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Abstract: China's policy of encouraging export processing has been the topic of much discussion in the academic literature and policy debate. We use a recently developed econometric approach that allows for time varying "treatments" and estimate economically and statistically significant positive causal effects of entering into export processing and ordinary export markets on subsequent firm level productivity. These productivity effects are shown to be larger than those accruing to firms who enter into ordinary exporting. Interestingly, the estimation of quantile treatment effects shows that the positive effects do not accrue similarly to all types of firms, but are strongest for those at the low to medium end of the distribution of the productivity variable. We also find that export processors gain more when entering the industrialised North rather than the South, while this does not appear to matter much for ordinary exporting.

Keywords: export processing; firm performance, China; time varying treatments

JEL Classification: F14, F61, O14

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1 Introduction

The ubiquitous "*Made in China*" label epitomizes China's transformation from a virtual autarky in the 1970s to a veritable exporting powerhouse in little more than a generation. This transformation arguably owes much to the country's ever-increasing integration in global value chains. This has undoubtedly been helped by policy. As early as the mid-1980s China introduced special "processing trade" schemes in an attempt to boost exports. The hallmark of this scheme is that there are tariff-exemptions on imported inputs as long as these are only processed in the country and then re-exported. Domestic sales of these processed goods are, in general, not permitted.[1]

An often-cited example of such export processing is the assembly of iPhones carried out by Foxconn in China. Using aggregate data, Gaulier et al. (2007) show that the contribution of export processing to China's total exports has grown substantially, from about 45 percent in the early 1990s to around 55 percent in the early 2000s. Similarly, Manova and Yu (2017) using data for 2005 also state that export processing amounted to 55 percent of total exports. While Lemoine and Unal (2017) argue that the importance of export processing has declined in the following decade up to 2015, it is nevertheless still a significant share of export activity by Chinese companies.

In this paper, we investigate, to our knowledge for the first time, what the effect of first-time entry into export processing is on subsequent firm performance in terms of total factor productivity. We also compare this with starting to engage in what is generally referred to as "ordinary exports". We do so using detailed Chinese firm level panel data which are obtained by linking two sources, namely, firm-level production data available from China's Annual Survey of Industrial Firms (CASIF) and transaction-level trade data from the Chinese Customs Trade Statistics (CCTS). These data allow us to distinguish firms engaged in export processing from ordinary exports.

Dai et al. (2016) as well as Wang and Yu (2012) show, using linked firm-trade data similar to ours, that export processors are less productive than ordinary exporters and non-exporters.[2] They attribute this to the fact that the least productive firms choose to do export processing, as the fixed costs involved and level of production technology employed are relatively low.[3] Such negative selection, however, implies that the aggregate productivity gains from exporting a la Melitz (2003) may not be present in the case of export processors. The benefits from such export activity would then have to come from

[1] As Yu (2014) points out, one can distinguish two types of processing trade. In one case, the Chinese firm imports intermediates from a foreign partner without payment and sells the processed output to the same partner, charging an assembly fee. In the other case, the Chinese firm buys intermediates from a foreign partner and, after processing, sells the exports to any foreign customer. As in Yu (2014), our measure of processing below includes both of these cases.

[2] In line with this, Ma et al. (2014) find that export processors are less capital intensive than non-exporters. While they also find this negative correlation for ordinary exporters compared to non-exporters, the correlation is stronger for export processors.

[3] While this on its own would imply that all firms wanting to export should engage in processing exports rather than ordinary exports, Dai et al. (2017) argue that there is a trade-off. Export processors generally add less value to the inputs, and therefore share a larger proportion of profits with their customer firms. Hence, the most productive firms select into ordinary exports in their model.

"learning by exporting". The identification of such post treatment effects is the focus and main contribution of our paper.

There is, of course, a large literature using micro level data for a multitude of countries that looks at the relationship between exporting and productivity. While there is almost unanimous agreement in the literature that more productive firms self-select into exporting, the evidence on causality going the other way from exporting to productivity (learning by exporting) is much more mixed (e.g., Wagner, 2012, Martins and Yang, 2009). There are, however, a number of studies showing positive learning effects from exporting for countries such as the UK (e.g., Girma et al., 2003, Crespi et al., 2008), Canada (Baldwin and Gu, 2003), Turkey (Yasar et al, 2006), Slovenia (De Loecker, 2007) and a group of African countries (Van Biesebroeck, 2005). Most importantly from our point of view, studies for China have also found evidence for learning by exporting, see the early paper by Kraay (2002) and the more recent study by Ma et al. (2014). Our paper shows that learning by exporting is not only confined to "ordinary exporters" but also to firms engaging in export processing.

Why should there be learning by exporting for processing exporters? In general, exporting allows access to foreign knowledge, which can improve exporters' productivity performance (e.g., Van Biesebroeck, 2005). This is, of course, true for ordinary as well as processing exporters. The use of imported intermediate goods provides another avenue for the absorption of foreign knowledge through technology transfer (e.g., Halpern et al., 2015, Görg et al. 2008). While this may again benefit both types of exporters, processing exporters may gain relatively more from this as they, by construction, depend more heavily on imported inputs than ordinary exporters. After all, export processing, by definition, consists of importing intermediates which are then processed in China for subsequent export. This is also borne out by our data below (Table 2), which show that firms switching into export processing have a higher intensity of imported intermediates than those that start ordinary exporting.

Another reason why exporting may lead to learning-by-exporting is that entering foreign markets changes incentives to innovate and thus can improve productivity even in the absence of technology transfer. Lim et al. (2018) have a model where firms can serve a domestic and an export market. Consumers demand different grades of a differentiated product, where grades are ordered going from low to high quality. Firms can invest in R&D activities in order to attain the next grade of product, which is akin to product innovation. The predictions of the model concerning exporting and innovation may be summarized as follows. Starting to export increases market size for the firm and this unambiguously raises the incentive for the firm to innovate. Competition has an ambiguous effect: if entering export markets allows firms to escape *domestic competition*, then this would raise innovation, all other things equal. If there is, however, *strong competition* on export markets (through foreign or other domestic producers) then this may reduce output and thus innovation expenditure.[4] While the market size effect may be expected to be similar for processing and ordinary exporters, one may argue that the positive "escape the competition" effect may be more prevalent for processing exporters. They may not face strong competition on export markets, as they are involved in a global value chain and supply within

[4] Aghion et al. (2018) have a similar model where innovation reduces production costs, hence, is more akin to process innovation. Also, they do not have an "escape the competition" mechanism.

the chain. By contrast, ordinary exporters may experience stronger negative competition effects on export markets, as they are competing with incumbents in the foreign markets.

The Lim et al. (2018) model also suggests that the export destination may play a role for the nature of the learning effects. Entering larger markets should have larger positive effects, as should entering export markets with less established competition. We investigate this point in an extension to our empirical analysis, where we distinguish exports (either processing or ordinary) to the industrialised North and the less developed South.

Using our linked firm-customs panel dataset we quantify the average treatment effects of entering into export processing or into ordinary exports on firms' total factor productivity. Given that we have longitudinal data firms may enter into exporting at different stages of our period of analysis, and their exporting status can change through time in ways related to intermediate outcomes. Hence, we have a time varying "treatment". As we discuss below, standard propensity score-based methods (as we have used in a cross sectional context in our own work, e.g., Girma et al. 2015) are unable to provide the true average treatment effect in such a case. We therefore apply a recently developed approach that is able to deliver unbiased estimates of average treatments in the presence of such time varying treatments (Robins and Hernán, M. A. (2008); Vandecandelaere et al. (2016)). To the best of our knowledge, this is the first application of such a method in the firm level literature on exporting.

A further novelty of our paper is that we do not just concern ourselves with estimating average treatment effects, as is common in the treatment literature, and indeed in the evaluation of learning-by-exporting effects. Rather, we expand on this and also estimate a series of quantile treatment effects. This allows us to make a more nuanced inference about the causal effects of exporting along the firms' performance distribution. For example, it enables us to estimate and compare effects of the same treatment on firms in the, say, tenth percentile of the productivity distribution compared to those in the ninetieth. In other words, we allow the treatment effects to be different for low and high productivity firms. As we show below, this does indeed provide a much richer picture of treatment effects that would be missed if we were to look at average treatment effects only.

Our paper contributes to the relatively small but growing literature that looks at the implications of China's export processing scheme using linked firm-trade data similar to ours. Manova and Yu (2017) investigate the choice between export processing and ordinary exports and argue forcefully that financial constraints are more binding for ordinary exports, enabling firms with lower access to finance to specialize in export processing. Van Assche and Van Biesebroeck (2017) provide evidence that there is functional upgrading in export processing, which goes hand in hand with productivity improvements at the sectoral level. In a similar vein, Tian and Yu (2019) show that firms switch import sources following trade liberalization, a result that holds for both ordinary and processing exporters. Kee and Tang (2016) show that there is an increase in domestic value added in export processing over time, which they explain by the availability of more varieties of domestic inputs as a consequence of globalization. Yu (2014) looks at the impact of tariff reductions on firm productivity and shows that effects differ for processing and ordinary exporters. Fernandes and Tang (2012) investigate the choice between vertical integration and arm's length trade in export processing. We complement this literature by providing robust empirical evidence on the effect of entering into export processing on plant performance.

We also contribute to a large literature that empirically investigates the causes and consequences of China's overall export performance using disaggregated data (e.g., Dai et al., 2018; Manova et al., 2015; Ma et al, 2014; Jarreau and Poncet, 2012; Girma et al., 2010, 2020). We focus on the difference between ordinary and processing exports. More generally, our paper is related to the burgeoning literature on the proliferation of global value chains. As, for example, Gaulier et al. (2007), Mirodout and DeBacker (2013) or Timmer et al. (2014) convincingly show, GVCs continue to grow and China plays an important part in the proliferation of GVCs world-wide. We take this literature to the firm level to show the implications for firm performance of a firm's choice to join a GVC via export processing.

The rest of the paper is structured as follows. Section 2 presents the data and shows some descriptive statistics. Section 3 discusses the econometric methodology used in the analysis. The main findings are discussed in Section 4, and Section 5 concludes.

2 Data sources and sample characteristics

The paper draws on two micro datasets from China - the firm-level production data available from China's Annual Survey of Industrial Firms (CASIF) and the transaction-level trade data from the Chinese Customs Trade Statistics (CCTS). The two datasets are linked over the period 2000-2006. As discussed in the Introduction, we are not the first to use such linked firm – trade data, other studies include Tian and Yu (2019), Dai et al. (2017), Manova and Yu (2017), Ma et al. (2014), Yu (2014) and Wang and Yu (2012).

CCTS consists of the universe of manufacturing importers and exporters. It provides export and import values in current US dollars as well as value per unit, and the destination country for exports and country of origin for imports. Crucially for our purposes, it also identifies whether trade is processing trade or ordinary trade based on customs declarations. CASIF includes the whole population of state-owned firms, and all non-state firms with annual sales above 5 million Chinese yuan, with about 230,000 firms by 2006.[5] Firms included in CASIF are estimated to account for more than 90% of Chinese industrial output. The dataset offers various balance sheet variables such as output, employment, assets, total value of exports as well as ownership structure, location and industry. CASIF is cleaned to exclude gross outliers such as firms reporting fixed assets greater than total assets or negative sales figures. We only consider firms in manufacturing industries.

CASIF and CCTS do not have a common firm identifier, so a straightforward matching procedure is not possible. As in other studies using these datasets, an indirect matching procedure is carried out based on the name, address (zip code) and telephone number of the firms. Applying this exercise, we match 79,447 unique firms, which are firms involved in either ordinary or processing exports between 2000 and 2006. This figure is quite close to the 79,730 firms matched by Wang and Yu (2012). These firms account for about half of total exports recorded by CCTS, broadly consistent with the matching results of Wang and Yu (2012) and Ma et al. (2014).

[5] CASIF has been used in related previous work by, for example, Brandt et al. (2017) and Girma et al. (2015).

Given that our aim is to evaluate the performance effects of switching to exporting, we rule out firms that were exporters at the start of the CCTS sample (i.e., year 2000) as well as those that have always been exporters in all the years under consideration. In other words, the data used in our study comprises all firms that do not have any export activity in 2000. Among those initial non-exporters, switchers (or the treatment group) are those that enter into ordinary exports or exports processing markets at any time between 2001 and 2006. The control group consists of firms that remain purely domestic market oriented (i.e., do not start to export) over the whole period 2000 and 2006. Thus, by design we start our sample in 2000 with only firms that have no recorded exports and we then observe some switching into export activity over the subsequent six-year period.[6]

In the final analysis our linked dataset consists of 808,052 firm-year observations across the period 2000-2006. In Table A1 in the Appendix we provide definitions of all variables used in the analysis. Following Yu (2014), amongst others, we use sector-specific output and input deflators that are constructed using information from China's Statistical Yearbooks and China's National Input–Output table.

Table 1 presents the distribution of firms according to trade status which shows, firstly, that export processing is less prevalent than ordinary exports. Overall, 5.4 percent of firm-observations are classified as switchers into export processing, 9.9 percent as starting ordinary exporting. It follows that, as expected, the number of domestically-oriented firms is quite large, amounting to about 85% of the firm-year observations in our final sample. Secondly, the table shows that switching into exporting is well distributed across the years of analysis, with, e.g., 4,857 switching into export processing in 2001, and a further 5,997 in 2002, and so on.

Occasionally, some firms switched from being non-exporters to doing both ordinary and processing exports. In such a case we assign a firm to be an ordinary exporter, as long as at least 25% of their exports is classified as being ordinary ones. To give some perspective on this issue, among firms we classified as ordinary exporters the median share of processing exports is 0 and the corresponding mean is 1.22 percent.

[Table 1 here]

3 Productivity estimation and descriptive statistics

The aim of the paper is to estimate the effect of switching into processing or ordinary exports on firm performance. The latter is proxied using total factor productivity. Following Brandt et al. (2017), who also estimate TFP using similar data, we initially estimated five alternative measures of total factor productivity based on a Cobb-Douglas production function. These five measures are based on (i) Olley and Pakes (1996); (ii) Levinsohn and Petrin (2003); (iii) Ackerberg et al. (2015); (iv) De Loecker and

[6] In fact, since CASIF contains the firm's aggregate export value, and we have this data from 1997 onwards, we made sure that the control group of domestically-oriented firms do not have any positive exports between 1997 and 2006.

Warzynski (2012) and (v) a nonparametric Tornqvist index (Caves et al., 1982).[7] The production functions are estimated for each two-digit industry separately.

Estimation of the parametric models is conducted using the PRODEST package in Stata, due to Rovigatti and Mollisi (2016) based on the value-added approach. To be sure, each measure has its own theoretical and practical shortcoming (see Rovigatti and Vincenzo Mollisi, 2016 for a discussion), even if they tend to be reasonably correlated in practice.[8] In this paper our preferred measure is based on the GMM approach of De Loecker and Warzynski (2012) where lagged exporting status is modelled as an endogenous driver of productivity dynamics within the Ackerberg et al. (2015) framework. It thus allows exporting to endogenously determine the productivity's law of motion.[9][10]

Table 2 shows differences in firm characteristics (defined in Table A1 in the Appendix) across the three groups of firms: purely domestic, entering processing, or entering ordinary exporting. It can be seen that there is a clear productivity ranking with purely domestic firms having the lowest levels of TFP, switchers into export processing being medium and firms entering into ordinary exporters having the highest TFP.[11] We also chart the TFP differentials in the raw data for the two types of exporters vis-à-vis purely domestic firms in Figure 1. This shows positive TFP premia in all years, though they appear to have fallen over time. These cannot be interpreted as causal effects, of course.

[Table 2 and Figure 1 here]

To get a better idea of the timing of effects, Figure 2 depicts results from a simple event study analysis of the TPF dynamics around the export switching year. Controlling for sector specific trends, we find descriptive evidence of beneficial effects of exporting, with productivity increasing after switching into exporting. Such effects are more pronounced and sustained amongst ordinary exports firms.

[Figure 2 here]

[7] All of these measures are revenue based and TFP estimates therefore may combine price and volume effects (as in many other applications in the literature). While we use sectoral price deflators, these do of course not allow us to control for firm level fluctuations in prices. Hence, with the data at hand we are not able to differentiate fully between price and volume effects (but see De Loecker and Warzynski, 2012 and Yu, 2015 for a discussion). This ought to be kept in mind in the interpretation of results below.

[8] Appendix A3 reports the sector-specific production function estimates using the different estimators.

[9] The inclusion of past exporting dummies – separately for ordinary and processing exports – also allows to address a potential issue with our production function, namely, that the standard assumption is that firms choose their variable inputs – labour and materials - with knowledge of their productivity shocks. For export processing firms that that do not make active input choices but instead passively receive materials from their foreign trading partners this assumption may not be adequate. Including dummies for the respective exporting activity in the production function may be a rough way of dealing with this problem.

[10] However, we also carried out robustness checks to probe the sensitivity of our finding to the measure of TFP used. Appendix B contains some results from this analysis. Further results are available upon request.

[11] Recall that Dai et al. (2017) and Wang and Yu (2012) find that export processors are less productive than ordinary exporters and non-exporters. However, they look at a cross-sectional comparison, while we look at firms that enter into the respective export mode, having previously not exported at all. The difference in results may be due to firms entering export processing before 2000 being different than those entering in our sample period. A full investigation of this is beyond the scope of the current paper, however.

This event study analysis potentially confounds beneficial effects of switching into exporting and changes in other related firm characteristics. Indeed, as is evident from Table 2, we find that the ranking found for TFP also holds for the probability of conducting R&D, and for product innovation. Furthermore, it is clear that a large share of processing exporters is foreign-owned, while domestic firms and ordinary exporters are mostly privately owned. The differences in firm characteristics observable in Table 2 suggest that the decision to enter export processing or ordinary exporting is unlikely to be random. These differences in observable firm characteristics need to be controlled for in order to identify the causal effect of entering into export processing or ordinary exporting on firm performance. In the next section we set out the methodology we use to identify such an effect.

4 Empirical strategy

In this section we detail the estimation strategy employed to evaluate the average treatment effects of the two forms of export participation. A key feature of the paper is the use of a dynamic or time-varying treatment effects estimation approach which is most appropriate in longitudinal designs as in our setting.

Standard propensity score-based estimation approaches can be misleading in situations where the treatment and outcome variables are observed at more than one point in time. This is because, firstly, the treatment status can change through time in ways related to intermediate outcomes (e.g., firms may switch into exporting and then drop out again due to learning-induced productivity changes). Secondly, relevant confounders (i.e. the pre-treatment observable covariates the treatment is conditioned on) are also time-varying and likely to be affected by previous treatment histories as well as previous outcome variables. For example, a firm's financial position may change over time, due to productivity growth over time. This makes it very difficult to isolate or disentangle the true average treatment effects. In short, standard treatment effects estimation approaches fail to deliver unbiased estimators, which is unfortunate as time-varying treatments are arguably a feature of most panel micro datasets.

In order to circumvent these shortcomings, we apply a recently developed approach that is able to deliver unbiased estimates of average treatment effects in the presence of time varying treatments (Robins and Hernán, M. A. (2008); Vandecandelaere et al. (2016)). This proceeds by using an inverse propensity score weighting approach (as, e.g., in Girma et al., 2015), but weighs observations separately at each point in time, in such a way that the treatment variable is independent of past time-varying covariates including, crucially, treatment and outcome variables that preceded it. To our knowledge this is the first paper to use a dynamic treatment effects estimator to evaluate the causal effects of exports markets entry.

For a binary treatment variable $d \in \{0,1\}$, outcome variable y, time-varying confounders X (including past outcome variables) and baseline (time-invariant) covariates X_0, the stabilized weight for firm i at time t ω_{it} is constructed as follows:

$$\omega_{it} = \prod_{s=1}^{t} \frac{Pr[d_{it}=1|\breve{D}_{it-1};X_0]}{Pr[d_{it}=1|\breve{D}_{it-1},\breve{X}_{it-1};X_0]} \quad [1]$$

where $\breve{D}_{it-1}$ and $\breve{X}_{it-1}$ indicate the treatment and covariate histories up to time t-1 respectively. This shows that the weight ω_{it} can change over time depending on the change in time-varying confounders X. If these confounders change in the direction that a firm becomes more likely to receive the treatment between t and t+1, then this leads to a reduction in the weight. The intuition is similar to that behind standard propensity score matching: as such firms that receive the treatment and show a high probability of receiving the treatment are overrepresented compared to the control group that has a high probability but does not receive the treatment, their weight needs to be reduced in order to assuage the thus induced selection problem.

The conditioning pre-treatment covariates used are the share of exporters in the two-digit industry, firm level employment, age, wages, total assets, leverage, share of informal finance, R&D, product innovation, government subsidy receipt, ownership (SOE, MNE and PRIVATE), technology intensity of industry as well as the entire history (starting from the beginning of the sample period) of the firms' exporting treatment status and TFP (outcome variable in general) histories.

These weights thus generated create a pseudo-population that mimics randomisation in the sense that treatment assignments at *each point in time* are independent of the potential outcomes conditional on the pre-treatment covariates.

The propensity scores $Pr[d_{it} = 1| \,.\,]$ are obtained using the covariate-balancing propensity scores (CBPS) estimator due to Imai and Ratkovic (2014).[12] The chief advantage of CBPS is that the propensity score is estimated such that it maximizes the resulting covariates balance alongside the usual (logit/probit) likelihood function optimization. This implies that there is no need for separate covariate balancing checking, as the algorithm deals with this simultaneously in the process of fitting the propensity score model.[13]

In an extension to the estimation of average treatment effects we also estimate a series of quantile treatment effects (QTE) based on using the inverse propensity-score weights given in equation 1 as weights in quantile regressions. For example, to evaluate QTE at quantile q (e.g. q=.5 corresponds to the median treatment effect) for category *s,* we estimate the difference between the quantiles of the marginal potential outcome distribution using all firms under category s and the *same* group of firms with non-exporting.

Moving away from ATE to QTE allows us to make a more nuanced inference on the causal effects of entering into exporting as we exploit heterogeneities along the firms' performance distribution

5 Empirical results

The first step in implementing our estimator is to come up with the conditional probabilities of receiving the two types of treatments (using a CBPS estimator) for every year (2001 – 2006). This is illustrated for 2006 (as the last year in our analysis) in Appendix B. While the CBPS estimator obviates the need for covariates balance checking, we still, for the sake of completeness, also report balancing

[12] We use the psweight Stata routine (Kranker, 2019) for this purpose.

[13] Nevertheless, for illustration purposes we report some balancing tests in Appendix Table A5.

checks in the Appendix, which show that the balancing properties are fulfilled. This suggests that our estimation approach has managed to eliminate almost all of the systematic pre-treatment differences between treated and non-exporting firms.

The estimated average treatment effects on firm level TFP are reported in Table 3, column 1. The results show that there are statistically significant and positive post-treatment effects on TFP for both types of export activity.[14] The point estimates are straightforward to interpret and suggest that entering into export processing has a stronger productivity growth effect (at 48.5 percent compared to firms not engaged in any type of exporting) than starting ordinary exports (25.9 percent).

[Table 3 here]

These results are the average treatment effects, i.e., based on the conditional mean of the distribution of the outcome variable. It might be illuminating to also consider the effect on different quantiles of the distribution, thereby investigating whether for example, low productivity firms are affected differently than high productivity ones. In order to do so, we now employ the quantile treatment effects estimator as discussed in Section 3.

The results are reported in Table 3, columns 2 to 6. This unearths an important result related to TFP that is missed when only looking at the average treatment effect: While treatment effects are always higher for entering into processing rather than ordinary exporting, these effects decline along the TFP quantiles for both types of exporting. In other words, low productivity firms tend to benefit more from entering into export markets. Importantly, while the effect is always statistically significantly positive for entering into export processing, starting ordinary exports is not associated with any statistically discernable productivity effect for firms above the 75th productivity quantile. Thus, high productivity firms experience no boost to TFP if they enter into ordinary exporting compared to having remained purely domestic market oriented.

In light of the existing literature explaining potential mechanisms for learning-by-exporting, as discussed in the introduction, the fact that firms entering into export processing experience larger treatment effects than those starting ordinary exporting may reflect two things. Firstly, by definition export processing involves imports of intermediate inputs, the use of which may boost productivity. While ordinary exporting may also involve imports of intermediates, this may be more important for export processing. Secondly, competition may play a role, as in Lim et al. (2018). Firms entering export processing may do so in order to escape domestic competition. As they become by definition part of a global value chain, and supply firms within the chain, they may not face strong direct competition on export markets. This is different for ordinary exports, who aim to sell their goods in direct competition with other firms in the destination market. These two issues may also help to explain the finding that firms in lower productivity quantiles benefit more. These firms are lagging behind others, and

[14] This mirrors the findings of positive post-exporting effects in Kraay (2002) and Ma et al. (2014).

therefore may have a stronger potential for learning from imported inputs. Also, they may have a stronger incentive to escape domestic competition by investing in product upgrading.[15]

In order to zoom in on the role of competition, we now look at heterogeneous treatment effects depending on the export destination. Assuming that competition on export markets for Chinese firms is stronger in more advanced industrial economies than in developed or emerging markets, we distinguish the treatment into whether firms enter the industrialised North or the developing South via exports[16]. Apart from different levels of competition, exporting to the industrialised North may arguably also (i) expose firms to a larger market size and (ii) be associated with stronger potentials for beneficial technology transfer than exporting to other emerging or developing countries.

Table 4 contains the results of these estimations. This shows that the positive productivity effects due to export processing are higher for processors exporting to the industrialised North (with the exception of the lowest percentile). Indeed, the gap between North and South widens the further up we move in the productivity percentiles. This may indicate that, firstly, negative competition effects, as expected, do not play a strong role for export processors, as they sell their goods within the value chain and are therefore not exposed to direct competition on export markets. Secondly, exporting to the North may expose firms to a larger market which provides stronger incentives for innovation and, thirdly, firms may have more to learn from exporting to the North, as the potential for positive technology transfer is higher.

For ordinary exports, however, there is no clear ranking in terms of productivity effects. Firms in lower quantiles appear to benefit more from exporting to the North, while this is reversed for the 50th or 75th percentile. Furthermore, in the highest quantile we do not find any statistically significant effects for either export destination. This may suggest that for highly productive firms, negative competition effects occur irrespective of whether they export to the North or the South. These appear to outweigh any potential benefits through technology transfer or increased market size.

[Table 4 here]

As pointed out above, learning effects may also differ between processing and ordinary exporters because of the importance of imports of intermediates. In our setting, this is not straightforward to investigate. The reason being that we would have to assume that importing is an exogenous mediator of the treatment effect from exporting. However, in actual fact importing may also be a treatment as firms choose to import or not. While one may attempt to account for this by modelling the decision to import explicitly (similar to the decision to export) we would then be unable to distinguish between

[15] The lower effects for firms in higher productivity quantiles may also stem from competitive pressure being more intense for such firms, as they may be in direct competition with more advanced international producers. Unfortunately, as pointed out above, our data do not allow us to distinguish such price from volume effects.

[16] For the purpose of this paper, the North is defined as consisting of the following countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland. Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States. We created a dummy variable equal to 1 if the majority of the firm's export is to the North; 0 else (i.e. South).

the two treatments when firms both export and import.[17] A full treatment of this issue is beyond the scope of this paper.

Notwithstanding this important issue, we performed an analysis where we take importing as an exogenous mediator variable. Based on firms' intensity to import (defined as imports / output, see Table A1) we generated two dummies for high and low import intensity, which are based on firms' import intensity being higher or lower than the median. We then interacted these dummies with the treatment variable. Results of this exercise are reported in Table 5. One can see that the estimated treatment effects for both types of exporters appear higher for exporters with a high import intensity (except exporters in the lowest quantile of the productivity distribution). This is in line with the hypothesis that importing contributes to learning effects. However, these results should be taken with a pinch of salt given the estimation issues discussed above.

[Table 5 here]

As a further extension, we look at two alternative outcome variables which are also closely related to technology, namely the probability of carrying out R&D, and the probability of reporting new product innovation.[18] As the results in Table 5 show, firms entering either ordinary or processing exporting both report higher levels of such innovation related activities post treatment. Distinguishing entering the North or the South shows, importantly, that these positive effects are only present when starting to export to industrialised countries. This is consistent with exporting to the North leading to innovation enhancing technology transfer.

[Table 6 here]

6 Conclusions

China's policy of encouraging export processing has been the topic of much discussion in the academic literature and policy debate. Our paper weighs into this debate, and documents economically and statistically significant positive causal effects of entering into export processing on subsequent firm level productivity. These productivity effects are shown to be larger than those accruing to firms who enter into ordinary exporting. Interestingly, the estimation of quantile treatment effects shows that these positive effects do not accrue similarly to all types of firms, but are strongest for those at the low to medium end of the distribution of the productivity variable. We also find that export processors gain more when entering the industrialised North rather than the South, while this does not appear to matter much for ordinary exporting.

[17] This is less of an issue when distinguishing exporting to the North and the South in Table 4. This is because these relate both to exporting, i.e., have the same underlying treatment variable which is at least explicitly modelled and whose endogeneity is accounted for through the propensity score matching approach.

[18] These variables are defined in Table A1.

Hence, our results show that there are gains from engaging in export processing through learning-by-exporting at the firm level. This suggests that the policy of promoting export processing may bring gains with it, in particular for low productivity firms, and for those entering industrialised economies via exporting. Hence, firms that join global value chains through export processing are able to subsequently improve their performance.

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Figures and Tables

Figure 1

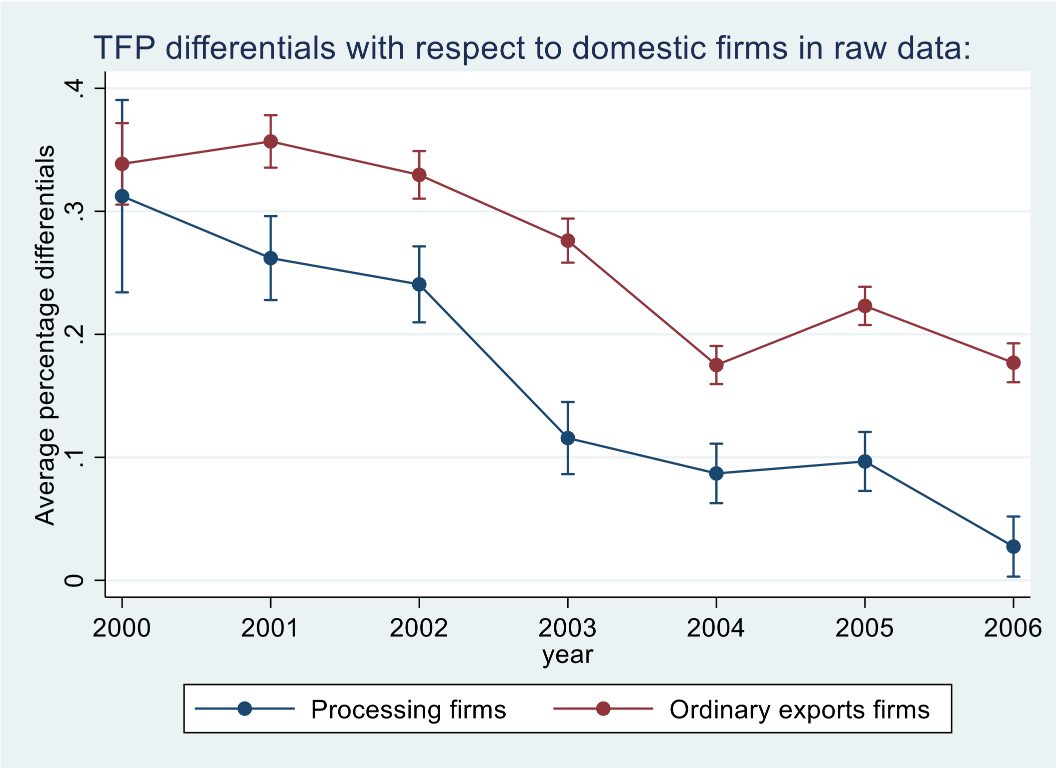

Figure 2

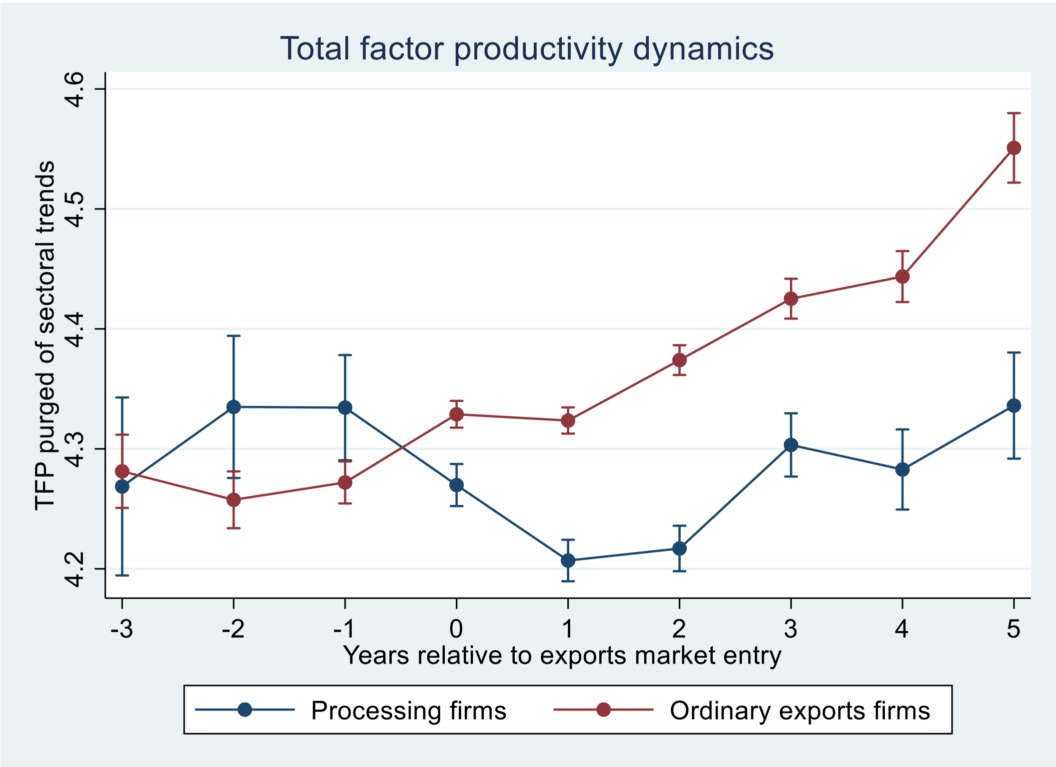

Table 1: Frequency distribution (percent) by year and exporting status

	Domestic	Processing	Ordinary	Total
2000	100.00	0.00	0.00	57,069
2001	88.67	5.48	5.85	88,695
2002	85.90	5.77	8.33	103,855
2003	84.77	5.50	9.72	114,018
2004	81.12	6.19	12.69	153,360
2005	81.74	5.87	12.38	148,346
2006	81.91	5.81	12.28	142,709
Total	84.67	5.40	9.94	808,052

Table 2: Summary statistics by exporting status

	Domestic		Processing		Ordinary	
	mean	sd	mean	sd	mean	sd
TFP (DW 2012 measure)	3.725	2.132	3.910	2.270	4.101	2.140
Proportion of export processing firms	0.0543	0.0646	0.144	0.106	.	.
Proportion of ordinary export firms	0.0994	0.0669	.	.	0.151	0.0740
Employment	4.640	0.985	5.396	0.998	5.169	1.010
Capital stock	8.330	1.502	9.161	1.557	9.002	1.551
Import intensity	n.a.		25.24	0.278	11.75	0.207
Wages	2.260	0.855	2.014	0.629	2.089	0.738
Age	6.949	1.101	8.050	1.070	7.768	1.088
Leverage	0.153	0.327	0.0778	0.229	0.112	0.270
Informal finance	0.817	0.368	0.251	0.379	0.633	0.428
R&D	0.0985	0.298	0.118	0.323	0.197	0.398
Product innovation	0.0606	0.239	0.0815	0.274	0.147	0.354
Subsidy	0.123	0.329	0.155	0.362	0.268	0.443
Low-tech industries	0.322	0.467	0.386	0.487	0.401	0.490
Medium low intensity industries	0.276	0.447	0.218	0.413	0.194	0.396
Medium high intensity industries	0.255	0.436	0.296	0.457	0.273	0.445
High intensity industries	0.147	0.354	0.0991	0.299	0.132	0.338
State owned enterprises (SOE)	0.117	0.322	0.0137	0.116	0.0332	0.179
Foreign firms (MNE)	0.0890	0.285	0.862	0.345	0.457	0.498
Private domestic firms	0.794	0.405	0.124	0.330	0.509	0.500
No. of observations	684147		43622		80283	

Note: Import intensity is not available for purely domestic firms, as these are by definition firms that do not export and that therefore are not linked to CCTS. Import information is not available in CASIF.

Table 3: Causal effects of export market entry on TFP

	Treatment effects distribution						
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile	Observations
Export processing							
Treatment dummy	0.485***	0.950***	0.568***	0.341***	0.303***	0.352***	209,975
	(0.0486)	(0.0628)	(0.0294)	(0.0299)	(0.0266)	(0.0524)	
Ordinary exporting							
Treatment dummy	0.259***	0.768***	0.341***	0.195***	0.0972***	0.0186	222,835
	(0.0254)	(0.0331)	(0.0230)	(0.0167)	(0.0167)	(0.0215)	

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Year dummies included in dynamic treatment effects estimation

Table 4: Export market entry by destination

	Treatment effects distribution						
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile	Observations
Export processing							
North dummy	0.533***	0.949***	0.580***	0.489***	0.477***	0.449***	209,976
	(0.0674)	(0.0780)	(0.0408)	(0.0377)	(0.0466)	(0.0453)	
South dummy	0.579***	0.956***	0.548***	0.434***	0.310***	0.135	
	(0.0654)	(0.125)	(0.0323)	(0.0473)	(0.0382)	(0.0856)	
Ordinary exporting							
North dummy	0.294***	0.820***	0.348***	0.180***	0.0739***	-0.00807	222,836
	(0.0332)	(0.0398)	(0.0309)	(0.0227)	(0.0237)	(0.0266)	
South dummy	0.220***	0.705***	0.332***	0.211***	0.115***	0.0466	
	(0.0385)	(0.0654)	(0.0351)	(0.0214)	(0.0221)	(0.0335)	

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Year dummies included in dynamic treatment effects estimation

Table 5: The role of import intensity (imports/output)

	Treatment effects distribution					
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
Export processing						
Low intensity	0.633***	1.062***	0.406***	0.350**	0.314***	0.215***
	(0.0948)	(0.0225)	(0.122)	(0.142)	(0.114)	(0.0302)
High intensity	0.514***	0.947***	0.603***	0.380***	0.375***	0.470***
	(0.0634)	(0.0965)	(0.0346)	(0.0441)	(0.0477)	(0.0423)
Ordinary exporting						
Low intensity	0.382***	0.959***	0.414***	0.258***	0.178***	0.207*
	(0.100)	(0.0695)	(0.0543)	(0.0696)	(0.0509)	(0.115)
High intensity	0.566***	0.950***	0.572***	0.435***	0.441***	0.380***
	(0.0601)	(0.105)	(0.0367)	(0.0443)	(0.0348)	(0.0623)

Low (high) intensity defined as below (above) median imports intensity respectively.
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Year dummies included in dynamic treatment effects estimation

Table 6: Exporting market entry and the probability of R&D and new product innovation:

	Processing		Ordinary	
	R&D	New Product	R&D	New Product
Exporting	0.0596***	0.0655***	0.0820***	0.0740***
	(0.00898)	(0.00810)	(0.00480)	(0.00406)
Destination				
South	0.00787	0.0137	-0.0149	0.0215
	(0.0125)	(0.0102)	(0.0255)	(0.0215)
North	0.0838***	0.0961***	0.0835***	0.0808***
	(0.0121)	(0.0113)	(0.00480)	(0.00407)
Observations	209796	209796	222836	222836

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Year dummies included in dynamic treatment effects estimation

Appendix

Table A1: Definition of variables used in the analysis

Treatment variable	Definition
Domestic	Dummy variable indicating firms without any kind of exporting activity (i.e. "purely" domestic firm).
Exports processing	Dummy variable indicating firms for which exports processing account for more than 25 % their total exports. In actual fact the median share of exports processing for these firm is more than 99%.
Ordinary exports only	Dummy variable indicating firms for which exports processing accounts for less than 25% their total exports. In actual fact the median share of exports processing for these firms is 0.
Baseline covariates	
Employment (Size)	Log of employment
Capital stock	Log of tangible and intangible assets (similar to Fernandes and Tang, 2012, Girma et al., 2015)
Import intensity	Imports / Output
Wages	Log of wages per worker.
Age	Log of firm age since establishment.
TFP	Log total factor productivity estimated sector by sector based on the methodology used by De Loecker and Warzynski (2012)
Subsidy	Dummy variable indicating if a firm received production subsidy.
Leverage	Total liability over total assets
Informal finance	Self-raised finance / total assets
R&D	Dummy variable indicating if a firm reported any R&D spending.
Product innovation	Dummy variable indicating if a firm reported that it produced output using new product or process innovation.
Industry dummies	Dummy variables for medium low-tech; medium high-tech and high-tech industries. Firms in low-tech industries belong to the base group (See Table A2 for definitions)
Ownership dummies	Dummies variables for majority foreign (MNE) , majority state-owned firms (SOE) and PRIVATE.

Table A2: Classification of manufacturing industries by technology intensity

Low-technology industries	Medium low-technology industries	Medium high-technology industries	High-technology industries
Food Processing	Petroleum Refining and Coking	Ordinary Machinery	Medical and Pharmaceutical Products
Food Production	Raw Chemical Materials and Chemical Products	Transport Equipment	Special Purposes Equipment
Beverage Industry	Chemical Fiber	Other Electronic Equipment	Electronic and Telecommunications
Tobacco Processing	Rubber Products	Electric Equipment and Machinery	Instruments and meters
Textile Industry	Plastic Products		
Garments and Other Fiber Products	Nonmetal Mineral Products		
Leather, Furs, Down and Related Products	Smelting and Pressing of Ferrous Metals		
Timber Processing	Smelting and Pressing of Nonferrous Metals		
Furniture Manufacturing	Metal Products		
Papermaking and Paper Products			
Printing and Record Medium Reproduction			
Cultural, Educational and Sports Goods			

Source: OECD classification scheme see http://www.oecd.org/sti/ind/48350231.pdf.

Table A3: Production function parameter estimates by industry

	Labour coefficient				Capital coefficient			
name	DW	ACF	OP	LP	DW	ACF	OP	LP
Food Processing	0.635	0.581	0.569	0.305	0.162	0.201	0.270	0.140
Food Production	0.743	0.673	0.643	0.168	0.215	0.246	0.387	0.148
Beverages	0.732	0.666	0.628	0.231	0.244	0.271	0.345	0.090
Textile	0.493	0.469	0.455	0.227	0.188	0.218	0.059	0.057
Apparel	0.596	0.541	0.499	0.253	0.177	0.201	0.146	0.094
Leather	0.584	0.568	0.517	0.239	0.143	0.210	0.241	0.123
Timber	0.619	0.568	0.550	0.258	0.045	0.069	0.212	-0.015
Furniture	0.761	0.747	0.697	0.290	0.131	0.154	0.319	0.054
Paper	0.533	0.494	0.474	0.146	0.212	0.259	0.313	0.086
Printing	0.603	0.573	0.517	0.141	0.351	0.415	0.384	0.053
Raw chemical	0.443	0.406	0.410	0.228	0.246	0.288	0.359	0.140
Medicine	0.642	0.587	0.510	0.158	0.260	0.325	0.088	0.068
Chemical fibres	0.510	0.440	0.368	0.122	0.170	0.187	0.019	-0.010
Rubber	0.430	0.383	0.397	0.091	0.281	0.272	0.398	0.099
Plastic	0.523	0.492	0.464	0.192	0.214	0.235	0.341	0.053
Non-metallic mineral	0.428	0.386	0.374	0.108	0.257	0.268	0.357	0.046
Smelting of ferrous Metals	0.752	0.682	0.589	0.576	0.135	0.105	0.207	0.242
Smelting of nonferrous Metals	0.840	0.766	0.728	0.903	0.018	-0.010	0.400	0.130
Metal Products	0.539	0.461	0.450	0.214	0.247	0.255	0.331	0.121
General machinery	0.416	0.374	0.401	0.125	0.232	0.286	0.394	0.125
Special machinery	0.475	0.379	0.437	0.082	0.217	0.256	0.498	0.181
Transport equipment	0.650	0.590	0.565	0.186	0.235	0.277	0.406	0.069
Electrical machinery	0.652	0.600	0.535	0.451	0.230	0.254	0.254	0.251
Communication equipment	0.771	0.703	0.624	0.269	0.140	0.206	0.248	0.089
Measuring instruments	0.558	0.480	0.481	0.165	0.195	0.253	0.352	0.105
Manufacture of artwork	0.592	0.503	0.510	0.232	0.190	0.213	0.306	0.118

Notes:

(i) OP: Olley and Pakes 1996); LP: Levinsohn and Petrin (2003) ; ACF: Ackerberg, Caves, and Frazer (2015) ; DW: De Loecker and Warzynski (2012)

(ii) Estimation is conducted using the PRODEST package (Rovigatti and Vincenzo Mollisi, 2016) using the “value-added approach”.

(iii) Standard errors are not reported to conserve space, but are available from the authors upon request.

(iv) As elaborated in Section 2, estimation sample consists of 808,052 firm-year observations across the period 2000-2006

Table A4: Propensity score estimation
Logistic model of the determinants of EXPORTING in 2006:

Covariate	Domestic vs. Exports processing		Domestic vs. Ordinary exports	
	Marginal effects	Standard errors	Marginal effects	Standard errors
EXPORTING 2005	0.0317***	0.00108	0.0564***	0.00147
EXPORTING 2004	0.00286***	0.000639	0.00556***	0.000645
EXPORTING 2003	-0.00164*	0.000703	-0.00256***	0.000737
EXPORTING 2002	-0.0000290	0.000668	0.00227*	0.000975
EXPORTING 2001	-0.00399***	0.00100	-0.0102***	0.00132
TFP 2005	0.000281***	0.0000814	0.0000359	0.000124
TFP 2004	-0.000285***	0.0000679	-0.000188	0.0000961
TFP 2003	-0.000192	0.000108	-0.0000931	0.000139
TFP 2002	0.0000623	0.000119	-0.0000320	0.000168
TFP 2001	-0.000472**	0.000151	0.0000353	0.000187
TFP 2000	0.000383*	0.000151	0.0000116	0.000185
Proportion exporters	0.00394	0.00236	0.00849*	0.00407
Employment	-0.000428	0.000407	-0.000204	0.000561
Wages	-0.00102***	0.000278	-0.00115**	0.000364
Age	0.00104**	0.000362	0.00130*	0.000550
Total assets	0.000391*	0.000164	-0.0000197	0.000211
Leverage	0.000200	0.000621	-0.00183*	0.000746
Informal finance	-0.00208**	0.000702	-0.00374***	0.00113
R&D	-0.000701	0.000593	-0.000919	0.000720
Product innovation	0.000767	0.000642	-0.000168	0.000757
Subsidy	0.00152**	0.000492	0.00131*	0.000583
Medium low intensity industries	0.000310	0.000453	0.00147*	0.000599
Medium high intensity industries	-0.000653	0.000481	0.000268	0.000595
High intensity industries	-0.00133*	0.000639	-0.00161*	0.000801
SOE	-0.000739	0.00106	-0.00473***	0.00139
MNE	0.00303***	0.000655	-0.000784	0.000910
Observations	121165		130680	

Note: * *p*<0.1, ** *p*<0.05, *** *p*<0.01

Table A5: Illustrative balancing tests

Covariate	Domestic vs. Exports processing		Domestic vs. Ordinary exports	
	Standardised difference	Variance ratio	Standardised difference	Variance ratio
EXPORTING 2005	0.142	1.317	0.011	1.018
EXPORTING 2004	0.139	1.302	0.010	1.015
EXPORTING 2003	0.115	1.318	0.007	1.015
EXPORTING 2002	0.089	1.290	0.002	1.006
EXPORTING 2001	0.088	1.299	-0.003	0.991
TFP 2005	0.162	0.521	0.015	1.162
TFP 2004	0.034	0.787	0.005	1.189
TFP 2003	-0.039	0.887	-0.014	1.028
TFP 2002	-0.067	0.836	-0.005	1.019
TFP 2001	-0.022	0.930	-0.009	1.035
TFP 2000	0.017	0.796	-0.009	0.837
Proportion exporters	0.238	1.135	-0.027	1.391
Employment	0.238	0.786	0.003	0.723
Wages	0.047	0.699	-0.050	0.923
Age	0.311	0.806	-0.003	0.762
Total assets	0.312	0.723	-0.011	0.900
Leverage	0.075	1.091	0.005	0.818
Informal finance	-0.180	1.205	0.042	0.899
R&D	-0.020	0.947	0.006	1.013
Product innovation	0.027	1.090	-0.001	0.996
Subsidy	0.023	1.051	-0.004	0.993
Medium low intensity industries	0.119	1.120	0.005	1.006
Medium high intensity industries	-0.016	0.983	0.007	1.007
High intensity industries	-0.031	0.936	-0.012	0.977
SOE	0.038	1.156	-0.163	0.311
MNE	0.172	1.227	0.012	1.016

Notes:

(i) As explained in the main text, the covariate-balancing propensity scores (CBPS) estimation ensures that covariates balance is maximized, and thus obviates the need for covariates balance checking. Nonetheless we report some illustrative covariate balancing statistics for the sake of completeness.

(ii) In the interest of space, the above table is based on estimation for the last year of the sample (2006), where the most complete treatment and outcome histories are available. Results for other years exhibit the same patterns and are available upon request.

(iii) Recall that by research design at the beginning of the sample period there are no exporting firms in 2000.

(iv) As rules of thumb, the variance ratio should be between 0.5 and 2 for balancing to be achieved, and standardized difference < 0.2 for key variables.

Appendix B

Sensitivity analysis:
Treatment effects distribution effects on export market
entry based on an alternative TFP measures

Recall that the discussion in the main text is based the TFP measure in the spirit of De Loecker and Warzynski (2012). For completeness, we treatment effect estimates based on a variety TFP measure; namely Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg et al. (2015) and the nonparametric Tornqvist index for total factor productivity.

Appendix Table B1

	Ackerberg, Caves, and Frazer (2015)					
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
Export processing	0.106***	0.120***	0.121***	0.0804***	0.0494***	0.0402***
Treatment dummy	(0.00937)	(0.0144)	(0.0212)	(0.00711)	(0.00854)	(0.00805)
Ordinary exporting	0.244***	0.336***	0.405***	0.157***	0.106***	0.107***
Treatment dummy	(0.0166)	(0.0596)	(0.0292)	(0.0111)	(0.0121)	(0.0279)
	Olley and Pakes (1996)					
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
Export processing	0.332***	0.156***	0.308***	0.157***	0.644***	0.625***
Treatment dummy	(0.0336)	(0.0366)	(0.0296)	(0.0188)	(0.134)	(0.0445)
Ordinary exporting	0.216***	0.106***	0.169***	0.0617***	0.181***	0.616***
Treatment dummy	(0.0162)	(0.0179)	(0.0165)	(0.00714)	(0.0265)	(0.0180)
	Levinsohn and Petrin (2003)					
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
Export processing	0.675***	1.862***	0.684***	0.551***	0.548***	0.750***
Treatment dummy	(0.0424)	(0.118)	(0.0379)	(0.0318)	(0.0437)	(0.0596)
Ordinary exporting	0.300***	0.382*	0.434***	0.275***	0.175***	0.100***
Treatment dummy	(0.0200)	(0.232)	(0.0187)	(0.0180)	(0.0180)	(0.0298)
	Tornqvist TFP index					
	Average	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
Export processing	0.199***	0.602***	0.187***	0.0600**	0.0265	0.0404
Treatment dummy	(0.0432)	(0.0681)	(0.0316)	(0.0272)	(0.0379)	(0.0595)
Ordinary exporting	0.0946***	0.487***	0.190***	0.0330***	-0.0671***	-0.103***
Treatment dummy	(0.0245)	(0.0504)	(0.0199)	(0.0125)	(0.0172)	(0.0252)