we find that firms' measured productivity increases but capital intensity declines after exporting. Figs. 1 (unbalanced panel) and 2 (balanced panel) show that, although the average firm capital intensity increased for both exporters and non-exporters from 1998 to 2007 in China, exporters were persistently less capital-intensive than non-exporters and there was no sign of convergence before 2007. We confirm that exporters have a relatively lower capital intensity than non-exporters, both within firms and within a narrowly defined industry, and for both domestic and foreign firms. To tackle the potential estimation bias due to firms' selection into exporting, we use various matching methods to compare exporters and non-exporters with similar ex ante characteristics (i.e., Heckman et al., 1997 and subsequent studies).[1] Within the same bins of ex ante productivity, capital intensity and sales, we find that new exporters experienced a significant decline in capital intensity relative to non-exporters. Moreover, we show that the *relative* decline in capital intensity after exporting is smaller for the ex ante more productive exporters, but is larger for the ex ante more capital-intensive ones.

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[1] In this paper, we address endogeneity issues by using the matching estimation techniques only. We do not have well-defined instrumental variables, such as tariff cuts as in Lileeva and Trefler (2010).

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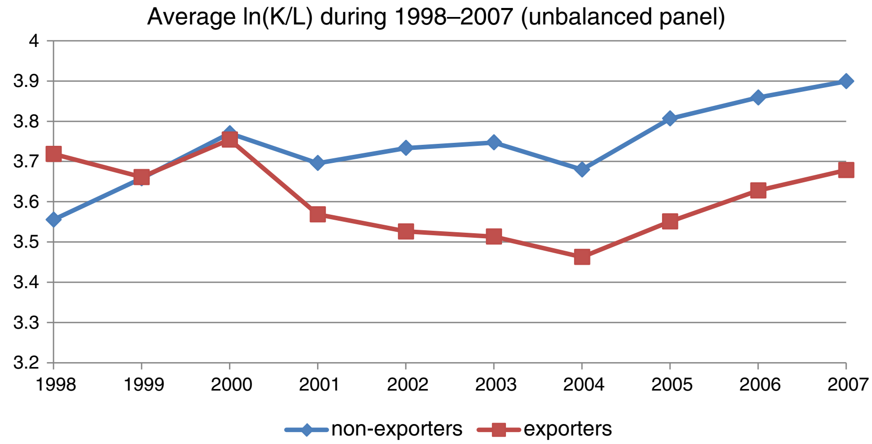

Fig. 1. Note: the unbalanced panel includes all firms in our sample.
Source: China's NBS above-scale manufacturing firm data.

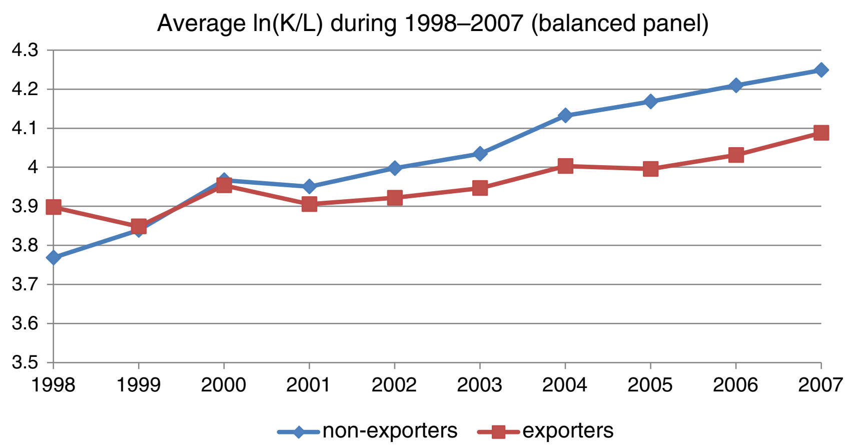

Fig. 2. Note: the balanced panel includes only those firms that appear every year in our sample. The balanced sample covers 7.6% of all firms in our sample.
Source: China's NBS above-scale manufacturing firm data.

Our findings regarding the relatively lower capital intensity among exporters contrast sharply with the existing evidence from both developed and developing countries (e.g., Bernard and Wagner, 1997; Bernard and Jensen, 2004; Van Biesebroeck, 2005; De Loecker, 2007). However, our results provide "mirror image" evidence supporting Bernard et al. (2006), who find that U.S. manufacturing firms in sectors facing more import competition from low-wage countries are more likely to switch industries and become more skill and capital-intensive over time. During our sample period, we find that Chinese firms exploited the country's comparative advantage and used less capital in production when they became exporters. These findings show that the classic Heckscher–Ohlin forces are operating at the firm level, serving as another channel through which trade can affect the factor markets in both developing countries and their trade partners.[2]

What accounts for the decline in firms' capital intensity after exporting and the heterogeneous outcomes across firms? To answer this question, we develop a variant of the multi-product model by Bernard et al. (2010, 2011) to consider both capital and labor as factors of production. In the model, heterogeneous firms can produce a continuum of products with different capital intensities of production. Besides firm heterogeneity in productivity ("ability") as in Melitz (2003), a firm's profitability from selling a product in a foreign market depends on a set of exogenous firm-product "consumer taste" attributes. In addition to the country-specific fixed export cost, exporting an additional product entails extra fixed costs (e.g., R&D expenditure to produce a blue print or overhead cost to manage a product-specific sales team). Thus, a firm will export a product only if its product attributes guarantee sufficiently high revenue to cover these extra fixed costs. Given China's labor abundance, labor-intensive products are on average associated with lower zero-profit thresholds than capital-intensive products for all firms. When a firm receives a favorable cost shock and starts exporting to a capital-abundant country, it will specialize in its core competencies — its labor-intensive products. Thus, a firm becomes more labor-intensive after exporting either by expanding sales of existing labor-intensive products (the intensive margin) or by adding more labor-intensive products (the extensive margin).

Although our model focuses on product churning as a driver of the observed change in firm factor intensity, this is not the only channel through which exporting has an effect. Firms may still invest in new capital or capital-intensive activities, as shown by some existing studies (e.g., Aw et al., 2011; Bustos, 2011). It should be noted that our empirical results show the net effect of exporting on capital intensity, implying that in China the standard investment effects proposed in the literature

[2] Although Bernard et al. (2007b) also embed a Heckscher–Ohlin framework within the Melitz (2003) model, firms in their model only differ in terms of productivity but not factor intensity within an industry.

could be dominated by product-churning effects. Importantly, our model is general enough to be extended to incorporate the investment decisions considered by existing studies for an examination of the gross effects of product churning through different channels.

Our model yields two predictions in addition to rationalizing the findings on exporters' lower capital intensity. Firstly, it shows how changes in product scope can affect a firm's measured total-factor productivity (*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*. Given fixed export costs and firm productivity, an increase in the sales of labor-intensive products implies a larger extent of increasing returns relative to capital-intensive products. Secondly, our model also predicts that the ex ante more productive exporters experience less product churning and have a smaller decline in capital intensity after exporting. We find supporting evidence for both theoretical predictions using firm-level data. Although recent studies on multi-product firms have made similar predictions, to the best of our knowledge there is little direct evidence of the effect of trade through the proposed product churning channel on firm productivity.[3] Our findings provide a new angle for interpreting the relationship between exporting and firm productivity, both ex ante and ex post, in addition to the existing empirical studies that focus mainly on learning by exporting or selection.

To provide further evidence of product churning's effect on firm's factor intensity after exporting, we use transaction-level trade data merged with manufacturing firm data. We compute the weighted average capital intensity of a product (HS 6-digit), using the capital intensity of the firms producing that product. Employing these product-level capital intensity measures, we investigate whether firms' product churning patterns are consistent with the model prediction that firms specialize in labor-intensive products after exporting. We find that over the 2000–2006 period, new exporters in China added products that are less capital-intensive than their existing products and dropped those that are more capital-intensive in the year following the first year of exporting. The newly added products were on average more labor-intensive if the destination country was more capital-abundant.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data source. Section 4 explores the basic patterns of export participation, capital intensity, and productivity. Section 5 examines the effect of exporting on new exporters' 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

Our paper relates to several strands of the literature. First, it contributes to the growing theoretical literature on multi-product exporters. A common feature of this literature is that diversification across products is costly and that access to foreign markets provides an opportunity for firms to specialize in their core competencies. 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 increases in product scope due to managers' limited span of control as in Lucas (1978). Eckel and Neary (2010) develop a model featuring each firm having a core product that is associated with the lowest marginal cost, with increasing marginal costs for products farther away from the core. Bernard et al. (2011) show that trade liberalization can theoretically 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 consumers and add those that are more appealing upon trade liberalization, raising measured firm productivity. The related empirical literature is also growing. Using U.S. publicly listed firms data, Liu (2010) shows that firms are more likely to drop peripheral products to refocus on core competencies in response to trade liberalization. Arkolakis and Muendler (2011) document the within-firm pattern of specialization in core competencies for Brazilian firms. They rationalize their findings using a multi-product model that features local entry costs that increase in the firms' product scope. Mayer et al. (2012) go further to show the relationship between destination market toughness and exporters' product mix. They show theoretically and empirically that firms increase sales of the best-performing products in tougher markets.

We provide evidence for the positive relationship between product churning and measured firm productivity, by using the change in capital intensity after exporting to capture the degree of specialization. Moreover, we extend the existing multi-product framework, which largely focuses on a single factor of production, to consider both capital and labor as inputs. We empirically verify that specialization in core competencies (labor-intensive products for exporters in developing countries) is associated with a higher measured firm productivity.[4]

Second, as mentioned in the introduction, our paper is related to the existing studies that consistently find exporters to be more capital- or skill-intensive (e.g., Bernard and Wagner, 1997; Bernard and Jensen, 2004; Van Biesebroeck, 2005; De Loecker, 2007). Although most of these studies are silent about the specific channels through which exporting affects firms' factor intensity, the conventional wisdom in the literature is that only the most productive firms select into exporting and that firms invest to upgrade their product quality or production technology before exporting. To the extent that firms' capability is positively correlated with skill or capital intensity (e.g., Yeaple, 2005; Harrigan and Reshef, 2012) or investments are skill and capital-biased (e.g., Verhogeen, 2008), the literature concerning the productivity premium of exporters can readily be used to explain higher capital and skill intensity of exporters. Our findings of lower capital intensity among Chinese exporters should not be taken as a rejection to the investment hypothesis. Instead, our findings imply that product churning appears to dominate the investment and selection mechanisms in China, which leads to a net decline in capital intensity among exporters.

Third, our paper contributes to the extensive literature on the productivity effects of exporting. Previous studies hypothesize that exporters can learn from foreign buyers about product designs and advanced production technology (World Bank, 1993; De Loecker, 2007). Firm-level empirical studies find mixed results for this learning-by-exporting hypothesis (e.g., Clerides et al., 1998; Bernard and Jensen, 1999; Van Biesebroeck, 2005; De Loecker, 2007).[5] Specific to China, Kraay (1999) finds that exporters are more productive than non-exporters based on survey data of over 2000 firms. Park et al. (2010) use exposure to the 1997 Asian financial crisis as an instrument and find that Chinese firms that export to developed countries experience

[3] For example, Bernard et al. (2010) and Mayer et al. (2012) theoretically show that a firm's specialization in core competencies can enhance its measured firm productivity. They provide consistent but not direct evidence for the model predictions.

[4] In the appendix of Bernard et al. (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. Our paper extends their model by explicitly solving for how relative factor endowment of the exporting country can serve as a source of within-firm comparative advantage.

[5] Clerides et al. (1998) and Bernard and Jensen (1999) are among the first studies to empirically distinguish the causal effect of exporting on productivity and self-selection into exporting. They find that exporters have higher productivity than non-exporters before exporting but not after. Other studies find more positive results. 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.

higher productivity. Notably, our work is related to Lu (2012), who also incorporates factor intensity in a heterogeneous-firm trade model. While she focuses on export participation across sectors with different capital intensity, we focus on within-firm product churning and its effects on firm performance. She finds that exporters have lower labor productivity than non-exporters due to the lower productivity cutoff for exporting in labor-intensive sectors, whereas we find that exporters have higher measured *TFP*. The findings that exporters are less capital-intensive in China can reconcile the drastic difference between our results.

Recent studies focus on firms' decisions to simultaneously invest and export. For instance, 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. They show that access to foreign markets enhances labor productivity and technology adoption for less productive firms. Bustos (2011) finds that Argentinian firms that experience sharper tariff cuts in Brazil increase investment in process innovation. Aw et al. (2011) structurally estimate a dynamic model to examine the complementary effects of exporting, investment in technology, and firm productivity. In comparison, Kasahara and Lapham (2013) structurally estimate a dynamic model to examine the complementary effects of exporting, importing, and firm productivity. Instead of focusing on these relationships, we focus on product churning.

3. Data

We use two data sets for the empirical analysis: the above-scale manufacturing firm panel data from China's National Bureau of Statistics (NBS) surveys and customs transactions-level trade data. The manufacturing firm data cover all state-owned firms and all non-state-owned firms with sales above 5 million yuan over the 1998–2007 period (about 0.6 million USD during the sample period).[6] This data set contains detailed balance-sheet information, such as ownership, output, value added, four-digit industry code (484 categories), exports, employment, original value of fixed asset, and intermediate inputs. The firms in the sample account for 57% of the total industrial value added in 1998 and 94% of that in 2007.[7] We exclude observations with missing values for key variables and those that fail to satisfy some basic error checks.[8] 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 a restructuring, merger, or acquisition. Where possible, we aim to track firms as their boundaries or ownership structures change, linking firms with information such as a firm's name, industry, and address.[9] These 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 latter part of the paper, we use transactions-level trade data from China Customs that cover all transactions of Chinese exporters and importers from 2000 to 2006. The trade data provide 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, and customs regime (ordinary trade and processing trade).[10] As an example, Appendix Table A7 shows the HS 6-digit products within the industry of "footwear, gaiters, and the like" (HS2 = "64"). The purpose of using the transaction-level trade data set is to study within-firm product churning after a firm starts exporting. We merge the manufacturing firm data with the transaction-level trade data based on firm names and their contact information.[11] Table A6 in the Appendix reports statistics of the merged data set. Using the merged data, we can identify new exporters in the trade data set and construct capital intensity measures at the product level (HS6).[12] See Appendix A.3 for details.

A firm's capital intensity is defined as the real value of the capital stock per worker. It is crucial to measure both firm capital and labor accurately. 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, while NVFS is OVFS less accumulated depreciation. Thus, OVFS and NVFS are nominal values from different years and cannot be used directly as measures of capital stock. To construct firm capital stock series correctly, we adopt the perpetual inventory method proposed by Brandt et al. (2012). Specifically, we first estimate the firm's initial capital stock using information from its founding year. Then we use the firm's annual investment and assumed depreciation rates to calculate its real capital stock in each year. Appendix A.1 provides the detailed procedure for this approach.[13] To test the robustness of our results, we also use the NVFS deflated by the industry-specific investment price index as an alternative measure of real capital stock. The investment price indices are taken from various issues of *China Statistical Yearbook*. From the same source, we also obtain the consumer price index to calculate average real wages at the firm level.[14]

As an attempt to adjust for the quality of workers employed by a firm, we use a firm's total wage bill instead of its employment to compute an alternative measure of labor. The problem with this approach is that it is likely to underestimate the total employee compensation, which should also include employee supplementary benefits (Qian and Zhu, 2012).[15] The magnitude of the underestimation may vary across ownership types, regions, and years. Therefore, we use employment as our primary measure for labor and only use total wage bill for a robustness check.

A firm's real output and value added are deflated by a sector-specific ex-factory price index.[16] We use these firm variables to estimate revenue-based *TFP*. To deal with the estimation biases arising from endogenous input choices, we adopt the Levinsohn and Petrin (2003) procedure that uses intermediate inputs as a proxy for unobservable productivity shocks.[17] For reasons that will become clear below, exporters and non-exporters can have a different factor intensity of production within a disaggregated sector. We thus assume different sector-specific production functions for exporters and non-exporters when estimating

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

[7] We focus on manufacturing and exclude mining and utility industries.

[8] Some firms have missing observations for variables required 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 eight employees as they fall under a different legal regime. As a result, 17% of firms in the original data set are dropped from the sample in 1998. The percentage excluded drops to 6% in each year after 2001.

[9] 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.

[10] The data also include information on quantity, units of quantity, customs offices (ports) where the transactions were processed, and transportation modes.

[11] As shown in Section 8, depending on the year, 37 to 49% of the export value in the trade data set is successfully merged to the NBS firm data set.

[12] To the best of our knowledge, Bernard et al. (2010) are the only group of researchers who did the similar data construction before. They 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.

[13] The correlation between the two capital stock measures is as high as 0.95.

[14] The price indices are from China Statistical Yearbook, various issues.

[15] In our data, labor's share of value added is only 34%, which is much lower than the 55 to 60% suggested by national income accounting. Hsieh and Klenow (2009) also experience the same problem with the same data set. They assume that non-wage benefits are a constant fraction of a plant's wage bill and select an adjustment factor so that the wage plus non-wage compensation equals half of China's aggregate value added.

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

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

firm *TFP*.[18] Pairwise correlations of the key firm variables are shown in Table A1 in the Appendix.

In this paper, a non-exporter is a firm that had never exported up to and including the reporting year. New exporters are firms that did not export in the previous years in the sample but started exporting in the year of analysis. Their pre-export characteristics can therefore be matched with those of the non-exporting firms. Existing exporters are firms that have export records in previous years and firms that start exporting already in their first year of the sample. This group of firms is dropped in our matching exercises because there are no pre-export characteristics for these firms. However, they are included in the sample for the fixed effects regressions below.

4. Basic patterns

Table A2 in the Appendix reports the key statistics of new exporters, continuing exporters, and non-exporters for the odd years in our sample. For each group of firms, we further separate the sample into domestic and foreign firms. The fraction of domestic exporters (continuing or new exporters) fluctuates between 16% and 24%. This is similar to the U.S., where roughly 20% of plants exported in 1992 (Bernard et al., 2003). Similar to U.S. firms, in China, over 80% of domestic new exporters also sell domestically, and about half of them derive less than 10% of the revenue from foreign sales. Compared to domestic firms, exporters are significantly more prevalent among foreign firms. Between 63% (in 1999) and 72% (in 2004) of foreign firms export.

To compare capital intensity and productivity between exporters (new and continuing exporters included) and non-exporters, we estimate the following specification:

$$\ln\ S_i = \beta E_i + \{FE\} + \varepsilon_i \tag{1}$$

where S_i is firm i's *TFP* or capital intensity. E_i is a dummy variable indicating the firm's export status. $\{FE\}$ stands for a set of fixed effects, and ε_i is the error term. The percentage differential in S_i between exporters and non-exporting firms can be calculated from the estimated coefficient as $100 \times (\exp(\beta) - 1)$.

In Table 1, Panels A–C report the estimates of Eq. (1) with (log) capital intensity as the dependent variable. In Panel A, real capital stock is measured using the perpetual inventory method and labor is approximated by firm total employment. Column (1) includes E_i and year fixed effects. Column (2) also includes ownership, 4-digit industry, and province fixed effects. To ensure that the change seen is not driven by unobserved firm characteristics, in column (3) we include firm fixed effects (along with year fixed effects). By including firm fixed effects, the correlation between the export status and capital intensity is identified only from firms that switch export status. We find that exporters are on average less capital-intensive than non-exporters. Specifically, in a given year, exporters are about 6% less capital-intensive than non-exporters within a four-digit industry and ownership type (column (2)), and about 5% less capital-intensive within firms (column (3)).

In columns (4) and (5), when we repeat the same analysis for column (3) on domestic and foreign firm samples respectively, we continue to find a negative coefficient on the exporter dummy. It should be noted that the capital intensity gap between exporters and non-exporters is more than double for domestic firms than for foreign firms. By splitting the sample into the pre-WTO period (1999–2001) and the post-WTO period (2002–2007), columns (6) and (7) show that the capital intensity gap increased after China's accession to the WTO, consistent with Figs. 1 and 2. These results contrast sharply with existing studies, which consistently find that exporters are more capital-intensive (e.g., Bernard and Wagner (1997) for Germany, Bernard and Jensen (2004) for the U.S., Van Biesebroeck (2005) for Sub-Saharan Africa, and De Loecker (2007) for Slovenia).

As a robustness check, we repeat the same set of regressions using alternative measures of firm capital intensity. In Panel B, we measure a firm's real capital stock by the net value of fixed assets deflated by the industry-specific investment price index, whereas in Panel C, it is measured using a firm's total wage bill instead of employment as the denominator. Regardless of how capital intensity is measured, exporters still appear to be less capital-intensive than non-exporters. The estimated capital intensity gap is larger in Panel C. Recent studies show that exporters are larger and tend to employ more skilled workers than non-exporters. This may explain why exporters' capital intensity is even lower when it is calculated using effective labor units.[19] To conserve space, we focus on the results using capital intensity measured by the perpetual inventory method. Using the wage-denominated capital intensity measure yields similar results.

Panel D reports estimates of Eq. (1) with ln(*TFP*) as the dependent variable. We find that on average, exporters have higher measured revenue-based *TFP* than non-exporters. This is observed within industries, within a firm, and before and after China's WTO accession, for both domestic and foreign firms. The result that exporters have a higher *TFP* is consistent with most findings in the existing literature.

We now address potential confounding factors in the data. The prevalence of processing exporters in China, who assemble imported intermediates into final products solely for foreign sales, must be considered. According to Kee and Tang (2012), consistently over half of Chinese aggregate exports belongs to processing trade. It is well known that processing exporters in China have lower value added and capital intensity than ordinary (non-processing) exporters. To verify that our results are not driven by the prevalence of processing firms, we repeat the analysis in Table 1 on processing and non-processing exporters. We identify processing and non-processing exporters from the subsample that can be merged with China Customs trade data (see Section 8 for more details on the merged data set). The estimation results are reported in Table A3 in the Appendix. In column (1), only processing exporters are included in the sample and all non-processing exporters are excluded. We still find a strongly negative correlation between export participation and capital intensity within a narrowly defined industry. When only non-processing exporters are considered (column (2)), the negative correlation is even stronger. These results confirm that our main findings are not driven by the prevalence of labor-intensive processing exporters. The lower panel of the table reports the results for firm *TFP* for processing and non-processing firms. We find that processing exporters are on average less productive than non-exporters, whereas non-processing exporters are more productive. These results confirm previous findings by Dai et al. (2011) and Manova and Yu (2012).

The potentially frequent changes in the export status may affect the results. To partially address this concern, we include three dummies related to export activities in Table A4 in the Appendix: new exporters (a dummy equals 1 for the first year of exporting), continuing exporters (a dummy equals 1 if the firm was exporting in the current year and the previous year), and export stoppers (a dummy equals 1 if the firm exported last year but not this year). We find that new, continuing, and previous exporters are all less capital-intensive (Panel A) and more productive (Panel B) than non-exporters.

The different export intensities of exporters may also affect our results. By using only one dummy variable to capture the export status, we are assuming the same average effects of exporting, regardless of how much the firm exports. In Table A5 in the Appendix, we break down the exporter dummy in Eq. (1) into three dummies to represent

[18] In an earlier version of this 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. The results obtained were qualitatively similar.

[19] Harrigan et al. (2012) show that in the US, skill-intensive exporters charge higher prices whereas capital-intensive exporters charge lower prices. This is another example of capital and skill intensity playing different roles in shaping export patterns.

Table 1
Comparing productivity and capital intensity between exporters and non-exporters.

	(1) All firms	(2) All firms	(3) All firms	(4) Domestic firms	(5) Foreign firms	(6) Before WTO	(7) After WTO
Panel A: dependent variable ln(K/L)							
Exporter	−0.192	−0.062	−0.055	−0.069	−0.033	−0.028	−0.067
	(0.031)***	(0.017)***	(0.008)***	(0.012)***	(0.009)***	(0.008)***	(0.009)***
N	1,977,348	1,977,348	1,977,348	1,563,451	413,897	573,694	1,403,654
Panel B: dependent variable ln(K/L), alternative measure of K							
Exporter	−0.175	−0.029	−0.028	−0.032	−0.022	−0.019	−0.035
	(0.032)***	(0.005)***	(0.007)***	(0.008)***	(0.008)***	(0.009)**	(0.010)***
N	1,979,823	1,979,823	1,979,823	1,564,570	415,253	573,694	1,403,654
Panel C: dependent variable ln(K/L), alternative measure of L							
Exporter	−0.311	−0.143	−0.116	−0.128	−0.098	−0.076	−0.135
	(0.043)***	(0.026)***	(0.021)***	(0.023)***	(0.025)***	(0.024)***	(0.023)***
N	1,976,637	1,976,637	1,976,637	1,562,599	414,038	568,121	1,431,480
Panel D: dependent variable ln(TFP)							
Exporter	0.137	0.087	0.124	0.154	0.034	0.144	0.112
	(0.039)***	(0.022)***	(0.035)***	(0.055)***	(0.017)**	(0.039)***	(0.032)***
N	1,916,347	1,916,347	1,916,347	1,503,658	412,689	543,921	1,372,426
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry (4-digit) FE	No	Yes	No	No	No	No	No
Ownership FE	No	Yes	No	No	No	No	No
Firm FE	No	No	Yes	Yes	Yes	Yes	Yes

Notes: this table reports estimation results for Eq. (1) in the text. The exporter dummy equals 1 if a firm is either a new exporter or a continuing exporter. In Panel A, real capital stock (K) is measured using the perpetual inventory method, while labor is the firm's total employment. In Panel B, capital stock is the net value of fixed assets deflated by the sector-specific investment deflator, while labor is the firm's total employment. In Panel C, capital stock is measured using the perpetual inventory method, while labor is the firm's total wage bill. In Panel D, ln(*TFP*) is measured using the Levinsohn and Petrin (2003) method. Columns (1)–(3) compare exporters and non-exporters using all firms in the sample; column (4) includes only domestic firms; column (5) includes only foreign firms; columns (6) and (7) split the sample into pre-WTO and post-WTO periods. Standard errors in parentheses are corrected for clustering at the four-digit industry level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

high intensity exporters (firms with the export/sales ratio larger than 0.9), normal exporters (firms with the export/sales ratio between 0.1 and 0.9), and low intensity exporters (firms with the export/sales ratio smaller than 0.1). Panel A shows significant correlations between each exporter dummy and firm capital intensity. More importantly, the magnitude of the coefficients suggests that a higher export intensity is associated with a lower capital intensity. In Panel B, we find that high intensity exporters are less productive than non-exporters. This is not surprising given that most of the intensive exporters are processing exporters.

5. Changes in capital intensity for new exporters

Table 1 and the corresponding Tables A3 to A5 in the Appendix show the average effects of exporting on capital intensity and *TFP*. In this section, we compare the first difference in capital intensity between non-exporters and new exporters that are ex-ante similar. Existing exporters, who reported positive exports in previous years, are always excluded from this analysis. As a first pass, we follow Lileeva and Trefler (2010) to compare firms within a quartile bin (4 on each dimension) based on firm *TFP* and capital intensity in the previous year. Within each two-digit industry, we assign each firm to one of the 16 bins based on its ex ante *TFP* and capital intensity quartiles. This controls for industry structure and ensures that each bin includes firms from all industries.

In Panel A of Table 2, each cell reports the difference between new exporters and non-exporters in their average capital intensity growth, $\Delta\ln(K/L)_{new\ exporter} - \Delta\ln(K/L)_{non\text{-}exporter}$. The first column shows that new exporters in the lowest quartile of *TFP* experience an average 0.047 log-point decline (average across all four entries in the column) in capital intensity after exporting compared to non-exporters within the same *TFP* quartile. The difference is significant at the 1% level. When we move to higher *TFP* quartiles (moving to the right in each row), we continue to find a post-export decline in capital intensity, but the decline is smaller the higher the *TFP* quartile is. For instance, the average drop in capital intensity (relative to non-exporters) is only 0.028 log points in the highest *TFP* quartile. We will empirically confirm and theoretically explain this negative relationship between firms' ex ante *TFP* and post-export drop in ln (K/L) below.

Table 2
Capital intensity growth: new exporters less non-exporters.
$\Delta\ln(K/L)_{new\ exporter} - \Delta\ln(K/L)_{non\text{-}exporter}$

Panel A		ln(*TFP*) quartiles before exporting			
		1	2	3	4
ln(K/L) quartiles before exporting	1	−0.033***	−0.031***	−0.018**	−0.002*
	2	−0.045***	−0.039***	−0.026***	−0.019**
	3	−0.051***	−0.043***	−0.038***	−0.039***
	4	−0.063***	−0.061***	−0.055***	−0.051***
Panel B		Low TFP		High TFP	
		Small firms	Large firms	Small firms	Large firms
ln(K/L) before exporting	Low	−0.035*** (bin 1)	−0.039*** (bin 2)	−0.011** (bin 3)	−0.021** (bin 4)
	High	−0.056*** (bin 5)	−0.053*** (bin 6)	−0.049*** (bin 7)	−0.043*** (bin 8)

Notes: This table reports the difference in capital intensity growth between new exporters and non-exporters in each bin. All firms are sorted according to their characteristics in the previous year. In Panel A, bins are defined by previous-year ln(*TFP*) and ln(K/L) quartiles. In Panel B, bins are defined by previous-year ln(*TFP*), ln(K/L) and ln(sales) median. We calculate these bins for each year and each 2-digit industry to ensure each bin covers all years and all industries.
* Indicates significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

Table 3
New exporters' capital intensity ln(*K*/*L*)-propensity score matching results.

Bin	TFP	Capital intensity	Size	(1) All firms	(2) Domestic firms	(3) Foreign firms	(4) Alternative *K*	(5) Alternative *L*
All bins				−0.051***	−0.054***	−0.042***	−0.027**	−0.069***
1	Low	Low	Small	−0.046***	−0.049***	−0.036***	−0.028***	−0.035***
2	Low	Low	Large	−0.048***	−0.048***	−0.037***	−0.024*	−0.046***
3	High	Low	Small	−0.029**	−0.031**	−0.029	0.001	−0.024***
4	High	Low	Large	−0.032**	−0.041**	−0.027	−0.009	−0.032***
5	Low	High	Small	−0.064***	−0.067***	−0.061***	−0.044**	−0.102***
6	Low	High	Large	−0.061***	−0.066***	−0.053***	−0.029*	−0.113***
7	High	High	Small	−0.063***	−0.068***	−0.051***	−0.043***	−0.096***
8	High	High	Large	−0.059***	−0.062***	−0.61***	−0.039***	−0.103***

Notes: This table reports the estimation results of the impact of exporting on ln(K/L) for new exporters, using the propensity score matching method. The matching is conducted within each bin. These bins (bin 1 to bin 8) are described in Panel B of Table 2. Column (1) includes all firms in the sample; column (2) includes only domestic firms; column (3) includes only foreign firms; column (4) measures capital stock as the net value of fixed assets deflated by the sector-specific investment deflator, while column (5) uses the firm's total wage bill to compute its capital intensity.

* Indicates significance at the 10% level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

The first row in Panel A shows that among the firms in the lowest quartile of ln (*K*/*L*), the average drop in capital intensity after exporting is 0.021 log-points (average across all four entries in the first row) compared to the non-exporters in the same quartile. When we move down across rows, we find that the relative post-export decline in capital intensity is larger for firms with higher ex ante ln (*K*/*L*). The magnitude of the decline increases to an average of 0.058 log points in the highest ln (*K*/*L*) quartile.

Firm size could be an important factor determining whether firms export, as larger firms are more likely to afford the fixed export costs. Following Lileeva and Trefler (2010), when we construct the bins, we add firm size (measured by ln (sales)) as the third dimension. We assign each firm into one of the eight bins based on its position in *TFP*, capital intensity, and size in its industry.[20] Panel B shows no obvious difference in the relative decline in capital intensity between small and large firms. However, the differences between the high and low *TFP* groups and the difference between the high and low capital intensity groups are still obvious.

In addition to assigning firms into different bins to compare firms with similar characteristics, we apply the difference-in-difference propensity-score matching estimator (Heckman et al., 1997) to match firms with ex ante similar characteristics. We estimate the propensity score of each firm based on a Probit model with the dependent variable equal to 1 if a firm starts reporting positive exports in the current year. We include a number of pre-export (previous-year) firm characteristics as regressors, namely *TFP*, wage rate, capital intensity, firm age, firm sales (all in log), 4-digit industry, ownership, and year fixed effects. To minimize the bias due to potentially omitting unobserved characteristics that may affect a firm's decision to export, we do our matching within each of the eight bins as defined in Panel B of Table 2, under the assumption that firms within the same bin are not too different in terms of unobserved characteristics. We use nearest-neighbor matching without replacement.[21] In total, from all eight bins, 50,856 new exporters were matched to non-exporters in the control group.

Table 3 presents the estimation results of the post-export change in capital intensity using propensity-score matching techniques. In column (1), we find a significant decline in a firm's capital intensity in the year when it starts exporting, compared to non-exporters. This capital intensity gap is observed for all eight combinations of productivity and capital-intensity bins considered in Panel B of Table 2. The gap is larger if the new exporter is ex ante more capital-intensive (bins 5 to 8), consistent with the results in Table 2. In columns (2)–(3), we split the sample into domestic firms and foreign firms for our analysis. We find the same pattern for both types of firms, with a larger drop in capital intensity observed in the domestic firm sample. In column (4), we measure capital stock as the net value of fixed assets deflated by the industry-specific investment price index. The results remain largely robust besides bins 3 and 4. In the last column, we find a larger post-export decline in capital intensity when the wage-denominated measure of capital intensity is used, similar to the findings in Table 1.

To summarize, we have found robust evidence that a Chinese firm becomes less capital-intensive after exporting. We have used various methods – regressions including an exhaustive set of fixed effects, comparisons within bins, and matching within bins – to ensure the robustness of our results. Our findings contrast with the exiting literature that consistently shows higher skill and capital intensity for exporters. Importantly, Tables 2 and 3 show heterogeneous effects on capital intensity across new exporters. The following theoretical section and additional empirical analysis in Sections 7 and 8 will examine these heterogeneous effects.

Given China's comparative advantage in labor-intensive goods, it may not be surprising that exporters in China are less capital-intensive than non-exporters. However, when the pattern is found for both domestic firms and foreign firms within narrowly defined industries and within firms, the standard factor-proportions theory of trade that emphasizes between-sector reallocation of resources cannot provide sufficient explanations. We thus develop a theoretical model to rationalize the findings. Guided by the model, we will further empirically explore the linkages between capital intensity and productivity, both before and after firms' exporting.

6. Theoretical explanation

To explain our empirical findings, we construct a variant of the model by Bernard et al. (2010, 2011) (BRS hereafter). We first briefly discuss the set-up of the BRS model before elaborating in greater detail our extension. Readers are referred to the original paper 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

[20] We no longer construct bins based on quartiles as we would need too many bins (64) for all three dimensions.

[21] Our results are robust to the use of other matching methods such as local linear regression matching estimator. We choose to do matching without replacement because we have a large number of firms in the control group.

horizontally differentiated varieties, facing their own demand. The consumption index for product s, C_s, takes the following form:

$$C_s = \left[\int_{\omega \in \Omega_s} (\lambda_s(\omega) c_s(\omega))^{\rho} d\omega \right]^{\frac{1}{\rho}}, 0<\rho<1, \tag{2}$$

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

Firms are exogenously different along two dimensions, namely firm-specific "ability" and firm-product-specific "consumer" appeals. More specifically, upon paying some fixed (sunk) costs to enter any market, a firm first draws its "ability", $\varphi \in [0, \infty)$, from a distribution $h(\varphi)$. φ is firm-specific and is constant across countries and products. The firm then draws a set of "consumer taste" attributes for each potential product produced, $\lambda_s \in [0, \infty)$, from a distribution $g(\lambda_s)$.[22] The set of λ_s is firm-product specific and is constant across countries.[23] To serve market j, either domestic or foreign, the firm has to pay an extra fixed cost f_j. In addition to f_j, a multi-product exporter needs to incur product-specific fixed costs, f_{sj}, for each product s sold in market j.[24] An exporter will export product s to market j when its λ_s is sufficiently high and generates enough revenue to cover f_{sj}. As in BRS, the more productive exporters have a wider product scope, all else equal, as higher φ generates positive profits for more low-λ_s products.

To rationalize our empirical findings that feature heterogeneous effects on 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:

$$TC_s = \left[f_s + \frac{q_s}{\varphi} \right] w^{1-\beta(s)} r^{\beta(s)}, \tag{3}$$

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. 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 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 (e.g., the U.S.), which is assumed to be more capital-abundant. 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 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 Appendix A.2 for details).[25]

Given that $P_j(s)$ varies across products, an exporter has a different export portfolio to country j compared to the domestic market, even when the set of product attributes (λ_s) is identical for different destinations.[26] Consider a firm with φ, the product attribute 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:

$$\pi_s(\varphi, \lambda_s^*(\varphi)) = \frac{R_s}{\sigma} \left(r^{-\beta(s)} \rho P(s) \varphi \lambda_s^*(\varphi) \right)^{\sigma-1} - f_s r^{\beta(s)} = 0, \tag{4}$$

where $\pi_s(\varphi, \lambda_s(\varphi))$ represents the firm's profit by selling product s domestically; R_s stands for domestic aggregate expenditure spent on product s. $P(s)$ is the ideal price index for product s.[27] Solving Eq. (4) yields the firm-product specific consumer taste cutoff $\lambda_s{}^*(\varphi)$. Similarly, we can use the zero-profit condition for export sales of product s to country j to solve for the corresponding product attribute cutoff, $\lambda_{sj}{}^*(\varphi)$.

Importantly, for product s, the firm's product cutoff for exporting to j equals

$$\lambda_{sj}^*(\varphi) = \Phi_j(s) \lambda_s^*(\varphi), \tag{5}$$

where $\Phi_j(s) = \tau_j \left(\frac{f_{sj}}{f_s} \frac{\hat{P}_j}{\hat{P}} \frac{R}{R_j} \right)^{\frac{1}{\sigma-1}} \left(\frac{P_j(s)}{P(s)} \right)^{-\gamma}$. $\Phi_j(s)$ is increasing in variable (τ_j) and fixed export costs (f_{sj}), as well as the relative aggregate price index of country j, $\frac{\hat{P}_j}{\hat{P}}$. $\Phi_j(s)$ is increasing in $\frac{\hat{P}_j}{\hat{P}}$ because a higher $\frac{\hat{P}_j}{\hat{P}}$ results in a lower purchasing power of foreign consumers relative to domestic consumers. For the same reason, $\Phi_j(s)$ is decreasing in the total spending of country j, R_j. If countries are symmetric (i.e., $\hat{P} = \hat{P}_j$, $R = R_j$, and $P_j(s) = P(s)$), $\Phi_j(s) = \tau_j \left(\frac{f_{sj}}{f_s} \right)^{\frac{1}{\sigma-1}}$ when international trade costs are higher than domestic trade costs (i.e., $f_{sj} \geq f_s$ and $\tau_j \geq 1$). Given a product attribute, λ_s, $\Phi_j(s) \geq 1$ implies a weakly lower probability of exporting product s, conditional on positive domestic sales. Deviating from the symmetry assumptions, Bernard, Redding, and Schott (2007a) and Lu (2012) postulate the possibility of having $\Phi_j(s) < 1$ and study the resulting implications.[28]

Suppose $\frac{f_{sj}}{f_s}$ and $\frac{R_j}{P_j}$ are invariant across j. If country j is more capital-abundant than China, $\frac{P_j(s)}{P(s)}$ is decreasing in s. Given the assumption that $\sigma > \kappa > 1$, $\frac{\partial \Phi_j(s)}{\partial_s} > 0$. In words, all else being equal, a product attribute that guarantees profitable domestic sales is less likely to generate profitable export sales to j, the higher the capital intensity of the product is.

Denote 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.[29] Capital intensity of a firm with productivity φ serving only the domestic market is

$$\Theta_d(\varphi) = \int_0^1 \theta_s \tilde{R}_s(\varphi, \lambda_s) I_s(\lambda_s \geq \lambda_s^*(\varphi)) ds = \int_0^1 \left[\int_{\lambda_s^*(\varphi)}^{\infty} \theta_s \tilde{R}_s(\varphi, \lambda_s) g(\lambda_s) d\lambda_s \right] ds,$$

[22] We could have modeled the firm-product specific draw as productivity, but it will not change any of the theoretical results. The reason is that with CES demand and monopolistic competition, firm-product productivity and firm-product demand shifter have exactly the same effects on firm revenue and profits in equilibrium, as is also argued by BRS.

[23] Due to the law of large number, as long as we assume that firms draw product-destination specific attribute, λ_{sj}, from the same distribution, our main theoretical results will continue to hold.

[24] Think of f_{sj} as R&D expenditure required to produce a blue print for the product or the overhead costs to manage the product-specific sales team.

[25] A similar point has been made by Lu (2012) who rationalizes why Chinese exporters are less productive than domestic producers in sufficiently labor-intensive sectors.

[26] 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 product attributes are independent of one another.

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

[28] In particular, Lu (2012) finds that in labor-intensive sectors, Chinese exporters are on average less productive than non-exporters. Based on an extension of Bernard et al. (2007b), 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.

[29] E.g. $rk_s = rk^p{}_s + rk^f{}_s$, where $k^p{}_s$ 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 subscript d denotes "domestic"; $I_s(\lambda_s \geq \lambda_s{}^*(\varphi))$ is an indicator function, which equals 1 if $\lambda_s \geq \lambda_s{}^*(\varphi)$. $\widetilde{R}_s(\varphi,\lambda_s) = \frac{R_s(\varphi,\lambda_s)}{R(\varphi)}$ is the ratio of the firm's domestic sales of product s to its total domestic sales. $g(\lambda_s)$ is the stationary distribution of consumer tastes, which is discussed in detail in BRS. The last equality holds because of the law of large number: the firm's capital intensity is equal to the *expected* weighted average across all products' capital intensity.

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

$$\Theta_j(\varphi) = \int_0^1 \theta_s \widetilde{R}_{sj}(\varphi,\lambda_s) I_s\left(\lambda_s \geq \Phi_j(s)\lambda_s^*(\varphi)\right) ds = \int_0^1 \left[\int_{\Phi_j(s)\lambda_s^*(\varphi)}^{\infty} \theta_s \widetilde{R}_{sj}(\varphi,\lambda_s) g(\lambda_s) d\lambda_s\right] ds,$$

where $\widetilde{R}_{sj}(\varphi,\lambda_s) = \frac{R_{sj}(\varphi,\lambda_s)}{R_j(\varphi)}$ is the ratio of the firm's product s sales in foreign market j to the its total sales there. We assume that θ_s is identical for product s in different markets.[30] A firm selling both at home and country j thus has the following capital intensity:

$$\Theta_{d+j}(\varphi) = \left(1 - \frac{R_j(\varphi)}{R(\varphi) + R_j(\varphi)}\right)\Theta_d(\varphi) + \frac{R_j(\varphi)}{R(\varphi) + R_j(\varphi)}\Theta_j(\varphi). \qquad (6)$$

As in BRS, given a continuum of products, the law of large number 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_i. Given φ and $\lambda_{sj}{}^*(\varphi)$, firm expected profit from serving market j is

$$\pi_j(\varphi) = \int_0^1 \left[\int_{\lambda_{sj}^*(\varphi)}^{\infty} \pi_{sj}(\varphi,\lambda_s) g(\lambda_s) d\lambda_s\right] ds - f_j$$

where f_j is measured in labor in BRS, but is measured in the domestic consumption bundle here.

Consider a firm that initially serves only the domestic market at period t (i.e., $\pi_{j,t}(\varphi) < f_i$). Suppose a shock hits the firm and lowers its fixed export cost to $f_j{}'$ such that $\pi_{j,t+1}(\varphi) > f_j{}'$. The firm starts exporting to country j at period $t+1$.[31] For the moment, consider sufficiently high trade costs so that all product cutoffs for foreign sales are higher than the corresponding ones for domestic sales, $\Phi_j(s) > 1$ and thus $\lambda_{sj}{}^*(\varphi) > \lambda_s{}^*(\varphi)\ \forall s$.[32] Since $\frac{\partial \widetilde{\lambda(s)}}{\partial s} > 0$, given the same distribution function $g(\lambda_s)\ \forall_s$, the firm is more likely to have a λ_s that is higher than both $\lambda_s{}^*(\varphi)$ and $\lambda_{sj}{}^*(\varphi)$ for labor-intensive (low s) products. In other words, the firm is less likely to have λ_s that justifies exports of capital-intensive (high s) products, even though the firm could be already selling the same product at home. Given a continuum of products, the (weighted) average capital intensity of the products sold domestically is the same before and after exporting (i.e., $\Theta_{d,t}(\varphi) = \Theta_{d,t+1}(\varphi)$). The (weighted) average capital intensity for the export bundle will be lower (i.e., $\Theta_{j,t+1}(\varphi) = \Theta_{d,t+1}(\varphi)$). In sum, we have the following proposition:

Proposition 1. *A firm's capital intensity $\Theta(\varphi)$ after switching from non-exporting at period t to exporting to a capital-abundant country j 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 $\Theta_t(\varphi)$ and $\Theta_{t+1}(\varphi)$ are the capital intensities of the firm before and after 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.

Given the definition of firm capital intensity in Eq. (6), Proposition 1 provides an explanation to our empirical findings that firms become less capital-intensive after exporting to a capital-abundant country. Notice that Proposition 1 does not require an assumption that $\lambda_{sj}{}^*(\varphi) > \lambda_s{}^*(\varphi)\ \forall s$. For it to hold, what is needed is simply $\frac{\partial \Phi_j(s)}{\partial_s} > 0$.[33] In Appendix A.2, we show that as long as there are some s with $\lambda_{sj}{}^*(\varphi) > \lambda_s{}^*(\varphi)$, $\frac{\partial \Phi_j(s)}{\partial s} > 0$ suffices to guarantee a decline in capital intensity of a new exporter serving j.

Furthermore, keeping all other aspects of the destination countries identical, there must exist a product $\tilde{s} \in (0,1)$ such that $\Phi(\tilde{s}) = \Phi_j(\tilde{s})$, $\Phi_j(s)/\Phi(s) < 1\ \forall\ s < \tilde{s}$ and $\Phi_j(s)/\Phi(s) > 1\ \forall\ s > \tilde{s}$. As such, a new exporter can adjust its product scope at two margins to end up with a lower capital intensity. The first margin is the intensive margin — firms will increase sales of the existing labor-intensive products after exporting. The second margin is the extensive margin — firms will also add products that have λ_s satisfying $\lambda_s{}^*(\varphi) > \lambda_s > \Phi_j(s)\,\lambda_s{}^*(\varphi)$ to the exported product portfolio, but not to the domestic product portfolio.[34] Notice that this situation is more likely to happen for labor-intensive products as $\frac{\partial \Phi_j(s)}{\partial_s} > 0$. Adjustments at either margin imply an increase in the share of labor-intensive products in the firm's product portfolio, contributing to a decline in its capital intensity.

Based on the intuition behind Proposition 1, we have the following corollary about the relation between destinations' capital abundance and exporters' capital intensity.

Corollary 1. *Between two ex ante identical firms, the one that starts exporting to a country that is more capital-abundant but identical otherwise will experience a larger decline in capital intensity.*

Proof. See Appendix A.2.

The main idea behind Corollary 1 is that in a more capital-abundant country j, the product cutoff schedule, $\Phi_j(s)$, is stepper.

Two remarks are in order before we move on to discussing the heterogeneous effects. First, to fix idea, our model focuses on exporting to a single country. It can be extended to consider a firm's exporting to multiple countries.[35] As long as the destination countries are on average more capital-abundant than the exporting country (China in this case), an extension to a multi-country setting will not change the main theoretical result. Our model does permit the situation that fixed cost shocks trigger exporting to the more

[30] Recent literature has shown that within the same narrowly defined product category, product quality is higher for exports to richer destinations (Bastos and Silva, 2010; Manova and Zhang, 2012a, 2012b). If product quality is positively corrected with skill and capital intensity, as is shown by Verhogeen (2008), adjusting for the effect of quality on factor intensity should strengthen our findings of lower capital intensity among exporters.

[31] 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 focused 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.

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

[33] In fact, we can do the same exercise as Lu (2012) and assume that there exists $\bar{s}(\varphi) < 1$ such that $\lambda_{sj}{}^*(\varphi) \leq \lambda_s{}^*(\varphi)\ \forall_s \leq \bar{s}(\varphi)$, and $\lambda_{sj}{}^*(\varphi) > \lambda_s{}^*(\varphi)$ otherwise.

[34] For simplicity, our model does not analyze product dropping due to the general-equilibrium competitive effects of trade liberalization (e.g., Bernard et al., 2011). Another way to analyze product dropping is to extend our model to incorporate firms' capacity constraints or cannibalization effects from introducing new products (e.g., Dhingra, forthcoming).

[35] For instance, the capital intensity of a firm exporting to N different countries will be

$$\Theta_X(\varphi) = \left(1 - \frac{R_X(\varphi)}{R(\varphi) + R_X(\varphi)}\right)\Theta_d(\varphi) + \frac{1}{R(\varphi) + R_X(\varphi)}\sum_{j=1}^{N}(R_j(\varphi)\Theta_j(\varphi)),$$

where $R_X(\varphi) = \sum_{j=1}^{N} R_j(\varphi)$.

labor-abundant countries. We will examine the differential effect of exporting to destinations with varying capital abundance in the empirical analysis below.

Second, our model focuses on product churning as the main driver of changes in a firm's factor intensity. By no means this is the only channel through which exporting matters. Firms may still invest in new capital or capital-intensive activities, as shown by existing studies (e.g., Aw et al., 2011; Bustos, 2011). It is worth noting that our empirical results so far show a net effect of exporting on capital intensity, which imply that the standard investment effects proposed in the literature is dominated by the product-churning effects on average in China. Importantly, our model is general enough to incorporate the investment decisions considered by those studies for an examination of the gross effects of product churning on a firm's factor intensity.

Besides rationalizing the main findings, our model yields additional predictions about the heterogeneous responses across firms. First, it relates the firm's ex ante productivity to its post-export change in capital intensity. In particular, our model shows that $\lambda_s^*(\varphi)$ is decreasing in φ for all s, which implies that the more productive firms have lower product cutoffs for both domestic and foreign sales and can afford to sell a wider range of products in any given market. Thus, the ex ante more productive firms are expected to have less product churning and thus a smaller decline in capital intensity after exporting. Using the same firm-level data, we will examine the following proposition.

Proposition 2. *An ex ante more productive firm experiences a smaller decline in capital intensity after exporting. Formally,*

$$\frac{\Theta_{t+1}(\varphi)}{\Theta_t(\varphi)} < \frac{\Theta_{t+1}\left(\varphi'\right)}{\Theta_t\left(\varphi'\right)} < 1 \;\; \textit{if} \;\; \varphi' > \varphi.$$

6.1. Revenue-based productivity estimates

Our empirical results show that firms become more productive after exporting. As discussed in the literature review, there are many reasons for that to happen. BRS has shown that trade liberalization would lead to more intense competition in the domestic product market, inducing firms to reduce their product scope and allocate resources toward the best performing products. Building on their model, our model naturally delivers similar predictions. Therefore we do not aim to replicate the theoretical results from BRS, but instead develop a testable hypothesis that relates the change in a firm's capital intensity due to product selection to its productivity after exporting.

The revenue-based *TFP* measure associated with domestic sales of product s by a firm with φ is

$$\mu_s = \frac{R_s(\varphi, \lambda_s)}{x_s(\varphi, \lambda_s)}, \tag{7}$$

where $x_s(\varphi, \lambda_s) = \Gamma_s l(\varphi, \lambda_s)^{1-\beta(s)} k(\varphi, \lambda_s)^{\beta(s)}$ is the associated input bundle, and Γ_s is a sector-specific constant that delivers a cost function equal to Eq. (3). By expressing the quantity produced as $q_s(\varphi, \lambda_s) = \varphi(x_s(\varphi, \lambda_s) - f_s)$ and revenue as $R_s(\varphi, \lambda_s) = \frac{r^{\beta(s)}}{\rho\varphi} q_s(\varphi, \lambda_s)$, we can rewrite Eq. (7) as:

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

$x_s(\varphi, \lambda_s)$ and thus μ_s are increasing in λ_s and φ. The intuition is that a firm with a higher φ or λ_s produces more and can spread the fixed cost of production f_s over a larger volume of output. Similarly, the product-specific measured *TFP* corresponding to foreign sales in country j is

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

By definition, the measured revenue-based *TFP* of an exporter that sells both domestically and in country j is the weighted average of μ's, with weights equal to the revenue shares of the products:

$$\begin{aligned}\widehat{TFP}_j(\varphi) = & \int_0^1 \mu_s \int_{\lambda_s^*(\varphi)}^{\infty} \frac{R_s(\varphi, \lambda_s)}{R(\varphi) + R_j(\varphi)} g(\lambda_s) d\lambda_s ds \\ & + \int_0^1 \mu_{sj} \int_{\Phi_j(s)\lambda_s^*(\varphi)}^{\infty} \frac{R_s(\varphi, \lambda_s)}{R(\varphi) + R_j(\varphi)} g(\lambda_s) d\lambda_s ds,\end{aligned} \tag{8}$$

where the first term corresponds to *TFP* measured based on domestic sales and the second term corresponds to *TFP* measured based on foreign sales. While a positive shock on a firm's φ will increase $\widehat{TFP}_j(\varphi)$, our model focuses on shocks that lower a firm's fixed export costs. This modeling approach is consistent with our empirical strategy that matches and compares firms with similar ex ante *TFP* and other characteristics. The identification assumption of our matching exercises is that in the absence of within-firm reallocation of resources, firms that are similar over a wide range of observables are expected to remain similar ex post in the observables. That said, we cannot rule out positive productivity shocks as a trigger to export participation.

How can product churning after exporting affect firms' measured *TFP*? Consider a model with symmetric countries (i.e., identical country size and factor endowment). Costly trade implies a selection of better performing products into a firm's export basket. This can be shown by $\Phi_j(s) > 1$ in our model under the symmetry assumption. The average λ_s (either simple or sales-weighted) is then higher for the products exported than those sold domestically. This pattern of product selection has been empirically verified by Arkolakis and Muendler (2011) and Manova and Zhang (2012a) and theoretically shown to contribute to a higher firm measured *TFP* by BRS (2010), among others.

However, when countries are asymmetric in size and/or factor endowment, the contribution of product switching to firm measured *TFP* becomes less straightforward. In particular, $\Phi_j(s)$ can be higher or lower than 1 when the relative price index is not constant across s. Complicating the analysis is that the revenue-based "productivity" of product s, μ_{sj}, depends positively on λ_s but negatively on f_{sj}. Specifically, higher fixed cost for exporting than domestic sales ($f_{sj} > f_s$) implies that on one hand, product selection pushes up firm measured *TFP*, but on the other hand forces μ_{sj} lower than μ_s for some products, which then reduces firm measured *TFP*. However, given f_s, f_{sj}, φ and λ_s we can show that $\mu_{sj} > \mu_s$ if[36]

$$\frac{f_{sj}}{f_s} < \left(\frac{P_j(s)}{P(s)}\right)^{\gamma} \Psi_j, \tag{9}$$

where $\Psi_j = \frac{R_j/\tilde{P}_j}{R/\tilde{P}}$ is constant across s.

Considering constant $\frac{f_{sj}}{f_s}$ across s, 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, this inequality is more likely to hold for labor-intensive products, all else being equal. Thus, the more specialized a firm is in labor-intensive products after exporting, the more weight it will have on exported products that have $\mu_{sj} > \mu_s$, which will in

36 $\mu_{sj} > \mu_s \Rightarrow \frac{f_{sj}}{x_{sj}(\varphi,\lambda_s)} < \frac{f_s}{x_s(\varphi,\lambda_s)}$
$\Rightarrow \frac{f_{sj}}{\frac{\tau_j q_{sj}(\varphi,\lambda_s)}{\varphi} + f_{sj}} < \frac{f_s}{\frac{q_s(\varphi,\lambda_s)}{\varphi} + f_s}.$
$\Rightarrow \frac{R_{sj}(\varphi,\lambda_s)}{R_s(\varphi,\lambda_s)} > \frac{f_{sj}}{f_s}.$

turn result in a higher measured *TFP*.[37] Intuitively, given constant fixed export costs across products, an exporter is able to derive higher profits from foreign sales than domestic sales for labor-intensive products, all else equal. Higher profitability is then translated into higher revenue-based *TFP* at the product level. We summarize the relation between the change in capital intensity and measured *TFP* of the firm in the following proposition:

Proposition 3. *Firms that experience a bigger decline in capital intensity after exporting have a larger increase in measured revenue-based TFP.*

7. Evidence on heterogeneous changes in capital intensity

Tables 1 to 3 have already shown robust evidence supporting Proposition 1. We now verify Proposition 2 by examining whether a firm's ex ante *TFP* can affect the change in capital intensity after exporting. To this end, we estimate the following equation:

$$\Delta \ln (K/L)_i - \Delta \ \ln \ (K/L)_i^{matched} = \delta \ln \left(TFP_{i,t-1}\right) + X_i\gamma + \{FE\} + \zeta_i, \qquad (10)$$

where $\Delta\ln(K/L)_i$ is the change in firm *i*'s capital intensity from year $t-1$ to t when it starts exporting. $\Delta\ln(K/L)_i^{matched}$ is the change in the capital intensity of *i*'s matched non-exporter over the same period. The match is determined by the propensity scores of the firms estimated for the analysis in Table 3. The regressor of interest is firm *i*'s ex ante *TFP*, $\ln(TFP_{i,t-1})$. X_i is a vector of firm *i*'s characteristics in year $t-1$, which include the firm's wage rate, capital intensity, and age (all in logs). $\{FE\}$ includes ownership, 4-digit industry, and province fixed effects. Proposition 2 predicts that $\delta > 0$.

The estimates of Eq. (10) are reported in Table 4. The positive coefficient on $\ln(TFP_{t-1})$ in column (1) shows that higher firm *TFP* before exporting is on average associated with a smaller decline in capital intensity after exporting, relative to the matched non-exporters. These results support Proposition 2. The positive and significant coefficient on ln (wage rate) also provides consistent results, if the more productive firm pay higher wages.

We also find that the ex ante more capital-intensive firms are on average associated with a larger decline in capital intensity after exporting. Our model specifies that two non-exporting firms with the same productivity should have the same capital intensity. It is thus silent about the relation between the level of firm capital intensity and export participation. But suppose a capital-intensive firm starts exporting, a wide range of the products that it sells in the domestic market, which tends to be capital-intensive, cannot be exported profitably to a capital-abundant country. As such, in a labor-abundant country, a more capital-intensive firm will tend to experience a larger decline in capital intensity after exporting to a capital-abundant country. In columns (2) and (3), we find strong evidence confirming the baseline results using both the domestic and foreign firm samples.

Next, we explore the relationship between the change in capital intensity in the first year of exporting and the gain in measured *TFP* to shed light on the "core competency" hypothesis, according to Proposition 3. We regress the change in measured *TFP* of new exporters relative to the corresponding change of the matched non-exporters. Table 5 reports the results. Column (1) shows a negative coefficient on the change in capital intensity after exporting, controlling for 4-digit industry, ownership, and year fixed effects, as well as a number of key firm attributes. This result suggests that firms with a deeper specialization in labor-intensive products (i.e., a decline in capital intensity) experience a larger increase in measured *TFP*, supporting Proposition 3. This correlation remains robust for both domestic (column (2)) and foreign exporters (column (3)).

[37] 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 $\hat{P}_j$).

Table 4
Ex ante productivity and ex post capital intensity.
Dependent variable $= \Delta\ln(K/L)_{new\ exporter} - \Delta\ln(K/L)_{matched\ non\text{-}exporter}$.

	(1)	(2)	(3)
	All new exporters	Domestic new exporters only	Foreign new exporters only
$\ln(TFP_{t-1})$	0.096	0.132	0.021
	(0.035)***	(0.049)***	(0.008)**
$\ln(K_{t-1}/L_{t-1})$	−0.298	−0.345	−0.276
	(0.074)***	(0.092)***	(0.077)***
$\ln(\text{wage rate}_{t-1})$	0.188	0.193	0.198
	(0.048)***	(0.054)***	(0.088)**
$\ln(\text{age}_{t-1})$	0.029	0.035	0.027
	(0.011)***	(0.013)***	(0.011)**
Ownership FE	Yes	No	No
Industry (4-digit) FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
N	49,742	33,409	16,333

Notes: All regressors are lagged by one year. New exporters and their matched non-exporters are matched using the propensity score matching method, which is done within their own bins. Standard errors in parentheses are corrected for clustering at the four-digit industry level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

8. Evidence on within-firm product switching

In the remainder of the paper, we use transaction-level (firm-product-year) trade data to verify our main theoretical predictions. We first merge the NBS above-scale manufacturing firm data with the customs transaction-level trade data as discussed in Section 3. We use various methods to merge the two data sets, merging by firm name, address, and manager names. The summary statistics of the merged data set are reported in Appendix Table A6. 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, 2012). It should be noted that trading companies are considered service providers, which are included in the trade data but not in the NBS industrial firm data. A large fraction of the unmerged firms in our sample are thus trading companies.

Table 5
Determinants of the change in firm TFP.
Dependent variable $= \Delta\ln(TFP)_{new\ exporter} - \Delta\ln(TFP)_{matched\ non\text{-}exporter}$

	(1)	(2)	(3)
	All new exporters	Domestic new exporters only	Foreign new exporters only
$\Delta\ln(K/L)_{t-1,t}$	−0.049	−0.055	−0.022
	(0.008)***	(0.019)***	(0.010)**
$\ln(TFP)_{t-1}$	0.121	0.135	0.119
	(0.025)***	(0.030)***	(0.031)***
$\ln(\text{wage rate})_{t-1}$	0.087	0.093	0.076
	(0.001)***	(0.002)***	(0.002)***
$\ln(\text{age})_{t-1}$	−0.076	−0.086	−0.078
	(0.029)***	(0.035)**	(0.037)**
Industry (4-digit) FE	Yes	Yes	Yes
Onwership FE	Yes	No	No
Province FE	Yes	Yes	Yes
N	50,019	33,637	16,382

Notes: All regressors are lagged by one year, besides $\Delta\ln(K/L)_{t-1,t}$, which is defined as the first difference in capital intensity from year $t-1$ to t. Standard errors in parentheses are corrected for clustering at the four-digit industry level.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

Table 6
Product switching of new exporters (customs transaction-level data).

	(1)	(2)	(3)	(4)	(5)
	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 (average) number of continuing products
2001	15,928	13,187	134,059 (10.17)	56,389 (4.28)	63,929 (4.85)
2002	21,383	18,410	176,066 (9.56)	82,096 (4.46)	98,364 (5.34)
2003	27,107	22,941	229,762 (10.02)	127,959 (5.58)	125,753 (5.48)
2004	37,646	31,583	322,921 (10.22)	207,112 (6.56)	161,901 (5.13)
2005	40,024	33,552	311,839 (9.29)	265,860 (7.92)	166,894 (4.97)
Average	28,418	23,935	234,929 (9.85)	147,883 (5.76)	123,368 (5.15)

Notes: A product is defined as an HS6 category. In columns (3) to (5), average number of products equals total number of products divided by the number of new exporters that survived to next year in column (2). We do not include 2006 new exporters because we have no information on their survival and number of products added and dropped in 2007.

Using the merged data set, we compute capital intensity of each HS 6-digit product. The computation procedures, similar to the method used by Bernard et al. (2010), are discussed in Appendix A.3. Appendix Table A8 reports the measured capital intensity by broad sector. Similar to the findings by Bernard et al. (2010) for the U.S., we find a large variation in capital intensity within a sector. For instance, the mean capital intensity of the "textiles and textile articles" sector is about 68 thousand yuan per worker, while the standard deviation across HS6 products within the same sector is about 55 thousand. There are many HS6 product categories within a sector. The number of HS6 product categories ranges from 9 (Works of art) to 818 (Textile and textile articles), suggesting that firms in the same sector have a wide range of products with vastly different capital intensities to choose from.[38] Using the transaction-level data, we find that exporters actively add and drop products over time. Table 6 shows that from 2002 to 2006, new exporters on average added about ten products, dropped six products, and continued only five products after the first year of exporting.[39] 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 products that were newly added, dropped, and continued from the previous year at the firm level. In the year immediately after a firm starts exporting, we assign its exported products (HS6) into three categories: the newly added, continued, and dropped products. For each of the new exporters in the year right after the first year of exporting, we compute three sales-weighted averages of capital intensities across products, one for each category. Using this data set, we estimate the following specification:

$$\ln(K/L)_{ik} = \eta_0 + \eta_1 \ new\_product_{ik} + \eta_2 \ dropped\_product_{ik} + e_i, \quad (11)$$

where $\ln(K/L)_{ik}$ is firm i's sales-weighted average capital intensity of product category k, $k \in$ {new products, dropped products, continued products}. $new\_product_{ik}$ and $dropped\_product_{ik}$ are dummy variables to indicate that firm i added new products and dropped old products respectively. More specifically, $new\_product_{ik}$ equals 1 if firm i added new products in the year after the first year of exporting, with the corresponding dependent variable $\ln(K/L)_{ik}$ measuring the average capital intensity of the these new products added. Similarly, $dropped\_product_{ik}$ equals 1 if firm i dropped some old products, with the corresponding $\ln(K/L)_{ik}$ measuring the average capital intensity of those dropped products. The omitted reference group is the category that firm i continuously exported some existing products. η_0 is a constant and e_i is the error term. Our model predicts that new products are less capital-intensive than the continued products, while dropped products are more capital-intensive. Thus, $\eta_1 < 0$ and $\eta_2 > 0$.

As shown in Table 7, 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% less capital-intensive than the continuously exported products and the dropped products are about 2% more capital-intensive.

We conduct several robustness checks in columns (2)–(6). In column (2), we use the deflator approach instead of the perpetual inventory approach. The capital stock is measured as the net value of fixed assets deflated by the sector-specific investment deflator. Again we find statistically significant results for both the new product dummy and the dropped product dummy. As discussed in Appendix A.3, our preferred method of calculating product capital intensity is to use the weighted average of the capital intensity of all firms exporting that product. However, by using the weighted average, our measure of product capital intensity may be dominated by a few large exporters that export multiple products. To reduce such bias, we use the median capital intensity in column (3) and the results remain qualitatively similar. Our results are insensitive to the exclusion of intermediaries (column (4)), and remain robust when we include only ordinary exporters (column (5)) or processing exporters (column (6)). These findings address the concern that our results are driven by the predominance of processing exporters in China.

Our model predicts that exporting to a more capital-abundant country should be associated with a larger decline in firm capital intensity. To examine this hypothesis, we split the sample into two, a group of exporters primarily serving the capital-abundant countries and a group of exporters primarily serving the labor-abundant countries. Our country capital abundance data come from Antweiler and Trefler (2002). A country is considered capital-abundant (labor abundant) if its relative capital endowment is higher (lower) than the median value in the Antweiler and Trefler (2002) sample. For multi-country exporters, we classify firms based on their largest export destination. We run the same regression over the two groups. As shown in columns

[38] Our product-level measure of capital intensity may introduce a selection or aggregation bias. The production choice of a firm depends on its productivity. More productive firms may produce more products. Since China is labor-abundant, firms will add products in decreasing order of capital intensity. As a result, our measure of the capital intensity of products may be biased upward, since our measure is based on the relatively more productive firms that sell more of these products than the less productive firms. By using the median capital intensity of the firms exporting a given product as the measure of product-level capital intensity, we find that the empirical results remain qualitatively similar.

[39] We do not observe the product mix of new exporters in the transaction-level trade data before they start exporting. Hence we cannot measure the decline in firms' capital intensity in the first year of exporting. We can only measure the changes between the first year of exporting and subsequent years. An implicit assumption behind this empirical approach is that there are adjustment costs preventing firms from reaching the optimal product mix within the first year of exporting.

Table 7
Capital intensity of new products and dropped products.

Dependent variable: ln(*K*/*L*)	(1) All New exporters	(2) Alternative measure of *K*	(3) Alternative construction of product *K*/*L*	(4) Excluding intermediaries	(5) Ordinary exporters only	(6) Processing exporters only	(7) Capital abundant destinations	(8) Labor abundant destinations
New product category dummy	−0.048 (0.012)***	−0.019 (0.005)***	−0.025 (0.005)***	−0.049 (0.014)***	−0.050 (0.015)***	−0.045 (0.013)***	−0.049 (0.013)***	−0.042 (0.014)***
Dropped product category dummy	0.023 (0.005)***	0.016 (0.004)***	0.009 (0.004)***	0.021 (0.007)***	0.024 (0.008)***	0.013 (0.005)***	0.022 (0.007)***	0.023 (0.007)***
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	326,784	326,784	326,784	281,035	252,887	73,897	262,733	41,536

Notes: This table reports the results of regressions of capital intensity on the new product category dummy and the dropped product category dummy. The omitted group is the continuing product category. Column (1) uses the capital stock measure computed using the perpetual inventory method (our benchmark method) to calculate product capital intensity. In column (2), capital stock is the net value of fixed assets deflated by the sector-specific investment deflator. In column (3), we use the median capital intensity of all firms exporting the same product to calculate product capital intensity. Column (4) excludes all trade intermediaries. Columns (5) and (6) use the subsamples of ordinary (non-processing) and processing new exporters. Column (7) and (8) use the subsamples of the exports to capital-abundant countries and labor-abundant countries. The classification of capital abundance is based on Antweiler and Trefler (2002). Robust standard errors are reported in parentheses.
** Indicate significance at the 5% level.
*** Indicate significance at the 1% level.

(7) and (8), products added by exporters serving capital-abundant destinations tend to be less capital-intensive than those added by exporters serving labor-abundant destinations. There is little difference in the factor intensity of the dropped products between the two groups of exporters.

9. Concluding remarks

This paper studies how a firm's specialization in its core products after exporting affects its factor intensity and productivity. Using panel data for China's manufacturing firms over the 1998–2007 period and several empirical methods, we find that a firm becomes less capital-intensive but more productive after exporting. For both domestic firms and foreign firms, this fact is established within firms, within a narrowly defined industry, and within a group of firms with similar ex ante characteristics.

As our findings on post-export capital intensity contrast sharply with the existing findings in the literature, we develop a variant of the model by Bernard et al. (2010, 2011) to consider firms producing multiple products with varying capital intensity. Our model predicts that firms in labor-abundant countries specialize in their core competencies by allocating more resources to produce labor-intensive products once they start exporting. We discuss how this within-firm reallocation of resources is related to firm measured productivity after exporting. Firm ex ante productivity is associated with a smaller decline in capital intensity after exporting, while a sharper post-export decline in capital intensity is associated with a larger increase in measured total factor productivity. Using transaction-level trade data, we find that during our sample period, new exporters in China add new products that are more labor-intensive than the existing exported products in subsequent years and drop those that are less labor-intensive. These product-churning patterns tend to be stronger when a firm exports to a more capital-abundant country.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jinteco.2013.11.003.

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