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Productivity effects of processing and ordinary export market entry: A time-varying treatments approach

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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 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.

Key Words: export processing; firm performance, China; time varying treatments

JEL Codes: F14, F61, O14

Data Sharing Statement: The data that support the findings of this study are available from the National Bureau of Statistics of China. Restrictions apply to the availability of these data, which were used under license for this study.

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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.

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) also state that export processing amounted to 55 percent of total exports.

In this paper, we investigate, to our knowledge for the first time, what the effect of entering 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. (2017) as well as Wang and Yu (2012) show, using data similar to ours, that export processors are less productive than ordinary exporters and non-exporters. 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.[1] Such negative

[1] 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.

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

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 (e.g., Halpern et al., 2015). 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.

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.[2] 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 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.

[2] 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 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 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. 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. Fernandes and Tang (2012) investigate the choice between vertical integration and arm's length trade in export processing, while Feenstra and Hanson (2005) look at the distribution of ownership and control between the foreign owner and the domestic assembly plant. 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., 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 of 2000-2006.

CCTS consists of the universe of manufacturing importers and exporters. It provides exports and imports values in US current dollar as well as value per unit; it also identifies whether trade is processing trade or ordinary trade, and the destination country for exports and country of origin for imports. 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. 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.

CASIF and CCTS do not have a common firm identifier, so a straightforward matching procedure is not possible. A fuzzy matching procedure is carried out based on the name and address of the firms. Given that our aim is to evaluate the performance effects of switching to exporting, we rule out firms that have always been traders 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 between 2001 and 2006, with the control group consisting of firms that remain purely domestic market oriented (i.e., do not start to export) over the whole period 2000 and 2006. Thus by research design we start our sample in 2000 with firms with no recorded exports.

In the final analysis our linked dataset consists of 808,052 firm-year observations across the period 2000-2006, 5.6% and 9.94% of which are export processors and ordinary exporters respectively. Table 1 presents the distribution of firms according to trade status which also shows that export processing is less prevalent than ordinary exports.

[Table 1 here]

Table 2 shows differences in firm characteristics (which are defined in Appendix A) 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 firm entering into ordinary exporters having the highest TFP.[3] As TFP is our main outcome variable, we also chart the TFP differentials 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.

[Table 2 and Figure 1 here]

As regards other firm characteristics in 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 the Table 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 an 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.

3. 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 and, 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

[3] Recall that Dai et al. (2017) and Wang and Yu (2012) find that export processors are less productive than ordinary exporters 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.

treatment histories as well as *previous outcome variables*. 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 weighting 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 and time-varying confounders X (including past outcome variables) and baseline (time-invariant) covariates X_0, the stabilized weight for individual i at time t ω_{it} is constructed as follows:

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

where $\breve{D}_{it-1}$ and $\breve{X}_{it-1}$ indicate the treatment and covariate histories up to time t-1 respectively. Specifically, 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 (Imai and Ratkovic, 2014).[4] 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 optimisation, obviating the need to iterate between propensity score model fitting and covariates balance checking.

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 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.

4. 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 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.

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

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. The point estimates are straightforward to interpret and suggest that entering into export processing has a stronger productivity growth effect (at 28.9 percent compared to firms not engaged in any type of exporting) than starting ordinary exports (13.1 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 positive for entering into export processing, starting ordinary exports is associated with a negative productivity effect for firms above the 75th productivity quantile. Thus, high productivity firms experience lower TFP effects if they enter into ordinary exporting than they would have done if they had 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 good in direct competition with other firms in the destination market. Unfortunately, with the data at hand we cannot dig deeper into trying to distinguish these mechanisms.

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 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.

Assuming that competition on export markets for Chinese firms is stronger in more advanced industrial economies than in developed or emerging markets, we now look at heterogeneous treatment effects depending on the export destination. Specifically, we distinguish the treatment into whether firms enter the industrialised North or the developing South via exports[5]. 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 shows the results of these estimations. This shows that the positive productivity effects due to export processing are consistently higher for processors exporting to the industrialised North. This may indicate that, firstly, negative competition effects, as expected, do not play a strong role for export processors, secondly that firms are exposed to a larger market size which provides stronger incentives for innovation and, thirdly, firms have more to learn from exporting to the North, as the potential for positive technology transfer is higher.

For ordinary exports, the picture is somewhat different. The positive effects for firms in lower to medium quantiles are similar irrespective of whether they export to the North or to the South. However, the negative effect for firms in higher quantiles is only observed for exporting to the North. This suggests that negative competition effects for high productivity

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[5] 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).

firms in industrialised countries outweigh any potential benefits through technology transfer, market size.

[Table 4 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 product innovation. 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.

5. 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.

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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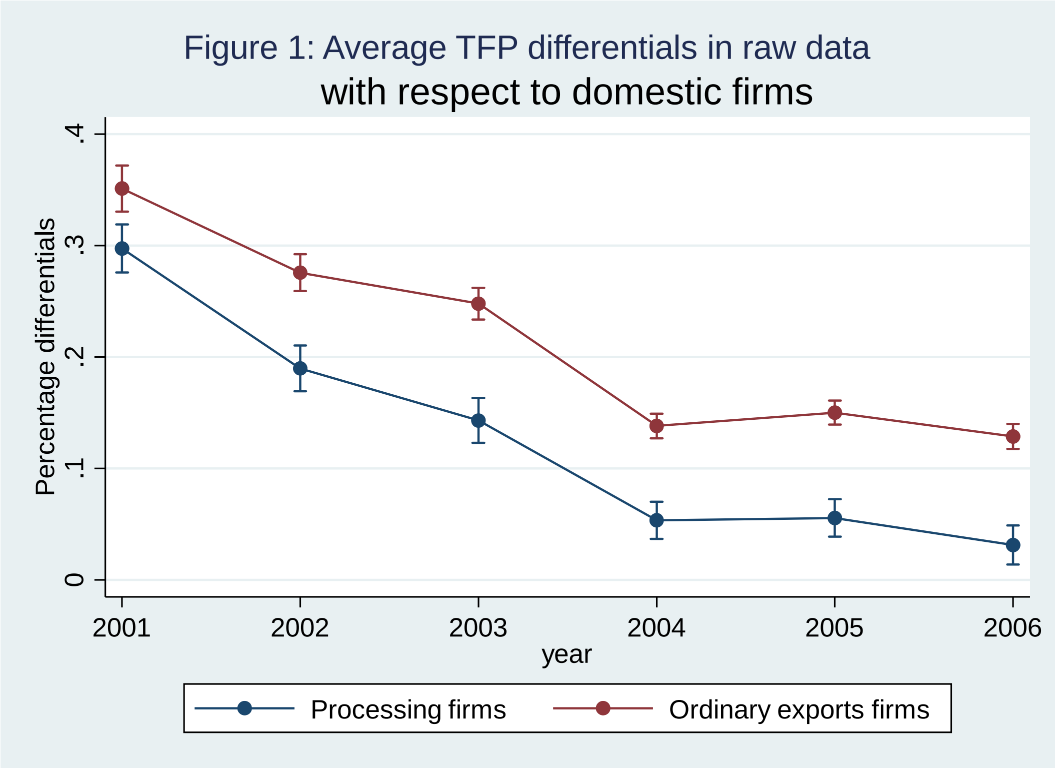
Figure 1: Average TFP differentials in raw data
with respect to domestic firms
Percentage differentials
0
.1
.2
.3
.4
2001
2002
2003
2004
2005
2006
year
Processing firms
Ordinary exports firms

Table 1: Frequency distribution by year and exporting status

	Domestic	Processing	Ordinary	Total
2000	57069	0	0	57069
2001	78649	4857	5189	88695
2002	89212	5997	8646	103855
2003	96656	6275	11087	114018
2004	124406	9493	19461	153360
2005	121265	8710	18371	148346
2006	116890	8290	17529	142709
Total	684147	43622	80283	808052

Table 2: Summary statistics by exporting status

	Domestic		Processing		Ordinary	
	mean	sd	mean	sd	mean	sd
TFP	-0.0281	0.797	0.0815	0.788	0.156	0.716
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
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
Total assets	8.330	1.502	9.161	1.557	9.002	1.551
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
SOE	0.117	0.322	0.0137	0.116	0.0332	0.179
MNE	0.0890	0.285	0.862	0.345	0.457	0.498
PRIVATE	0.794	0.405	0.124	0.330	0.509	0.500
Observations	684147		43622		80283	

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	0.289***	0.549***	0.329***	0.272***	0.251***	0.239***	209,976
	(0.0172)	(0.0389)	(0.0330)	(0.0227)	(0.0291)	(0.0323)	
Ordinary exporting							
Treatment dummy	0.131***	0.458***	0.240***	0.120***	0.00699	-0.0663***	222,836
	(0.00895)	(0.0165)	(0.0130)	(0.0118)	(0.0134)	(0.0171)	

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	0.312***	0.607***	0.390***	0.286***	0.262***	0.293***	209,976
	(0.0221)	(0.0415)	(0.0384)	(0.0269)	(0.0390)	(0.0279)	
South dummy	0.204***	0.472***	0.268***	0.152***	0.177***	0.138***	
	(0.0266)	(0.0447)	(0.0296)	(0.0340)	(0.0520)	(0.0326)	
Ordinary exporting							
North dummy	0.119***	0.477***	0.246***	0.113***	-0.0112	-0.131***	222,836
	(0.0120)	(0.0226)	(0.0144)	(0.0153)	(0.0175)	(0.0259)	
South dummy	0.144***	0.437***	0.226***	0.134***	0.0416*	0.00304	
	(0.0129)	(0.0254)	(0.0198)	(0.0178)	(0.0221)	(0.0235)	

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

Table 5:
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 A

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.
Employment (Size)	Log of employment
Wages	Log of wages per worker.
Age	Log of firm age since establishment.
TFP	Log total factor productivity estimated using the Levinsohn and Petrin (2003) approach.
Total assets	Log of tangible and intangible assets
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 undertook R&D activity.
Product innovation	Dummy variable indicating if a firm 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).

Appendix B

Propensity score estimation and covariate balancing

Appendix Table B1:
Determinants of EXPORTING in 2006:

	Exports processing vs. domestic	Ordinary exports vs. domestic
EXPORTING (t-1)	0.032***	0.056***
	(0.0011)	(0.0015)
EXPORTING (t-2)	0.002***	0.005***
	(0.0006)	(0.0006)
EXPORTING (t-3)	-0.002***	-0.003***
	(0.0006)	(0.0007)
EXPORTING (t-4)	0.000	0.002**
	(0.0006)	(0.0009)
EXPORTING (t-5)	-0.005***	-0.010***
	(0.0010)	(0.0012)
TFP (t-1)	0.001*	0.001*
	(0.0004)	(0.0005)
TFP (t-2)	-0.000	-0.001
	(0.0004)	(0.0005)
TFP (t-3)	-0.000	-0.000
	(0.0005)	(0.0006)
TFP (t-4)	-0.000	-0.000
	(0.0006)	(0.0007)
TFP (t-5)	-0.002***	-0.000
	(0.0007)	(0.0008)
TFP (t-6)	0.001*	0.000
	(0.0007)	(0.0009)
Proportion exporters	0.004*	0.009**
	(0.0024)	(0.0041)
Employment	-0.001	-0.000
	(0.0004)	(0.0006)
Wages	-0.001***	-0.001***
	(0.0002)	(0.0003)
Age	0.001***	0.001**
	(0.0004)	(0.0006)
Total assets	0.000**	-0.000007
	(0.0002)	(0.0002)
Leverage	0.000007	-0.002**
	(0.0006)	(0.0007)
Informal finance	-0.002***	-0.004***
	(0.0007)	(0.0011)
R&D	-0.001	-0.001
	(0.0006)	(0.0007)

Product innovation	0.001	-0.0002
	(0.0006)	(0.0008)
Subsidy	0.002***	0.001**
	(0.0005)	(0.0006)
Medium low intensity industries	0.000	0.001**
	(0.0005)	(0.0006)
Medium high intensity industries	-0.001*	0.0001
	(0.0005)	(0.0006)
High intensity industries	-0.001**	-0.002**
	(0.0006)	(0.0008)
SOE	-0.001	-0.005***
	(0.0010)	(0.0014)
MNE	0.003***	-0.001
	(0.0007)	(0.0009)
Observations	121165	130680

Notes:

(i) Average marginal effects from a logistic regression are reported

(ii) Robust standard errors in parenthesis

(iii) * p<0.1, ** p<0.05, *** p<0.01

Appendix Table B2:
Evidence of balancing:

	Domestic vs. Exports processing		Domestic vs. Ordinary exports	
Covariate	Standardised difference	Variance ratio	Standardised difference	Variance ratio
EXPORTING 2005	0.0951	1.2019	0.00185	1.00312
EXPORTING 2004	0.0928	1.1950	0.00169	1.00254
EXPORTING 2003	0.0729	1.1945	0.00134	1.00267
EXPORTING 2002	0.0636	1.2012	0.00207	1.00629
EXPORTING 2001	0.0559	1.1854	0.00169	1.00578
TFP 2005	0.0266	1.3149	0.00517	0.69120
TFP 2004	0.0296	1.1928	0.00371	0.68612
TFP 2003	0.0408	0.8763	0.00664	0.62453
TFP 2002	-0.0105	0.8033	0.00544	0.58236
TFP 2001	-0.0209	1.0656	0.00351	0.46630
TFP 2000	-0.0021	1.4194	0.01368	0.39404
Proportion exporters	0.1200	0.9243	0.00030	1.57193
Employment	0.2044	0.6575	0.00221	0.72404
Wages	-0.0001	0.5572	-0.00140	1.05721
Age	0.2784	0.7072	0.00268	0.74526
Total assets	0.2528	0.6758	0.00058	0.87954
Leverage	-0.0635	0.6794	0.00946	0.83081
Informal finance	-0.0693	1.0720	0.00198	0.96833
R&D	-0.0100	0.9740	0.00214	1.00428
Product innovation	-0.0270	0.9092	0.00051	1.00130
Subsidy	0.0356	1.0803	0.00102	1.00184
Medium low intensity industries	0.0240	1.0271	0.00167	1.00209
Medium high intensity industries	-0.0284	0.9731	-0.00014	0.99990
High intensity industries	0.0208	1.0443	-0.00446	0.99180
SOE	-0.1047	0.5582	-0.00604	0.97398
MNE	0.1076	1.1415	0.00144	1.00204

Notes:
(i) As explained in the main text, the covariate-balancing propensity scores (CBPS) which ensures that covariates balance is maximized, thus obviates the need for covariates balance checking. Nonetheless we report the covariates balance 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.