

A large blue and red container ship, the 'E.R. RIGA', is docked at a pier on a wide river. The ship is heavily loaded with multi-colored shipping containers. In the background, a bridge spans the river, and another smaller ship is visible further upstream. The sky is clear and blue.

KCG Working Paper

Exports and New Products in China – A Generalized Propensity Score Approach with Firm-to-Firm Spillovers

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Abstract: Underpinning China’s technological advancement are the twin-engines of exports and innovation. To better understand China’s meteoric economic transformation, we explore the extent to which new products are triggered by exports (direct effects) and by exposure to other exporters (indirect effects). Our methodology (generalized propensity score model) tackles two sources of selectivity bias – at the level of the firm and neighbourhood. Given that production is highly specialized and localized, it would be unusual if firms failed to learn from exposure to local exporters.

Our findings reveal an overwhelmingly positive direct effect of exports on new product introductions. Also, a more modest spillover effect. Interestingly, firms with a reduced need to innovate (processing exporters) can also appropriate export spillovers. Our findings have implications for other developing countries seeking to maximise exporting in economic clusters, promoting innovation and ultimately growth.

Keywords: export and innovation, export spillovers, Generalized Propensity Score

JEL Classification: C38, D22, O12, O33

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We are happy to share do files to facilitate replication. To our knowledge, access to the data, Annual Reports of Industrial Enterprise Statistics, is subject to the application procedures and private agreement with the China National Bureau of Statistics. For researchers interested in using this data, we are happy to assist.

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1 Introduction

Reflecting on China's enormous growth success over the past years, experts have noted the unevenness of this growth (Alder, Shao and Zilibotti, 2016; Gao, 2004). China's cities, for instance, represent a patchwork of different industrial policies and growth rates. Additionally, production in cities is highly specialized. To illustrate, 50 percent of the world's optician glasses are manufactured in Danyang and 90 of global production of e-cigarettes hails from Shenzhen (See Wu, 2019).

Against this backdrop of high growth and specialization, experts agree that the productivity growth of exports has outstripped expectations for a country of its income levels (Woo, 2012), a reason China's economic development is often hailed as a blueprint for other middle-income countries to follow.

Although the productivity of China's exports is broadly unchallenged, there is mixed evidence for the role of exports in triggering innovation. The purpose of our analysis is, therefore, to identify this causal relationship and to analyse the impacts of China's exports on key innovation metrics (new products and R&D). A further novelty is that we decompose the impact of exports into its direct as well as its indirect (spillover) components. This additional focus on spillovers aims to reconcile the lack of empirical evidence for knowledge transfers with the realities of manufacturing in China – a country shaped by deep regional specialization and increased self-reliance. Without any documented evidence of knowledge transfers – from foreign markets to exporters and from exporters to non-exporters – China's success story becomes more of a puzzle. Finally, an important feature of many developing countries is the importance of processing exporters, which are likely to have different incentives to innovate compared to ordinary exporters. We therefore distinguish between these two types of exporters in our analysis.

Applying a generalized propensity score approach with firm-to-firm spillovers to firm-level data for 229 neighbourhoods in China, our methodology allows us to deal with two of the most obvious selection biases connected with exporting and new product introductions – when 1) more innovative firms are more able (and hence more likely) to start exporting and when 2) more innovative neighbourhoods are favoured by firms.

We find a strong and significant innovation premium for ordinary exporters. For processing exporters, the innovation premium is only significantly positive when the share of processing exporters rises to between 20-50 percent within a neighbourhood. Interestingly, we find evidence that non-exporters can learn from their exporting peers and that the learning effect is conditioned on the share of exporters within the non-exporters' neighbourhood.

Our analysis is organized in the following way. In Section 2, we sketch the literature relating to the links between export and innovation, discuss stylised facts of the Chinese market, introduce our econometric framework and discuss how it can be mapped to the china context. Section 3 contains the empirical model, followed by a description of the data in Section 4. Section 5 contains the empirical analysis, including robustness checks. We conclude in Section 6.

2 Exports and Innovation – Stylized facts of the Chinese market

Economists generally agree on a connection between exports and innovation – the former fuelling the latter (Salomon and Shaver, 2005; Monreal-Pérez et al, 2012). For China, several studies report this relationship (Jarreau and Poncet, 2012; Xie and Li, 2018).

But there is a further effect – an indirect or ‘spillover’ effect (Barrios, Görg and Strobl, 2003; Choquette and Meinen, 2015; Fu, 2015; He and Walheer, 2020). Spillovers happen when information accumulated by exporters, gets spilled over to non-exporters in the same region or sector. In the case of China, spillovers are recorded for *multinational* firms (Chang and Xu, 2008; Fu, 2008; Liu and Buck, 2007; Xie and Li, 2015). However, there appears to be no evidence for spillovers from *domestic* firms (Fu, 2015; Sun and Du, 2010). Specifically, Wang and Kafouros (2009) argue that the lack of such evidence may be the result of “incomplete theorizing”.

Similarly, Sun and Du find no signs of domestic technology transfer within China. This lack of evidence for technology transfers from domestic actors is surprising when we consider the broad patterns of specialization/agglomeration across China’s provinces and cities (Jarreau and Poncet, 2012).

In the following sub-sections, we introduce some stylized facts for China, before mapping these to an empirical model of exporting and innovation.

2.1 Not all firms produce their own ideas

Similar to many developing and middle-income countries, not all firms are reliant on creating their own ideas or technologies. A sizeable share of China’s firms merely assembles end-products from inputs manufactured elsewhere in the Asian hub, or further afield (Jarreau and Poncet, 2012). The requirement for radical innovation is subordinate to the need for efficient ways to reduce the cost of assembly and shipment. Here, the need for in-house R&D is not always essential.

There is a raft of papers documenting the features of export processing firms, which make the case for distinguishing these firms as a group (Jarreau and Poncet, 2012; Mayneris and Poncet, 2015; Wang and Yu, 2012). Otherwise, any empirical results can be biased, for example if a disproportionate share of exports in the export processing sector is manufactured using imported inputs. However, processing exporters are slowly converging towards ordinary exporters, at least on one dimension – value-added. A number of relatively recent work has highlighted the increasing domestic content of China’s exports, even from this once highly distinctive group of firms (Kee and Tang, 2016; Lemoine and Unal, 2017; Manova and Yu, 2016; Upward et al, 2013).

We should note another point in our discussion about the origin and originality of innovation in China - Chinese firms are seen as having evolved from imitators to innovators. But at the time reflected by our data, China’s firms were still characterized as imitative (Zheng and Wang, 2012). Anyhow, our empirical framework is sufficiently flexible to capture the imitative aspect of learning described by spillovers.

2.2. Spillovers happen within provinces (not between them)

Several studies for China have documented how China's 31 provinces operate, to some extent, autonomously from each other (e.g., Fu, 2015; Hanley, Liu and Vaona, 2015; Scherngell and Hu, 2011). This is reflected in different regional policies which shape, inter alia, the absorptive capacity of firms. This remark also holds for knowledge spillovers that get transferred from firm to firm – spillovers happen within (not between) neighbourhoods (e.g., Girma and Gong, 2008). Scherngell and Hu (2011) argue that collaboration between firms in different provinces is unlikely. Fu (2008) demonstrates that regional differences moderate the assimilation of new ideas – the innovation constraints and the incentives facing firms, differ from region to region. Indeed, Fu uses regional differences as a proxy for the absorptive capacity of China's firms. Elsewhere, Gao (2004) argues that transactions between firms (a spur to innovation) are characterized by region.

This observation that policies and economic patterns differ across China's regions allow us to make the following assumption – firms within the 229 neighbourhoods that comprise our data, transact with firms in the same neighbourhood (but less so, or not at all, with firms from outside the neighbourhood).

2.3 Adjusting our regression using inverse probability weights estimation

Having reviewed the stylized facts for China, we can now see how best to map the main variables of interest (innovation and exporting) into a causal model. In this section, we begin by illustrating why a standard regression is not fit for purpose. We then adjust our model using inverse probability weights to deal with several sources of selection bias.

We start with estimating the impact on innovation y , taking the export treatment d_{export} and China's geo-economic heterogeneity, Neighbourhood (share of exporters in China's 229 neighbourhoods) into account:

$$y = d_{ij\text{export}} + \text{Neighbourhood}_j + d_{ij\text{export}} \cdot \text{Neighbourhood}_j \quad (1)$$

But this straightforward estimation falls short. The problem is that any results estimated using a variant of the above are likely to be biased. Why? There is a dual selection problem – at the firm level i and the neighbourhood level j . It is clear these two sources of selection are characterized by different levels of aggregation. At the level of the firm i , ex ante more innovative firms are likely to select into exporting, analogous with Melitz-type selection (Melitz, 2003). The second source of selection arises at the level of China's geo-economic neighbourhood j , where structures for ideas-generation are highly differentiated across, but not within neighbourhoods (regional-government investment and innovation policies, targeting of FDI, etc.).

The method we propose to tackle this dual selection bias is a multi-step regression using probability weights to correct the standard errors for the effect of exporting and neighbourhood on the innovation outcome. We should stress that this is not a propensity score matching model – rather we estimate propensity scores – which in turn are used as inverse probability weights for the exporting term. The

propensity score probability weights help ensure that firms which, on the basis of the selection regression are the most ‘obvious exporters’, receive a reduced weight in the outcome regression. On the other hand, firms which the selection estimation characterizes as ‘less obvious exporters’, receive a higher weight in the final, outcome regression.

There is an additional modification to our weighted regression – the level of aggregation. Our first-stage selection regression is estimated at the level of the firm. Thereafter, our outcome regression is calibrated at the level of the neighbourhood. In concrete terms, this means our outcomes are interpreted as ‘exporting share’ in a neighbourhood, rather than an exporting dummy.

A final adjustment concerns identifying spillovers, within a causal framework. We need to modify the standard method of estimating the propensity score – the Generalized Propensity Score technique. This additional adjustment is necessary because a very basic (and difficult to justify) assumption of the propensity score technique is that the actions of the firm have no effect on the performance of other firms. This is an obvious weakness of the technique, as the transfer of ideas for new products from firm to firm is well documented in previous studies (e.g., Grossman and Helpman, 2015; Holmes et al, 2015). Using the Generalized Propensity Score (GPS) technique allows us to partially relax this restriction, in the spirit of the FDI study by Girma et al (2015).¹ However, the technique has not yet been used for modelling spillovers from exports.

Having applied the above modifications (weighting, aggregation considerations, relaxation of the no-spillover assumption²) to our model, we are now able to identify the impact of export spillovers on innovation for China.

2.4 Modelling exposure to exporters in a neighbourhood

To model the exposure of China’s firms to exporters in their vicinity, we adapt the convention used most recently by Girma et al. (2015), using the proportion of treated firms within a group as a measure of interaction between individual firms. To illustrate, we have data for 229 geographic units (each, more or less mapping to China’s 334 prefectures) set within China’s 31 provinces. This allows us to record interactions between firms for $R=229$ neighbourhoods. Let us assume that there are $i=1\dots N$ firms in each neighbourhood and N_r is the number of exporters in the neighbourhood (in other words, are designated as *treated* firms). Mathematically, we can describe the proportion of treated firms as

$$p_r = \frac{N_r}{N}, r = 1, \dots, R \quad (2)$$

¹ Another even more recent study, directly examines the innovation effects from FDI to China, although without modifying the matching model to accommodate spillovers (Olabisi, 2017).

² This no-spillover assumption is a specific case of a more general assumption called the Stable Unit Treatment Value Assumption (SUTVA) (see Rubin 1974). This assumption is not very appropriate for China, as our review of the studies demonstrates (section 2.2), in the context of China’s reasonably permeable knowledge environment. Fortunately, empirical advances have partially relaxed Rubin’s SUTVA assumption, allowing spillovers to arise under certain limited circumstances (e.g., Hudgens and Halloran, 2008).

Earlier, we highlighted the fact that China's exporters can be broadly classified into two groups – ordinary exporters and processing exporters – each group characterized by a different incentive to commence exporting and/or introduce new products. We need to consider these differences between firms when categorizing the possible outcomes, when a firm is exposed to the treatment. In a nutshell, we can classify firms into three categories, each category receiving a different probability weight for how we expect spillovers to boost the innovation potential of individual firms in the category. These categories are defined as follows - $d_{ir}=0$ if firm i in neighbourhood r is a non-exporting firm, $d_{ir}=1$ if firm i in neighbourhood r is an ordinary exporter and $d_{ir}=2$ if firm i in neighbourhood r is a processing exporter. These categories neatly reduce to $\frac{\sum_i^N d_{ir}}{N}$, where the proportion of treated firms is denoted as p_r . The proportion illustrates the share of each type of firm in each of the 229 neighbourhoods in our data, and how this share affects the innovation status of the firm i , contingent on the status r of d_i (e.g., is d_i an export processor exposed to a higher share of export processors in its neighbourhood). Taken together, the above expressions describe how we expect knowledge to spill over to our firm d_i , from exporters in the same neighbourhood.

We now turn to our outcome variable. Innovation can be understood most intuitively as the introduction of new products. Alternatively, innovation has been proxied by R&D in the literature. However, we argue that new product introductions represent a more immediate measure of innovation – the R&D measure is at times criticized because it is an input to (not output from) the innovation process. An additional caveat is that R&D is sometimes subject to severe overreporting (König et al, 2020). Notwithstanding these caveats, we use R&D as an alternative innovation measure.

In terms of our framework, we allow for spillovers in each neighbourhood. Now the overall innovation effect can be described as a function of the firm's own decision to export (or not) and the proportion of exporting firms in the firm's neighbourhood, p_r

$$y_{ir}^d \equiv y_{ir}^d(p_r); d=0, 1, 2 \quad (3)$$

where d denotes non-exporters, ordinary exporters and processing exporters respectively and p_r is the exposure rate (or share) of treated firms in the neighbourhood. It follows that we can calculate for each of the 229 geographic units, the expected value of spillovers (potential outcomes), as a function of the magnitude and type of spillover exposure (i.e. share of ordinary exporters or processing exporters in a neighbourhood). Following Hudgens and Halloran (2008) and Girma et al (2015), having calculated these expected values (average potential outcomes) for each neighbourhood, we can then calculate the treatment effects. In so doing, the expected values can be used to calculate direct, indirect and total effects of exporting on the introduction of new products. In the next section, we will show in greater detail, how these expected values get used in the estimation model.

2.5 The final model – direct, indirect and total impact of exports on innovation

The *direct effect* of the treatment compares expected value (average potential outcome for an exporting firm with the potential outcome for a non-exporting firm), keeping the neighbourhood-specific treatment level constant at p (i.e. keeping possible interactions fixed).

$$\bar{\gamma}_{pp}^{10} = \bar{y}_p^1 - \bar{y}_p^0 \quad (4)$$

The subscript is denoted as pp because interactions p are held constant – we do not assume any increase or decrease in the proportion of exporters *within the neighbourhood*.

The direct effect is likely to differ across all 229 neighbourhoods, for which we have data – different neighbourhoods having different concentrations of exporters. This is why we can depict the final innovation outcome – average rates of new product introductions – as exporter concentrations increase.

Now we come to the indirect (spillover) effect, where the rates or proportions of exporters in a neighbourhood are allowed to vary. Here, we look *across neighbourhoods* to define the model. What now remains constant is the exporting status. Below, we illustrate the expression for a non-exporter which is exposed to varying rates of exporting in its neighbourhood –

$$\bar{\gamma}_{p0}^{00} = \bar{y}_p^0 - \bar{y}_0^0 \quad (5)$$

In other words, we calculate the difference between the expected value of non-exporting firms in a neighbourhood which are exposed to the share of exporting firms p and the counterfactual (the expected value for these non-exporters in a neighbourhood without any exporting firms (*across neighbourhood*)).

The total effect is the sum of both these effects is -

$$\bar{\gamma}_{p0}^{10} = \bar{y}_p^1 - \bar{y}_0^0 = \bar{\gamma}_{pp}^{10} + \bar{\gamma}_{p0}^{00} \quad (6)$$

This expression captures the change in the potential treated outcome when the proportion of exporting firms in the neighbourhood is $p > 0$ compared to the non-treatment outcome that would occur if $p = 0$.

3 Model Estimation

We recall our initial problem when attempting to describe firm-to-firm export spillovers in China. In line with stylized facts – ex ante ‘better’ firms can more easily overcome the sunk costs of exporting and commence selling their products in foreign markets. Additionally, production is highly localized, with few interactions between firms in different neighbourhoods but firms can select into these neighbourhoods based on pre-existing production patterns within these neighbourhoods e.g., higher

capital to labour ratios in one neighbourhood. To deal with these dual sources of export selection (firm- and neighbourhood-level), we will describe the Generalized Propensity Score (GPS) model below and calculate treatment effects as the difference between treated and non-treated neighbourhoods. We should recall, our technique is adapted from the technique used by Girma et al (2015).³

3.1 Estimating expected outcome value by neighbourhood

The purpose of our model, as we have already highlighted, is to deal with the selection of firms into more highly innovative or export intensive neighbourhoods. Unless selection bias is eliminated, it is difficult to identify the effect of exporting on innovation. Accordingly, in a 3-step procedure, we first estimate the propensity score of a firm receiving treatment. In the second step, we use the score obtained as weights in the outcome regression. In turn, this outcome regression, calculates expected values for different levels of treated firms (exporter concentrations) in a neighbourhood. In this way, we eliminate an important sources of selection bias (Hirano, Imbens and Ridder, 2003).

For each neighbourhood, the estimation involves -

- a. Generating the firm level propensity-score (ρ) of being treated using a logistic regression with the covariate vector X , to satisfy the balancing conditions balancing conditions, which is the case for all covariates.⁴ Our list of covariates comprises total factor productivity, leverage, employment, age, profitability, new product introduction, R&D activity, capital labour ratio, firm sophistication dummies (medium low-tech, medium-tech, high-tech) and ownership dummies (foreign, state-owned, private)⁵. All time varying covariates are defined with 1-year lags. Based on this covariate vector, we estimate the propensity score of a firm receiving treatment by conditioning the treatment categorical variable (non-exporter, ordinary exporter or processing exporter)
- b. As a next step, we use the inverse of the obtained propensity scores to estimate the following outcome equation for each neighbourhood using an inverse propensity score regression -

$$y_{ir} = \alpha + \beta d_{ir} + \delta X + error; i=1...N \quad (7)$$

- c. Finally, we calculate the expected values within each neighbourhood for processing exporters, ordinary exporters and non-exporters respectively -

$$\bar{y}_r^2 = \frac{1}{N} \sum_{i=1}^N (\hat{\alpha} + \hat{\beta} d_2 + \hat{\delta} X) \quad (8)$$

³ Readers preferring a more comprehensive description of the generalized propensity score (GPS) technique might find this useful.

⁴ See Table 5 for the results of the balancing test. This covariate balancing test, tests for the difference in the means of the covariates in treatment and control groups, conditional on the estimated propensity score. We did not reject the null hypothesis of equality of means in any of the tests. See Girma and Görg (2007) for a detailed discussion.

⁵ It is essential to distinguish between these different categories of firm. A recent study by Walheer and He (2020), has used data envelopment techniques to underscore differences in the efficiency and technological level of China's foreign-owned, domestic and State-owned firms.

$$\bar{y}_r^1 = \frac{1}{N} \sum_{i=1}^N (\hat{\alpha} + \hat{\beta} d_{ir} + \delta X) \quad (9)$$

$$\bar{y}_r^0 = \frac{1}{N} \sum_{i=1}^N (\hat{\alpha} + \delta X) \quad (10)$$

- d. Recall that $d_{ir}=0$ if firm i in neighbourhood r is a non-exporting firm, $d_{ir}=1$ if firm i in neighbourhood r is an ordinary exporter and $d_{ir}=2$ if firm i in neighbourhood r is a processing exporter.

3.2 Calculating treatment effects for new product introductions

In this section, we want to introduce our key outcome variable, new product introductions, and how we calculate treatment effects. Looking at step c) above, we sketched out – in general terms - the estimation of *expected outcomes*. More specifically, these expected values mean that for each of the 229 neighbourhoods in our data, we estimate these neighbourhood-level expected values of new product innovation for each exporting category (processing, ordinary and non-exporting) respectively - \bar{y}_r^2 , \bar{y}_r^1 and \bar{y}_r^0 . Additionally, the share of each type of exporting firm, in each neighbourhood, is defined as our (continuous) treatment, where the derived treatment measure is bounded between 0 and 1.

Now that the treatment is no longer binary (i.e. Does the firm commence exporting, or not?) but rather continuous (i.e. How high is the share of exporting firms in the neighbourhood?), we apply the generalised propensity score (GPS) technique at the neighbourhood level. Apart from relaxing the SUTVA assumption, the GPS has the added benefit of working well for continuous treatments (e.g., Hirano and Imbens, 2004).⁶ Since our dependent variable (the share of exporters) is a continuous variable and a proportion between 0 and 1, we estimate the determinants of the treatment using the fractional logit model (Papke and Wooldridge, 1996, 2008). Having a naturally bounded treatment variable between 0 and 1 is in line with the situations discussed in Papke and Wooldridge (1996, 2008) of proportions of income spent on charitable contributions, participation rates in voluntary pension plans or test pass rates. We then calculate the treatment effect as the difference between treated and non-treated clusters.

4 Data Description

In order to investigate the direct and indirect impact of exporting on innovation empirically, we draw on two comprehensive Chinese firm datasets. The first dataset is the firm-level panel from the Chinese manufacturing sector which is based on the Annual Reports of Industrial Enterprise Statistics, compiled by the China National Bureau of Statistics. This dataset covers all firms in China with an annual turnover of more than 5 million Chinese Yuan (about \$773K). These companies account for an estimated 85-90 percent of total output in most industries and provide us with detailed information of the firms' location in order for us to create 'township' neighbourhoods. For the purpose of this analysis, we have

⁶ For details, see Girma et al. (2020).

information on more than 170,000 firms for the period of 2004-2006 with 2005 being the treatment year (exporting), 2004 being the pre-treatment period and outcome variables being measured in 2006.

The second dataset used is the Chinese Customs Trade Statistics collected by the Chinese Customs Office, containing all Chinese trade transactions to 243 destination/source countries. It also splits exporting into ordinary or processing exports (imports or pure assembly), respectively. We merge both datasets together, the combined data allowing us to investigate the impact of both types of exporters (ordinary exporters and processing exporters) on innovation activities in this paper.

Table 1 summarises our variables of interest, by exporting status. Our exporter treatment variables are measured in a 1-year lag (2004) as are our pre-treatment covariates. Outcome variables are measured in 2006 values.

We analyse two different outcomes - our key outcome variable is a new product dummy if a firm has sales of a new product in the year and as a robustness check we use a R&D dummy if a firm spends on R&D in the year. Among the total number of 170,643 firms in our sample, around 70k (41 percent) are non-exporting firms, 53k (31 percent) are ordinary exporters and 48k (28 percent) are processing exporters.⁷ As one might expect, there are substantial differences between non-exporters, ordinary and processing exporters, justifying the adoption of a treatment effects evaluation framework. The raw data suggests that ordinary exporters are more likely to demonstrate higher productivity, higher profitability, more employees and are more innovative. Additionally, they have a higher tendency to be characterized as foreign-owned and occupy high-tech industries, compared to both non-exporting firms and processing exporters. Therefore, it is important for us to control for these firm-level characteristics in our estimation when addressing any firm-level selection bias.

When we look at the firms' post-treatment innovation characteristics, there are also clear differences between ordinary and processing exporters. Processing exporters have significantly fewer new product introductions (6 vs 18 percent) and less R&D (8 vs. 16 percent). It is worthwhile noting that the R&D dummy of processing exporters in the pre-treatment period (7 percent) is already an indication that processing exporters are building up their own absorptive capacity and are not content to merely process products for export.

In this paper, we classify firms into neighbourhoods based on 229 towns in which firms are located. Table 2 provides summary statistics for our neighbourhood-level variables across these 229 towns. On average, neighbourhoods have a reasonably high share of ordinary exporters (23 percent) and processing exporters (29 percent) in the treatment year (2005). But this share is associated with a high variance, values ranging from 1 to 96 percent for the share of ordinary exporters. We also observe the differences across neighbourhoods in terms of productivity, leverage, profitability, R&D and new product development. One reason for these differences could be due to the policy and institutional differences across the neighbourhoods as we discussed in Section 2.2. We recall that production can be highly specialised across China's cities and prefectures (Jarreau and Poncet, 2012; Poncet and de

⁷ Ordinary exporters are firms with more than 50 percent ordinary exports. Processing exporters are firms where more than 50 percent of their exports is processing exports.

Waldemar, 2013). Additionally, these neighbourhoods can differ from each other in terms of policies made by their respective institutions e.g., education (Zhu et al, 2019). As Wu (2019) notes, these neighbourhoods are often global production centres but highly focussed on the production of a particular product or service for export. Moreover, some towns have a much stronger policy focus on promoting exports.

5 Main Findings

Before presenting the findings of our analysis, it is worth recalling our research question, namely to analyse the impact of China's exports on key innovation metrics (new product introductions and R&D). Additionally, we decompose exports into their direct as well as their indirect (spillover) components.

We begin by presenting a simple logistic estimation – illustrating the non-causal link between exports and innovation (**Section 5.0**). After this, we begin our causal analysis, by analysing export and innovation at the neighbourhood-level (**Section 5.1**). We then calculate the causal effect of exporting on innovation outcomes, both direct, indirect as well as total effects (**Section 5.2**).

5.1 Exports and innovation: baseline regression

To set the stage, we start with a simple illustration, showing how exports impact upon innovation outcomes. We should note, this is not the model described above – only a sketch of key relationships in the data. Accordingly, we estimate a simple binary logistic estimation, with innovation outcomes modelled as new products and R&D investments, respectively (Table 3)⁸.

The first set of covariates, direct and indirect export covariates, comprise the focus of our study. The coefficient of Ordinary Exporter captures the direct effects of ordinary exports and is positive but insignificant for new products.

The coefficient of Ordinary Exporter share, capturing the indirect effect (positive and significant) - reveals how new product ideas get transmitted to every firm, even to non-exporters. Now, we turn to the interaction term, Ordinary Exporter * Exporter share, which demonstrates the direct effect conditional on the proportion of exporters in the neighbourhood.

For ordinary exporters, the interaction shows a premium to new product introductions from exporting, with rising exporter share (coefficient of 1.3, significant to 1 percent level). Regions with higher exporter share, are also associated (unsurprisingly) with a higher share of new products. However, this baseline regression does not describe any causal link. For this, we need to proceed to the next sections.

Before doing so, a few remarks about processing exporters - in short, while the direct effect is significant and positive, the interaction is significantly negative. This means that rising concentrations of exporters lead to a dampening of innovation outcomes for processing exporters.

⁸ 'New Product Introductions' are the main focus of our analysis. R&D investments are included as an additional robustness check.

5.2 Export and innovation at the neighbourhood level

Next follows the two steps of our Generalized Propensity Score (GPS) model as described in **Section 3**. We start by examining the determinants of the ‘treatment’ variable, calculated as the share of firms that export (ordinary and processing exporters) in a neighbourhood. To do this, we use the fractional logit model within the generalised propensity score (GPS) technique. Table 4 provides the results based on the estimated coefficients and the marginal effects at the neighbourhood level. We draw attention to several key findings. In **Table 4**, the regressions are spilt, according to whether we are estimating the exporter share for the ordinary exporter or for the processing exporter group. Somewhat intuitively, higher shares of ordinary exporters, depress the share of exporting processors, and vice versa – underlining the trade-off between the two exporting types. Both types are recorded as mutually exclusive in the data.

More interesting is the connection between new products and the exporting share – positive, and significant in the case of ordinary exporters. With a rising share of new product introductions (1-year lag), exporting similarly increases. This is evidence of selection – more innovative regions attract higher numbers of exporters. The results for the R&D dummy are more nuanced – significantly negative for the Exporter group. One explanation for the negative coefficient might be the use of the first lag for R&D. 12 months may be an insufficient time-horizon for a positive exporting outcome to arise. Research expenditures have notoriously long time-horizons, often several years before research investments achieve commercial success. In this case, a negative coefficient might be expected. A negative coefficient might also be expected if firms see a trade-off between research investments and commercialization. During the period of our data, China’s exports focussed on products that arguably needed little R&D.

In **Appendix 1**, we have provided additional background data to this issue of technological focus. From the Comtrade data, we can see that the bulk of exports for the time period under observation, comprised mechanical appliances, electrical machinery and the parts thereof (product groups 84/85). There was also a sizable trade in textiles and footwear (product groups 60/64). Many of these products were focussed on producing existing technologies at a lower cost. Given the emphasis on existing technologies, it is debatable whether many of these products required heavy R&D investments.

Having dealt with the main variables, we will now comment on the remaining covariates – all similarly aggregated to the level of neighbourhood - which are statistically significant. State-owned firms are associated with reduced exporting shares in their neighbourhood, all things equal. Otherwise, exporter share is marginally linked to higher borrowing and negatively connected to capital labour ratios. This result is slightly unexpected, given that we expect capitalization to positively correlate to exporting. However, in China, an incremental approach to innovation suggests that potential exporters can enter export markets using second-hand equipment. Alternatively, the capital to labour ratio can decrease where potential exporters hire additional staff to help finish products for export. Such is not an unlikely scenario in a labour- intensive economy – as China was characterized back then.

To sum up the findings so far, our regressions support the view that China’s exports were shaped – not by research investments – but by lower-tech products, manufactured at a competitive price.

5.3 Treatment effects of exporting

Having dealt with the initial task of estimating the share of exporters in any of China's 229 neighbourhoods, we now investigate the treatment effect of exporting on new product introductions – where new products represent our key innovation outcome. We follow this up with a robustness check, using R&D as an alternative innovation outcome.

We recall that our methodology breaks the total effect of exporting into the direct and the indirect effect, respectively. **Figure 1** illustrates our main results – charting the effect of higher exporting share on new product introductions.⁹

(Figure 1 here)

Looking at ordinary exporters first, the direct effect of exporting on new product development is broadly positive and highly significant – a higher share of exporters in a neighbourhood leads to a higher share of new product introductions. Our result echoes the findings of other China-based studies which report a positive association between exporting and innovation (Jarreau and Poncet, 2012; Xie and Li, 2018). However, our study provides the first evidence of a *causal* link between China's exporting and innovation.

Going beyond the direct effects, we additionally report the indirect (spillovers) effect and the total effect (direct and indirect). We first turn to the total effect, again for ordinary exporters. Like the direct effect, this effect is similarly positive. However, our results prove, for the first time that firm-to-firm spillovers are not driving this positive total effect. Indeed, the indirect effect (spillovers) is even (slightly) negative.

We now move to the results for processing exporters. We recall that we expect fewer effects for this category of exporters. We base this assessment on Jarreau and Poncet (2012), who concluded that ordinary exporters (not domestic processing exporters) are the key drivers of new product development. Indeed, our findings for processing exporters confirms this conjecture, as can be seen by the lower coefficients for processing exporters than for ordinary exporters.¹⁰

However, contrary to Jarreau and Poncet (2012), the total effect for processing exporters, is also positive and significant for a share of processing exporters between 20 and 50 percent in the neighbourhood. In other words, a minimum share of processing exporting is required. Interestingly, this effect is mainly driven by indirect effects (spillovers), i.e. when it comes to new products, firms benefit from spillovers from neighbouring processing exporters. This is in line with processing companies imitating more what their neighbouring firms are doing, e.g., due to the usual motives for spillovers (labour mobility, demonstration or linkages).

⁹ **Figure 2** is based on the estimates in **Appendix 2**

¹⁰ For an excellent description of differences between foreign-owned and domestic-owned processing exporters see Amiti and Freund (2008)

These differences between our findings and those of Jarreau and Poncet could stem from several reasons. We apply a more granular definition for our main regression, to that used by Jarreau and Poncet – drilling down to the level of prefecture. Spillover effects are likely to occur at relatively close proximity. Additionally, our regressions capture effects across a whole continuum of treatments – we are able to observe the effects on new product introductions along the continuum of exporting share – from zero to 60 percent. This allows us to demonstrate that the share of processing exporters needs to exceed a threshold of around 20 percent for positive spillovers to occur. Finally, there are differences in how we define the innovation outcome.¹¹

Figure 1 also displays the associated 95 percent confidence intervals. This clearly shows that the potential outcomes for new product development (for treated and untreated firms) vary systematically with the level of exporters (ordinary or processing) in the neighbourhood. Given our econometric approach, we can interpret this as a causal relationship, whereby changes in exporter concentration lead to innovation outcomes. Our positive findings for spillovers, indicates that the no-spillovers SUTVA assumption does not hold within neighbourhoods in our analysis.

How confident are we in concluding that higher exporting shares lead to a higher share of new products? To underpin our findings, we use R&D as an alternative innovation measure. R&D represents the focus of other studies (e.g., Xie and Li, 2018). **Figure 2** presents the treatment effects of exporting on the probability of R&D investment.

(Figure 2 here)

Looking at the effects of ordinary exporter concentration on R&D, we again reveal a positive direct effect. This suggests that ordinary exporters are more likely to invest in R&D to stay competitive. However, there is a striking non-linearity to this result. The positive returns really only gather momentum from exporter concentrations of 30-35 percent and above. There is an interesting dynamic at work, at the prefecture level. As we have seen with new product introductions, R&D returns grow (almost exponentially) for neighbourhoods with above-average exporter concentrations.¹² There is a possible explanation for this non-monotone pattern. Where exporting penetration is very low - e.g., less internationalized prefectures – it may make better sense for firms to imitate their peers, rather than invest in internal R&D capacity. In a less crowded market, firms may be able to piggy-back on the R&D efforts of others. But R&D is a powerful competitive tool, enabling firms to achieve domestic, as well as, international competitiveness. R&D certainly seems to gain more impetus in a more crowded exporter market. A similar threshold has been evidenced in another China-based study - though in the context of FDI penetration (Huang, Liu and Xu, 2012).

Turning to the indirect effects (spillovers) for ordinary exporters – these are mostly negative. This negative pattern suggests that other firms in the neighbourhood respond to higher local exporting, *decreasing* their investment in R&D. Due to the negative indirect (spillover) effect, the total impact is

¹¹ Jarreau and Poncet (2012) use growth in China's provinces as a measure of export sophistication. We use new product introductions.

¹² Average exporter concentration stands at 23 percent and 29 percent for ordinary exporters and export processors, respectively. See Table 2 for a fuller summary.

only positive and significant for a very small segment of the exporting share continuum (45 percent, and above). This reinforces the impression as a neighbourhood becomes progressively crowded with exporters – firms strive to remain distinctive from the crowd, redoubling their efforts to introduce new products or invest in internal R&D efforts. Innovation, rather than imitation, becomes the strategy of choice.

For processing exporters, the total effect of exporter concentration on R&D is negative and significant throughout. Again, we see a threshold, where for proportions in excess of 60 percent the effect turns slightly and insignificantly positive. However, we can discount the right tail of the exporter distribution since there are few cases where we can observe exporter concentrations in excess of 60 percent. Overall, we can infer from this negative effect for R&D, that higher concentrations of export processors do *not* stimulate R&D. This is in line with the commercial orientation of export processors – the supply of pre-tailored inputs or assembly outputs to international customers, with little scope (or necessity) to invest in internal R&D.

6 Conclusion

Employing data for over 170,000 firms in China and using a methodology which allows us to control for dual sources of selection (firm and neighbourhood), our findings confirm that increased concentration of ordinary exporters helps catalyse new products. For the most part, this innovation boost is a direct consequence of exporting. Even when we apply an alternative measure of innovation (R&D), the same positive pattern emerges. Our result echoes the findings of other China-based studies, reporting a positive association between ordinary exporting and innovation (Jarreau and Poncet, 2012; Xie and Li, 2018).

However, our study provides the first hard evidence, of a *causal* link between China's exporting and innovation. New products and R&D represent powerful competitive tools, enabling firms to achieve domestic, as well as, international competitiveness. Both innovation outcomes seem to gain more impetus in a more crowded exporter market.

Going beyond the direct effect to the indirect spillover effect – we see these are *negative and significant* – increased concentrations of ordinary exporters crowding out the creativity of non-exporters. The exception to this rule, is for neighbourhoods with exceptionally high exporter concentration.

When we examine the direct and indirect (spillover) effect for exporter processors, we expect a less stimulating effect of export on innovation due to the lower innovation investment of processing industries. In terms of the direct effect, we find far lower coefficients (mostly negative) than for ordinary exporters. However, the total effect for export processors is positive and significant, which is driven by indirect effects (spillovers). This is in line with processing companies imitating what their neighbouring firms are doing, e.g., through the usual motives for spillovers (labour mobility, demonstration or linkages).

There are two main lessons we can extract from this causal study of China's exporting on its innovation metrics: specialization and export processing. We turn first to specialization. The innovation boost to exporters and non-exporters alike, in neighbourhoods with high exporting concentrations, hints at the reinforcing mechanism of knowledge transfers (direct and indirect) in these highly internationalized prefectures. This finding has relevance for policy makers in developing countries attempting to cultivate Special Economic Zones (SEZs), focussing research and human-capital efforts on a few core products. Since much of China's production is geographically specialised (e.g., e-cigarettes from Shenzhen or violins from Huangqiao), this positive innovation dynamic hints at an interesting possibility - neighbourhoods with exceptionally high exporting, help to stimulate innovation from exporters and non-exporters, alike.

Secondly, our research has uncovered a positive role for export processing as a way to ascend the product quality ladder. While some may dismiss export processing as an economic cul-de-sac, our evidence for strong spillovers at the prefecture level, points at the potential for export processing to lock into export markets and deliver much-needed innovation. In sum, for policy makers in other developing countries, the results demonstrate the efficacy of cultivating a strong processing export sector. Particularly for processing exports, it is vitally important to motivate local clusters to reap the full benefits of exports for the local economy through spillover effects.

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List of Tables

Table 1. Summary statistics of firm-level variables

	Ordinary Exporters (No. of firms=53,108)		Processing Exporters (No. of firms =47,713)		Non-exporters (No. of firms=69,822)	
	Average	Std.dev	Average	Std.dev	Average	Std.dev
<i>Outcome variables (2006)</i>						
New products dummy	18%	0.38	6%	0.24	8%	0.27
R&D dummy	16%	0.37	8%	0.28	12%	0.33
<i>Pre-treatment covariates (2004)</i>						
<i>Innovation inputs</i>						
New products dummy	13%	0.34	5%	0.21	6%	0.23
R&D dummy	14%	0.35	7%	0.25	12%	0.32
<i>Firm type</i>						
Foreign firms	45%	0.50	22%	0.42	11%	0.32
State-owned	2%	0.15	5%	0.22	6%	0.23
Private firms	47%	0.50	62%	0.48	72%	0.45
<i>Industry</i>						
Medium low-tech	24%	0.43	31%	0.46	34%	0.47
Medium tech	24%	0.43	23%	0.42	24%	0.43
High tech	11%	0.32	8%	0.28	9%	0.29
<i>Miscellaneous covariates</i>						
TFP	0.01	0.33	0.00	0.37	0.00	0.35
Leverage (total liability over total assets)	7.11	262.62	7.24	73.83	6.23	104.23
Log employment	5.13	1.11	4.56	1.09	4.50	0.98
Log age	1.95	0.83	1.90	0.88	1.95	0.94
Profitability (total profits over sales)	0.03	0.48	-0.01	6.17	0.02	2.09
Log cap labour ratio	3.43	1.42	3.49	1.37	3.69	1.27

Notes: Low-tech industries and Collectives firms are the base groups in industry and firm type categories respectively. TFP calculated as log total factor productivity estimated sector by sector based on the methodology used by Akerberg et al (2015). Similar to the Olley-Pakes (OP) and Levinsohn-Petrin (LP) productivity estimators, the Akerberg estimator involves a 2-stage regression, using a proxy to control for historic productivity. Because of the functional dependence of the inputs (labour and capital) in the OP and especially the LP model, the Akerberg et al estimator now estimates all these inputs – both capital and labour - in the second stage.

Table 2. Summary statistics of neighbourhood level variables

	Mean	Std. dev	Min	Lower quartile	Median	Upper quartile	Max
<i>Treatment variables (2005)</i>							
Ordinary Exporters (share)	23%	0.17	1%	12%	17%	31%	96%
Processing exporters (share)	29%	0.12	2%	21%	29%	38%	58%
<i>Pre-treatment covariates (2004)</i>							
<i>Innovation inputs</i>							
New products dummy	10%	0.11	0%	3%	6%	11%	60%
R&D dummy	12%	0.07	2%	7%	10%	15%	67%
<i>Firm type</i>							
Foreign firms	15%	0.13	1%	6%	10%	19%	74%
State-owned firms	8%	0.07	0%	3%	6%	11%	35%
Private firms	68%	0.14	19%	57%	70%	79%	94%
<i>Industry</i>							
Medium low-tech	29%	0.12	2%	21%	28%	36%	64%
Medium tech	18%	0.10	0%	10%	16%	23%	60%
High tech	9%	0.05	0%	6%	8%	11%	53%
<i>Miscellaneous covariates</i>							
TFP	0.01	0.06	-0.19	-0.03	0.01	0.04	0.26
Leverage	5.40	4.20	1.07	2.79	4.11	6.60	29.38
Log employment	4.80	0.25	4.09	4.62	4.81	4.95	5.39
Log age	1.96	0.24	1.29	1.80	1.93	2.12	2.68
Profitability	0.01	0.07	-0.75				0.12
Log cap. labour ratio	3.62	0.31	2.66	3.43	3.62	3.80	4.62
<i>Outcome variables measured in 2006</i>							
New products dummy	12%	0.15	0%	3%	7%	13%	95%
R&D dummy	12%	0.06	2%	8%	11%	16%	54%

Notes: Low-tech and collective firms represent base groups in industry and firm-type categories respectively. Exporter treatment variables (measured for 2005).

Table 3. Baseline regression - Exporter share on innovation

Binary Logit y: innovation	New products coeff.	Std. Err.	R&D coeff.	Std.Err.
<i>Direct & indirect export covariates</i>				
Ordinary Exporter	0.06	(0.58)	0.37***	(0.05)
Ord. Exporter share	1.73***	(0.11)	0.35***	(0.10)
Ord. Exp * Ord. Exp. share	1.30***	(0.15)	-0.87***	(0.14)
Processing Exporter	0.16*	(0.09)	0.12	(0.08)
Proc. Exporter share	-2.84***	(0.12)	0.03	(0.12)
Proc. Exp* Proc. Exp share	-0.47*	(0.29)	-0.93***	(0.25)
<i>Innovation inputs</i>				
New product dummy	3.13***	(0.03)	0.93***	(0.03)
R&D dummy	1.20***	(0.03)	3.26***	(0.02)
<i>Firm type</i>				
Foreign firms	-0.36***	(0.04)	0.15***	(0.04)
State-owned firms	-0.01	(0.06)	0.37***	(0.06)
Private firms	0.11***	(0.04)	0.34***	(0.04)
<i>Miscellaneous covariates</i>				
TFP	-0.00	(0.03)	-0.02	(0.03)
Leverage	0.00***	(0.00)	0.0002***	(0.00)
Log employ	0.18***	(0.01)	0.31***	(0.01)
Log age	0.05	(0.01)	0.03**	(0.01)
Profitability	0.004*	(0.00)	0.003	(0.00)
Log capital labour ratio	0.17***	(0.01)	0.20***	(0.01)
<i>Industry</i>				
Medium low-tech	-0.01	(0.03)	0.27***	(0.03)
Medium tech	0.45***	(0.03)	0.79***	(0.03)
High tech	0.47***	(0.03)	0.95***	(0.03)
constant	-4.74***	(0.08)	-6.03***	(0.08)

Notes: All covariates measured in 2-year lags. In brackets are Huber-White Sandwich robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Industry base category is Low Tech. Firm type base category is collective firms. Units are China's 229 townships (neighbourhoods)

Table 4. Fractional Logit

y: Exporters (share)	Ordinary Exporters		Processing Exporters	
	Raw coeff.	Marginal effects	Raw coeff.	Marginal effects
<i>Export covariates (share)</i>				
Ordinary Exporters	.	.	-2.63***	-0.53***
	.	.	(0.28)	(0.06)
Processing Exporters	-3.27***	-0.54***	.	.
	(0.58)	(0.10)	.	.
<i>Innovation inputs</i>				
New products dummy	3.59***	0.59***	0.44	0.09
	(0.70)	(0.12)	(0.39)	(0.08)
R&D dummy	-2.24***	-0.37***	-0.81	-0.16
	(0.80)	(0.13)	(0.61)	(0.12)
<i>Firm type</i>				
Foreign firms	1.81	0.30	-0.05	-0.01
	(1.17)	(0.19)	(0.85)	(0.17)
State-owned firms	-2.72*	-0.45*	-0.78	-0.16
	(1.61)	(0.27)	(1.08)	(0.22)
Private firms	-0.60	-0.10	-1.32	-0.27
	(1.30)	(0.21)	(0.88)	(0.18)
<i>Miscellaneous covariates</i>				
TFP	-0.24	-0.04	0.58	0.12
	(0.71)	(0.12)	(0.61)	(0.12)
Leverage	0.02*	0.00*	0.01	0.00
	(0.01)	(0.00)	(0.01)	(0.00)
Log employ	-0.02	-0.00	0.05	0.01
	(0.20)	(0.03)	(0.15)	(0.03)
Log age	0.32	0.05	-0.44**	-0.09**
	(0.29)	(0.05)	(0.23)	(0.04)
Profitability	0.40	0.07	-0.54	-0.11
	(1.48)	(0.24)	(0.88)	(0.17)
Log capital labour ratio	-0.94***	-0.16***	-0.55***	-0.11***
	(0.15)	(0.02)	(0.12)	(0.02)
<i>Industry</i>				
Medium low-tech	-0.70*	-0.12*	-0.93***	-0.19***
	(0.40)	(0.07)	(0.32)	(0.06)
Medium tech	-0.23	-0.04	-0.51	-0.10
	(0.45)	(0.07)	(0.36)	(0.07)
High tech	0.26	0.04	0.48	0.10
	(1.36)	(0.22)	(0.71)	(0.14)

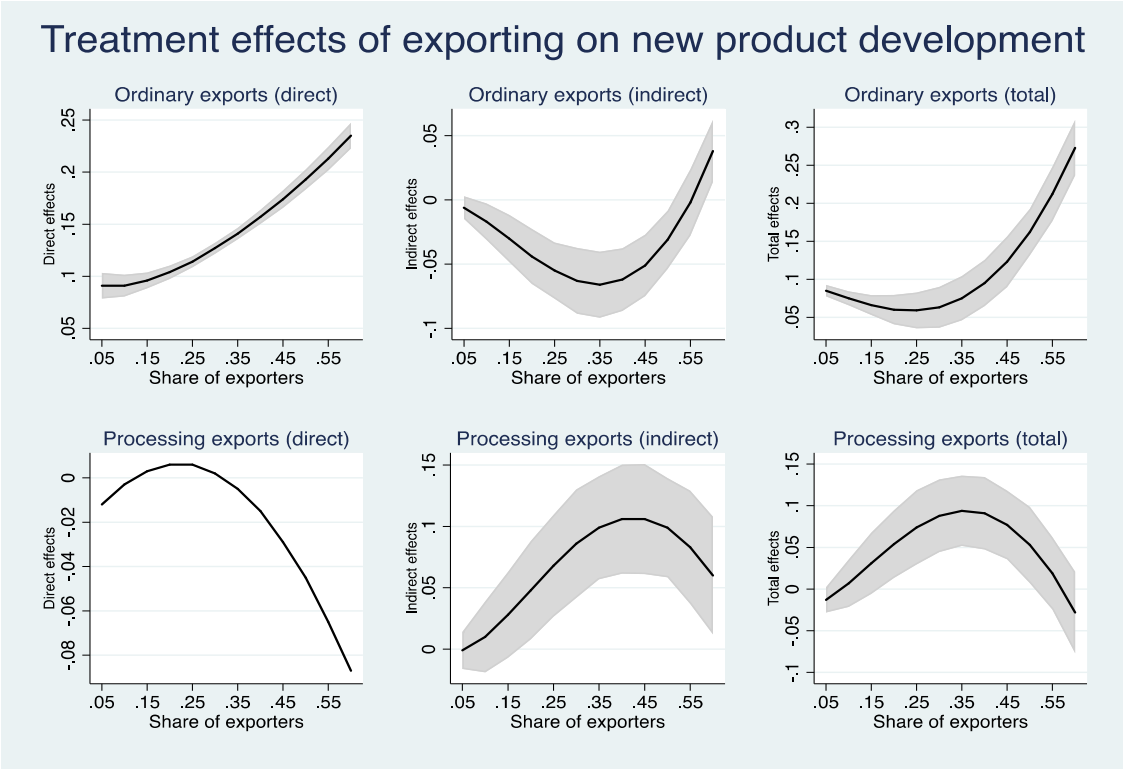
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard deviations in brackets. Low-tech and Collective firms represent base groups in industry and firm-type categories respectively. Covariate in lagged 1-year values.

Table 5. p-values from balancing tests

	Ordinary Exporters	Processing Exporters
<i>Innovation inputs</i>		
New product dummy	0.22	0.11
R&D dummy	0.23	0.30
<i>Miscellaneous covariates</i>		
TFP	0.25	0.38
Leverage	0.36	0.15
Log employ	0.29	0.56
Log age	0.39	0.33
Profitability	0.24	0.46
Log capital labour ratio	0.25	0.19
<i>Firm type</i>		
Foreign firms	0.33	0.31
State-owned firms	0.20	0.23
Private firms	0.39	0.36
<i>Industry</i>		
Medium low-tech	0.50	0.36
Medium tech	0.32	0.29
High tech	0.57	0.29

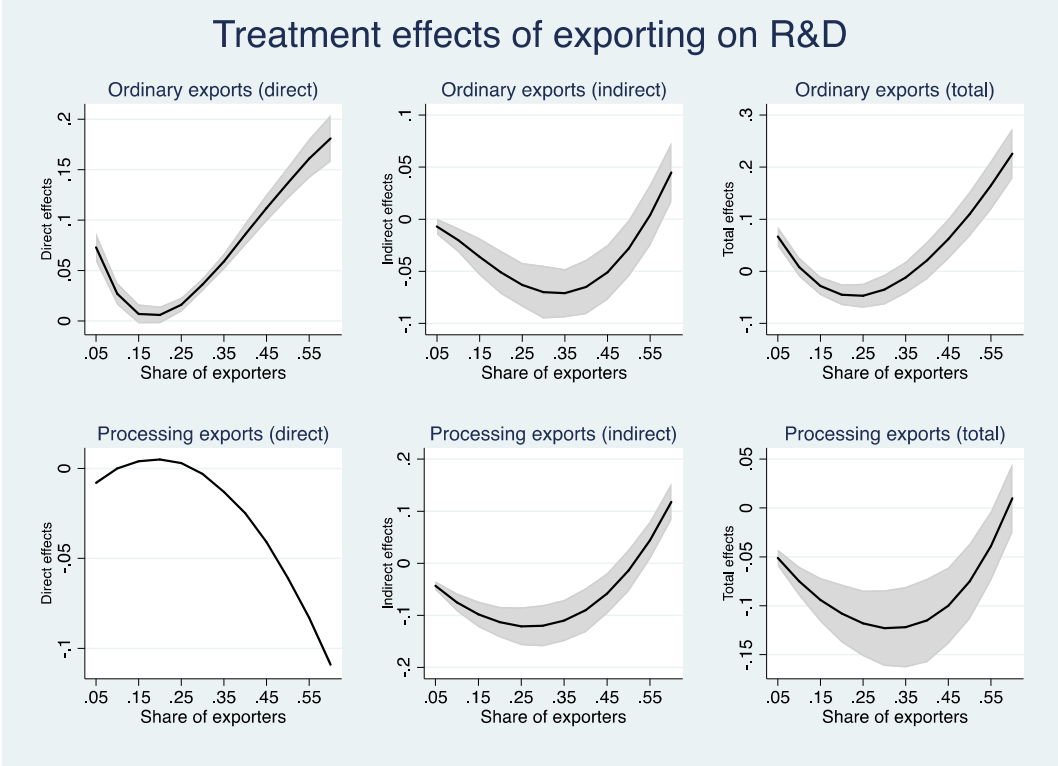
Notes: All independent variables are pre-treatment covariates measured in 2004. P-values are for the test of equality of means between treatment and control groups. We did not reject the null hypothesis of equality of means in any of the tests whose p-value are reported above.

Figure 1. Treatment effects of exporting on new product development¹³



¹³ Causal effects of exporting with 95% confidence intervals based on boot-strapped standard errors

Figure 2. Treatment effects of exporting on R&D investment¹⁴



¹⁴ Causal effects of exporting with 95% confidence intervals based on boot-strapped standard errors

Appendices

Appendix 1. Exports from China in 2007. (From Comtrade <https://comtrade.un.org/Data/>)

Code	Commodity	Trade Value (US\$)	percent
29	Organic chemicals	20,595,299,152	2.0
30	Pharmaceutical products	2,055,723,548	0.2
38	Miscellaneous chemical products	5,841,281,115	0.6
39	Plastics and articles thereof	26,585,024,054	2.6
40	Rubber and articles thereof	10,124,510,008	1.0
54	Man-made filaments	7,800,963,846	0.8
57	Carpets and other textile floor coverings	1,320,038,943	0.1
58	Special woven fabrics	4,690,997,965	0.5
59	Impregnated, coated, covered or laminated textile fabrics	2,841,124,401	0.3
60/63	Knitted or crocheted fabrics	128,210,547,925	12.4
64	Footwear, gaiters and the like	25,350,736,984	2.4
68	Articles of stone, plaster, cement, asbestos	4,510,202,183	0.4
70	Glass and glassware	7,249,836,131	0.7
72	Iron and steel	39,958,005,049	3.9
73	Articles of iron or steel	36,739,592,335	3.5
76	Aluminum and articles thereof	11,575,029,471	1.1
80	Tin and articles thereof	429,072,114	0.0
81	Other base metals; cements; articles thereof	3,512,115,965	0.3
82	Tools, implements, cutlery, spoons and forks	7,237,716,968	0.7
83	Miscellaneous articles of base metal	8,226,989,698	0.8
84	Nuclear reactors, boilers, machinery and mechanical appliances	228,589,000,000	22.1
85	Electrical machinery and equipment; sound recorders, TV, parts thereof	300,307,000,000	29.0
86	Railway or tramway locomotives; mechanical (including electro-mechanical)	9,539,756,964	0.9
87	Vehicles other than railway or tramway rolling-stock and parts	31,810,264,037	3.1
88	Aircraft, spacecraft, and parts thereof	1,414,222,098	0.1
90	Optical, photographic, measuring, precision, medical or surgical instruments	37,084,861,248	3.6
91	Clocks and watches and parts thereof	2,446,971,036	0.2
92	Musical instruments; parts and accessories of such articles	1,223,492,061	0.1
94	Furniture; bedding, mattresses illuminated signs; prefabricated buildings	35,977,021,090	3.5
95	Toys, games and sports requisites	27,152,345,265	2.6
96	Miscellaneous manufactured articles	6,062,139,774	0.6
		1,036,537,366,855	100.0

Appendix 2. Direct, indirect and total effects of exporting on the probability of new product development

Exporter share	Ordinary Exporters						Processing exporters					
	Direct effects		Indirect effects		Total effects		Direct effects		Indirect effects		Total effects	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
5%	0.091	14.4	-0.006	-1.3	0.085	22.1	-0.012	-34.6	-0.001	-0.1	-0.013	-1.7
10%	0.091	17.1	-0.017	-2.3	0.075	15.9	-0.003	-11.8	0.010	0.7	0.007	0.5
15%	0.096	24.6	-0.03	-3.2	0.066	9.9	0.003	22.0	0.028	1.6	0.031	1.7
20%	0.104	31.6	-0.044	-4.0	0.06	6.1	0.006	72.0	0.048	2.3	0.054	2.6
25%	0.114	42.2	-0.055	-4.9	0.059	4.9	0.006	59.8	0.068	3.2	0.074	3.3
30%	0.127	47.4	-0.063	-4.8	0.063	4.6	0.002	15.0	0.086	3.8	0.088	4.0
35%	0.141	50.7	-0.066	-5.0	0.075	5.1	-0.005	-26.2	0.099	4.6	0.094	4.4
40%	0.157	45.5	-0.062	-4.9	0.095	6.1	-0.015	-80.4	0.106	4.7	0.091	4.1
45%	0.174	40.6	-0.051	-4.2	0.123	7.2	-0.029	-123.2	0.106	4.6	0.077	3.7
50%	0.193	39.6	-0.031	-2.7	0.162	10.4	-0.045	-203.0	0.099	4.8	0.053	2.3
55%	0.213	36.9	-0.002	-0.2	0.212	11.6	-0.065	-210.2	0.083	3.5	0.019	0.9
60%	0.235	37.5	0.038	3.1	0.273	14.7	-0.087	-226.1	0.060	2.5	-0.028	-1.1

Appendix 3. Direct, indirect and total effects of exporting on the probability of R&D investment

Share of exporters	Ordinary exporters						Processing exporters					
	Direct effects		Indirect effects		Total effects		Direct effects		Indirect effects		Total effects	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
5%	0.073	10.2	-0.007	-1.8	0.067	7.1	-0.008	-16.1	-0.043	-10.1	-0.051	-11.9
10%	0.027	4.8	-0.02	-3.4	0.008	0.8	0	-0.5	-0.075	-8.6	-0.075	-9.8
15%	0.007	1.4	-0.036	-4.0	-0.028	-3.1	0.004	23.4	-0.098	-7.8	-0.094	-8.2
20%	0.006	1.4	-0.051	-4.8	-0.045	-4.4	0.005	62.1	-0.113	-7.6	-0.108	-7.1
25%	0.016	4.5	-0.063	-5.9	-0.047	-4.0	0.003	32.0	-0.121	-6.5	-0.118	-6.9
30%	0.036	11.1	-0.070	-5.4	-0.035	-2.4	-0.003	-24.8	-0.12	-5.9	-0.123	-6.2
35%	0.059	14.8	-0.071	-6.0	-0.012	-0.8	-0.013	-76.5	-0.11	-5.4	-0.122	-5.8
40%	0.086	15.3	-0.065	-4.9	0.021	1.1	-0.025	-121.4	-0.09	-4.2	-0.115	-5.3
45%	0.112	16.4	-0.051	-3.8	0.062	3.2	-0.041	-168.1	-0.058	-2.9	-0.100	-5.0
50%	0.137	17.0	-0.028	-2.0	0.11	5.0	-0.061	-156.1	-0.014	-0.7	-0.075	-3.8
55%	0.161	16.3	0.004	0.3	0.165	6.8	-0.083	-145.7	0.044	2.4	-0.039	-2.1
60%	0.181	15.3	0.045	3.1	0.226	9.2	-0.109	-131.6	0.118	6.6	0.010	0.6