The Impact of Exporting and FDI on Product Innovation: Evidence from Chinese Manufacturers

Michael Olabisi
University of Michigan; Pepperdine University
molabisi@umich.edu*

Abstract

To understand the drivers of product innovation at the firm level, I compare the effects of foreign direct investment (FDI) and exporting on product innovation using a rich firm level database of manufacturing and industrial enterprises. The paper focuses on product innovation, as it is vital to economic development. Estimates from linear regressions and propensity score matching tests show that learning-by-exporting is a stronger predictor of product innovation. Firms that receive foreign investment also tend to engage in more product innovation, but not at the same level as the firms that export. Additional tests confirm that as they start and stop exporting, firms change their patterns of investment in the drivers of product innovation - fixed capital and research.

JEL classification: D22, F14, F23, L25, O31
Keywords: Product Innovation, Learning by Exporting, Foreign Direct Investment (FDI).

*This paper was written while visiting the Economics Department of the National University of Singapore for the East Asia Pacific Summer Institute - funded by the National Science Foundation (NSF) and the National Research Foundation of Singapore (http://www.nsfsi.org/). I am deeply indebted to my host, Professor Albert Guangzhou Hu for his support and suggestions during this visit. The Business Economics department of the Ross School of Business provided financial support. My advisors, formal and otherwise - Jan Svejnar, Rosemarie H. Ziedonis, Jagadeesh Sivadasan and the late Katherine Terrell, who supported my application for the NSF grant, all deserve mention. Thanks to Charlie Sawyer and conference participants at the Western Economic Association International July 2016 meeting. Special thanks also go to Kyle Handley, and participants at the first Kathy Terrell Doctoral Symposium at the University of Michigan.

1 Introduction

Emerging countries are no longer content to be sources of cheap hands and low-cost brains. Instead they too are becoming hotbeds of innovation ... They are redesigning products... They are redesigning entire business processes to do things better and faster than their rivals in the West. Forget about flat – the world of business is turning upside down.
The Economist Magazine - (Masters of Innovation: 2010)

Exporters and foreign-owned firms do more product innovation. The mechanism behind this pattern is not clear, nor is it clear that technology transfer through foreign ownership translates to more product innovation at the firm level compared to homegrown efforts. It is clear however, that product innovation is vital to development. Economies that consistently create more varieties have better growth outcomes. Policymakers in developing economies charged with promoting innovation-driven private-sector led development typically consider two approaches – export promotion or foreign investment (FDI). I compare the relative efficacy of these two well-known approaches.[1]

China is an excellent case for this study: it has grown to be the world's largest exporter, and became the number one FDI destination among developing economies while expanding the scope of its industrial output. Chinese exporters featured in 85% of US imported manufactured goods categories in 2005, up from 9% in 1972 (Schott, 2008). Firm level evidence buttresses the point. In the Chinese annual survey of manufacturing firms between 2005 and 2007, 13% of firms reported creating new product varieties and 10% by value of aggregate output in the data was from product varieties that were new to the firms. In sum, one cannot ignore product innovation in the narrative of China's growth experience.

To understand the firm level drivers of product innovation in China, this paper uses a comparison-study of two firm categories – exporters and foreign-owned firms. The literature on product innovation motivated this approach. Gorodnichenko et al. (2010) and Damijan et al. (2010) indicate that exporters tend to do more product innovation, while others attribute product innovation to foreign-ownership, e.g. (Guadalupe et al., 2012). There are good reasons for both arguments, and the reverse could be true. Firms that start exporting may learn the methods required for product innovation, as may firms that receive foreign

[1]Section 2 discusses the relationship between product innovation and economic growth briefly. While the scope of studies on innovation include new production process, new management skills, this paper focuses on product innovation.

capital. Likewise, large, productive firms may be more likely to introduce new products, export and find foreign owners.

I use a propensity score matching approach to address concerns about endogeneity in estimating the effects of exporting and foreign ownership (or FDI). Effectively, I limit comparisons of product innovation by exporters or foreign-owned firms to firms with very similar observed characteristics. The set of control variables was broad enough that one could assume any difference between exporters and non-exporters with the same set of characteristics was close to random. For example, in comparing only firms in the same industry and with nearly the same size, the approach addresses concerns that larger more innovative firms in a particular sector are more likely to experience the exporting or foreign-ownership 'treatment' (Abadie and Imbens, 2009; Caliendo and Kopeinig, 2008). I use Chinese firm level data from the NBS annual survey of industrial enterprises between 2005 and 2007.

The results show that export participation leads to a higher likelihood of product innovation. The matching estimates show that new products are a greater share of output for exporters – 20% for exporters, versus 14% for non-exporters with matched propensities. New products are 12.9% of the output of majority foreign-owned firms, compared to 19.0% for Chinese-owned similar firms that were chosen to control for selection into FDI status (i.e. foreign ownership).[2] This raises an interesting contrast for papers that find statistically significant effects for foreign ownership on product innovation in other contexts like Eastern or Western Europe, e.g. (Commander and Svejnar, 2011; Guadalupe et al., 2012). The differences suggest that context may determine the level of product innovation that foreign owners undertake.

Two causal mechanisms for product innovation feature in the paper – research and development (R&D) and investments in fixed capital. This builds on earlier papers that provide evidence of a positive correlation between exporting and R&D, e.g., (Lileeva and Trefler, 2010; Aw et al., 2008, 2000). I use difference-in-differences estimates to show that on average, both of these inputs to product innovation increase as firms start exporting, and decrease for the firms that stop exporting. The same pattern does not register for foreign ownership.

I organize the rest of the paper as follows: Section 2 discusses the related literature, while the subsequent section covers the methods, data and results. The paper concludes in Section 5 after several robustness checks in Section 4.

[2]Tables 1 and 3 below delve further into these comparisons. (The tables address the fact foreign ownership and exporting are not mutually exclusive categories). In the main results, I show that these differences in product do not depend on whether I measure the intensity or the incidence of product innovation

2 Related Literature

This paper focuses on the direct impacts of exporting and foreign direct investment (FDI) on product innovation for exporting or foreign-owned firms. (I will not discuss spillovers from FDI and exporting; if these exist, they should bias my estimates toward zero and leave any main findings unchanged. High levels of innovation spillovers from other firms imply that the findings are imprecise, but it is reasonable to expect that the direct impacts of FDI and export participation vastly exceed the spillover effects).[3]

2.1 Product Innovation

Product innovation is vital to economic development. It is no accident that larger economies produce and consume greater numbers of product varieties, as documented by (Hummels and Klenow, 2005). This follows the Schumpeterian view of development (Schumpeter, 1942); economies grow because firms successful create new varieties as the old ones disappear. Madsen (2008) finds support for a Schumpeterian growth hypothesis that links R&D and the creation of new product varieties to economic growth. That paper used international data from OECD economies. The argument in that paper builds on earlier work like Segerstrom (1991), that motivate an unambiguous positive relationship between promoting innovation and economic growth. Benhabib et al. (2014) also provides a model of firm-level growth that is driven by innovation in a related paper. More recent papers provide formal models and evidence that link product innovation to welfare through consumers' love of variety e.g., (Broda and Weinstein, 2006; Krugman, 1980).

In the Chinese case, product innovation helped increase the scope, volume and sophistication of aggregate exports (Amiti and Freund, 2010; Schott, 2008). For firms, the creation of new varieties adds new profit streams and increases the utilization of human and physical capital (Bernard et al., 2011; Eckel and Neary, 2010). They can also help to diversify a firm's portfolio against potential adverse product-specific shocks. Given the importance of product innovation to growth, especially for China, this paper tries to understand the factors driving the creation of new varieties, starting from its well-documented drivers – FDI and

[3]The paper's main goal is evaluating the effects of FDI and exporting on product innovation. If one was to consider spillovers - i.e. we say it is possible that non-exporting firms to have higher levels of product innovation because they learn from other firms nearby that are exporters, then the positive estimated effect of exporting on product innovation will be larger than the effects reported in the empirical section of this paper. The same applies to the firm's ownership status. As long as spillovers are expected to be from foreign-owned to Chinese-owned, exporter to non-exporter, the estimated effects in the following specifications that ignore spillovers will be biased towards zero, and therefore conservative.

exporting.

This paper contributes a novel comparison of these two drivers of product innovation in the Chinese context, to the literature on firm-level innovation and international participation. In considering exporting as a potential driver of product innovation, the paper comes close to the learning-by-exporting literature, which I describe next.

2.2 Exporting and Product Innovation

Much of the work on learning-by-exporting focuses on revenue productivity, e.g. (De Loecker, 2013, 2007; Clerides et al., 1998). These papers argue that in equilibrium exporters are more productive because firms learn to be more productive as they export, not just because the most productive firms self-select into exporting.

Few papers have tested learning-by-exporting with respect to product innovation. Notably, Damijan et al. (2010) examines whether the higher level of product innovation by exporters is due to selection, or learning-by-exporting. That paper found evidence in support of learning-by-exporting, using Slovenian data.

Gorodnichenko et al. (2010) provides evidence that exporters engage more in new product innovation, identifying the causal mechanism as information exchange through vertical linkages to foreign firms. Their tests use 2002 and 2005 data from the World Bank's firm level BEEPS survey in 27 transition economies from Eastern and Central Europe. Others have reported similar results for Italy (Bratti and Felice, 2012; Castellani and Zanfei, 2006) and Slovenia (Damijan et al., 2010).[4] This paper extends the research objective of Gorodnichenko et al. (2010) to Chinese industrial enterprises, in combination with the question of foreign investment's impact on product innovation.

2.3 FDI and Product Innovation

Guadalupe et al. (2012) uses propensity score methods to test for the effects of foreign investment on product innovation, but does not include a comparison with exporting, like this paper. Furthermore, their paper does not test for a causal mechanism that drives product innovation in foreign-owned firms. Furthermore, we define product innovation differently: I define product innovation as a continuous measure of output share, while the Guadalupe

[4] All these papers support the learning-by-exporting hypothesis. That said, one must emphasize the distinction between the product innovation and productivity dimensions of learning-by-exporting. Keller (2004) reviews the debate on learning-by-exporting for productivity. A related question, which this paper cannot address for lack of data, is learning-by-importing (Vogel and Wagner, 2010).

et al. (2012) paper uses a dummy that indicates whether a firm introduced new products. Even with these differences, our conclusions are similar.

Several earlier works suggest that FDI or foreign ownership should lead to more product innovation (Girma et al., 2012; Iacovone et al., 2009; Girma et al., 2008; Lai, 1998). The reasons offered by this literature include: [1] Foreign owners support subsidiaries' R&D efforts, [2] FDI enables access to needed credit or finance for innovation [3] foreign multinationals transfer their innovations to subsidiaries to facilitate low cost production. As a parallel to the learning-by-exporting literature, papers that link FDI to productivity have a history that goes back to Iacovone et al. (2009); Javorcik (2004); Djankov and Hoekman (2000); Aitken and Harrison (1999).[5]

In sum, the foregoing suggest that the causal mechanism linking FDI to product innovation is that foreign investment usually comes with the knowledge and financial resources needed to create new products. Therefore foreign-ownership of firms should be associated with product innovation. The related explanation for product innovation is that firms serving foreign destinations learn about customer demand or preferences. The knowledge gained from the broader customer base is also expected to stimulate the creation of new products to address customer demand.[6]

2.4 Exporting and FDI's Effects on Product Innovation

This paper's primary contribution is a direct comparison of the direct impact of exporting against foreign direct investment (FDI). The papers cited above generally examine the role of trade in product innovation, without exploring the effect of foreign ownership. The following papers argue that foreign investment promotes product innovation, also without providing a comparison to exporting (Guadalupe et al., 2012; Girma et al., 2008). Note that I use the term 'foreign ownership' to describe FDI in most of the paper; the term seems more relevant to firm level descriptions.

Commander and Svejnar (2011) compare the effects of foreign ownership and exporting like this paper, but for the ratio of sales to inputs. In their analysis, both exports and foreign ownership are associated with higher efficiencies or throughput ratios. However, the foreign

[5] There may be reason to think innovation may not accompany FDI –when foreign parent companies are concerned about property rights. There is evidence that firms undertake more innovation in locations with better property rights protection (Lin et al., 2010).

[6] The rest of the paper will focus on these two policy-driven channels that lead to product innovation, narrowly defined. A theoretical framework section is not required to answer the main research questio, given the paper's clearly defined scope and empirical approach.

ownership variable takes away the significance of the export variable in a regression model with both variables.

The tests that follow recognize that FDI and exporting are not orthogonal features of firm level data. The prevalence of export-platform FDI implies that in many cases, exports happen because of FDI. Conversely, one can make the case for foreign investment that follows a successful exporting relationship. Examples of the first scenario include Kneller and Pisu (2007) which uses aggregate data for Europe and Sun (2009), which uses Chinese firm level data to show that FDI increases exports as a share of total output.

3 Methods, Data and Results

This section reports three sets of results: (1) OLS regressions that test the effects of FDI and exporting on product innovation, (2) Propensity Score Matching tests that show the same idea more robustly and (3) tests that show drivers of product innovation before and after export entry.

The baseline OLS exercise helps to establish that FDI and exporting as drivers of innovation are relevant to the Chinese context, as documented in the literature. It is a simple comparison of foreign-owned and exporting firms with all other firms in the data. Correlation between these categories and product innovation does not imply causation, so I use propensity score matching (PSM) to mitigate bias that may result if the firms most likely to introduce product innovations also happen to be foreign owned or exporters.

One may designate exporting or foreign-ownership as instrumental variables. In principle, being in these categories leads to product innovation because firms *do things differently* – using new methods, equipment, or processes. Therefore, in Section 3.4 I further support the claim of a causal relationship between exporting and product innovation by testing whether firms that start exporting also change their pattern of spending on innovation drivers. The innovation drivers I use for this paper are R&D and asset purchases. (I show before the aforementioned test that these variables are strong predictors of product innovation).

3.1 Data

The data comprises all annual surveys of Chinese industrial firms from 2005 to 2007. China's National Bureau of Statistics compiled this firm level data. The sample approximates a census of all firms with revenues greater than 5 million Yuan (about $600,000), supplemented with a stratified random sample of firms below this threshold. The entire dataset is an unbalanced panel of 763,036 firm-year observations, covering over 329,000 unique firms. 55% of the firms are present in all three years, while another 20% show up in at least two.[7]

I identify exporters from the reported sales and exports values for each firm-year. Foreign ownership is determined from the reported components of paid up capital. The data cover a period of strong export participation and foreign investment for Chinese firms: this was after China's WTO accession in December 2001. To illustrate the significance of the timing, the number of firms in the data increased from 249,028 to 311,186 between 2005 and 2007, and the share of those numbers that were exporters in 2007 was 25%. Firms with majority foreign ownership were 8% of the sample in 2007.[8]

Only a minority of firms undertake product innovation - 90% of firm-year observations registered zero new products. The nearly 76,000 observations with positive values of new products belong to 45,340 firms that account for 115,315 of the total firm-year observations. (The firms that undertook product innovation between 2005 and 2007 did so in only 2 of 3 years on average).

To preview whether product innovation co-occurs more with foreign ownership or exporting, one could sort the data into four groups that combine the two sets of categories: from Chinese-owned non-exporters to Chinese-owned exporters and from foreign-owned non-exporters to foreign-owned exporters. A non-parametric comparison of average innovation intensities for these groups may provide the first hint of what to expect in the results.

Table 1 summarizes the differences in levels of product innovation for the four exclusive subgroups created by the two categories of interest. New products as a share of total output value vary significantly between these groups, with the exporting sub-groups having higher averages. Foreign owned firms do not appear to undertake product innovation significantly above the mean according to the table, although they are larger and more likely to export than the average firm, which fits the pattern documented elsewhere in the literature, e.g. (Guadalupe et al., 2012; Commander and Svejnar, 2011; Gorodnichenko et al., 2010).

[7] Before these assessments, I dropped 12,293 observations with one or more of these issues: negative sales, negative paid-up capital, foreign capital that exceeded total paid up capital, and exports that exceeded sales. (These observations accounted for 1% of the output observed in the data). This was after I excluded observations for industries outside manufacturing, to avoid comparability issues. The relevant Chinese two-digit industry codes are between Food Manufacturing(14) and Instruments and Office Equipment Manufacturing(41).

[8] The dataset reports firms' ownership capital in each of six source categories - individual, collective, national, other corporations/legal persons, non-Chinese foreign and Chinese-foreign i.e. Hong Kong, Macau and Taiwan. The first four categories correspond to private and state-owned sources of funds from mainland China. I define foreign-owned firms as those with majority stakes from non-Chinese sources, i.e. outside mainland China, Hong-Kong, Macau and Taiwan. Sections 4.2 and A.4 report estimates with alternative definitions of foreign ownership.

Table 1: Group Summaries

Group	Attribute	2005	2007
Chinese-owned Non-Exporter	Product Innovation	.058	.056
	Group Share of Total Output	.41	.448
	Number of Firms	151,975	205,033
	Group of Share of Total Number	.677	.719
Chinese-owned Exporter	Product Innovation	.173	.207
	Group Share of Total Output	.421	.38
	Number of Firms	54,134	57,156
	Group of Share of Total Number	.241	.201
Foreign-Owned Non-Exporter	Product Innovation	.054	.043
	Group Share of Total Output	.031	.033
	Number of Firms	5,966	7,911
	Group of Share of Total Number	.027	.028
Foreign-Owned Exporter	Product Innovation	.13	.135
	Group Share of Total Output	.138	.14
	Number of Firms	12,264	14,966
	Group of Share of Total Number	.055	.053

The numbers in Table 1 imply that the two sets of categories are meaningfully distinct, i.e. foreign-ownership is *not nearly* a perfect predictor of export participation and *vice versa*. The distinction is useful for the comparisons proposed by this paper.

Table 1 also provides the first hint of a reasonable overlap between exporters and non-exporters, as well as firms with and without foreign-ownership. (The overlap is necessary for the tests that match on observed characteristics in subsequent sections of the paper). 24% of exporters have foreign capital, more than a third of majority-foreign-owned firms do not export and more than a quarter of wholly Chinese-owned firms participate in the export market. As foreign-owned firms and exporters are larger than average, these numbers imply that the odds of finding large non-exporters as a comparison group for exporters of any ownership are not ignorable - several large foreign-owned firms should help to populate the counterfactual category. Similarly, large foreign-owned firms would have no small measure of comparably large Chinese-owned firms as a comparison group. (To illustrate output per firm comparisons; exporters being 29% of firms, accounted for 55% of output in 2005 and the 8% of firms that were foreign-owned in the same year accounted for 17% of output).[9]

A small set of firms switched categories between 2005 and 2007. These 'transition firms' help with the estimation procedures that follow the OLS regressions and propensity score estimation in the next two subsections.

3.2 Baseline Estimates - OLS

The simple OLS approach below provides the first formal test of the paper's main question. It is easy to interpret. The specification below reports the conditional mean share of output due to new products, or the likelihood of undertaking product innovation with exporting and foreign ownership as competing explanatory factors.

Formally,

$$Product\ Innovation_{it} = \alpha + \beta Exporting_{it} + \gamma FDI_{it} + \delta Exporting_{it} * FDI_{it} + FE_{pst} + \varepsilon_{it}, \tag{1}$$

where *Product Innovation* measures the share of output represented by products each firm produced only for the first time that year. It could also be a dummy to indicate the incidence of product innovation for each firm-year.[10] *Exporting* is a dummy variable equal to one for firm-years with non-zero exports. By comparison, *FDI* indicates whether the share of a firm's capital owned by entities outside China, Hong Kong, Taiwan and Macau exceeds 50%.[11] Desai et al. (2004) motivated the choice of majority-ownership as the threshold for indicating foreign ownership. Their paper argues that majority- or wholly owned foreign affiliates experience more technology transfer from parent companies than minority-owned affiliates. ε_{it} is the error term.

[9] From the group estimates, one may deduce that 4% of total output in all years was new to the producing firms. Related summary statistics not present in the table include: 27.4% of firm-years involved exporting, 8% involves foreign-ownership, and the hypothetical average firm employed 193 persons to produce 102.840 million Yuan of output per year.

[10] Being tax-irrelevant, this measure comes with fewer concerns about misreporting. Nevertheless, the definition is firm specific - one firm's new product may be another firm's staple. The official guidance advises firms to report only substantially new products under this heading.

[11] The data report the ownership capital for each firm as well as the components of that capital that come from Chinese and non-Chinese sources. I do not consider capital from Hong Kong, Taiwan and Macau as foreign. The strong historical ties and similar business cultures suggest that these locations should be considered Chinese - an issue I address in the robustness checks section. An additional rational for defining foreign capital as I do is round tripping. Xiao (2004) suggests that, to avoid regulation, some persons invest funds from mainland China through entities in these locations, so that ownership is only nominally from outside mainland China.

Other control variables include industry, year and province: the FE_{pst} term represents fully interacted province p, industry sector s and year t fixed effects. The default level of product innovation is usually industry-specific. For example, makers of cotton yarn are not expected to introduce new product varieties at the same rate as the firms that turn the yarn into clothing. (Hering and Poncet, 2010) also describe the persistent and large differences between Chinese provinces in terms of economic development and R&D. These, and the possibility of year-to-year changes in the investments that support product innovation motivated this specification. I leave out other variables to avoid clutter in this first-stage comparison of the firm categories.[12]

Table 2 reports positive relationships between product innovation and *Exporting*. A similar pattern shows up for FDI. The conclusions do not depend on whether one measures product innovation as a share of output, or with a dummy variable. Column 1 of the table suggests that new products as a share of exporters' output will be twice the average for firms in the same sector, province and year. To interpret this term, consider that product innovation's mean value in the data is 3.9%, while 28% of firms export in the average year. Column 4 reports nearly identical predictions: firms that export are 13% more likely to introduce a new product on average, compared to non-exporters. By comparison, 10% of firm-years in the data register product innovation, which implies that exporters have about twice the rate of the average firm.

Column 2 reports on the FDI term, yielding a lower R^2, and a coefficient that indicates new products are 0.3% higher as a share of output for foreign-owned firms', relative to firms in the same sector, province and year. The direction and size of the coefficient agree with prior works, e.g. (Guadalupe et al., 2012; Girma et al., 2008). 8% of firm-years fall in this majority foreign-owned category. Column 5 suggests that 0.5% more of the foreign-owned firm-years report product innovation.

Columns 3 and 6 include FDI and *Exporting* in the same regression, as well as an interaction term for the two variables. The point estimates strongly suggest that exports had a much bigger impact on innovation, and the FDI variable's contribution changes signs to negative in Column 3. (The coefficient of the FDI variable is not statistically significant in that column, however). In column 6, the coefficient of the FDI term is positive and

[12] I also consider using a dummy variable to capture differences between private enterprises and state-owned enterprises (SOEs). The results do not change substantially - suggesting that by 2005, one could observe the results of policy reform that promoted innovation for Chinese SOEs. Girma et al. (2009) also showed that state-owned enterprises in China, which were generally not innovative in last century, embraced product innovation after they started exporting.

Table 2: Comparing Innovation: Exporting vs. FDI

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Innovation			Product Innovation > 0		
Exporter	0.039***		0.042***	0.126***		0.142***
	(0.000)		(0.000)	(0.001)		(0.001)
FDI		0.003***	-0.001		0.005***	0.005**
		(0.001)	(0.001)		(0.001)	(0.001)
Exporter*FDI			-0.018***			-0.080***
			(0.001)			(0.003)
Constant	0.029***	0.040***	0.029***	0.065***	0.099***	0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	760,777	760,777	760,777	762,883	762,883	762,883
R-squared	0.081	0.072	0.082	0.141	0.110	0.143

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Product innovation measures new products as a share of total output. This is the dependent variable in Columns 1-3. In columns 4 -6 the dependent variable is a dummy that indicates whether product innovation is greater than zero. The Exporting and FDI variables indicate exporting and majority-ownership by foreign entities respectively. Not shown are fully interacted fixed effects for two-digit industry, province and year.

statistically significant, but notably less than the export participation dummy. A comparison with Commander and Svejnar (2011) is interesting: In that paper, the coefficient of the export variable effectively became zero when an FDI variable was added to the regression. The reverse is observed here. (However, their paper focuses on input-output performance, not product innovation). One may argue that differences in the role of export-platform FDI as well as the nature of the transition to trade in Eastern Europe may be responsible - which invites a separate study to compare the effects of exporting and foreign ownership in China and Eastern Europe.

The exploratory step in Table 2 is highly informative, but comes with many caveats: province, year and sector-fixed effects are the only controls, and the observed correlation does not clearly account for the possibility that the most innovative firms may self-select into exporting or foreign ownership. The propensity score matching tests that follow address these concerns.

3.3 Tests that Control for Selection into Exporting or FDI

To mitigate concerns about self-selection, I repeat the estimations in Table 2 using propensity score matching.[13] Some definitions are in order: The causal effect of exporting on product innovation is the difference between the average performance of firms given the export treatment and comparable non-exporters. Propensity score matching relies on contrasts between exporters and non-exporters that are similar on just about every other measure. The approach relies on having a sufficiently large set of descriptors for the firms, such that any difference not captured by the matching variables should be essentially random, i.e. the Conditional Independence Assumption.

I use 12 variables for this matching process: These include firm size, age, research, financing cost ratios, SOE dummies that indicate whether the firm is state-owned or private and a dummy that indicates the firm's province. Two variables measure firm size – total assets and employee numbers.[14] I also include a categorical variable to capture firms' four-digit industry groups. (There are 445 of these). Section A.1 describes these variables further and provides summary statistics. While evaluating the propensity to export, I include a

[13] Leuven and Sianesi (2012) explains this method and tools for implementing it. I also run but do not report OLS tests with firm-fixed effects. In the 3 years of data available for this paper, only 2.2% and 6.6% respectively change FDI and exporting status. The OLS tests with firm fixed effects yield coefficients of 0.03 for exporting and -0.005 for FDI on 83,005 observations.

[14] Using total assets may create a capital-intensive bias in the measure of size, and using total employees might do the reverse; using both variables attempts to alleviate both concerns.

variable to capture the fraction of paid-up capital owned by foreign entities. Similarly, the test step for FDI includes a measure of export intensity.

I match exporters and FDI recipients to their nearest-neighbors. Nearest neighbors are the counterfactual items whose propensity scores are most similar to the reference observation. The propensity score is the predicted value of the exporting or FDI dummy in a first-stage probit regression using the instrumental variables that I describe in the next paragraph. Table 3 presents the propensity score matching estimates, which show the effects of export participation and foreign ownership in columns 1 and 2 respectively, corrected for the average likelihood of selection into a treatment.[15]

Table 3: Innovation vs. Exports and FDI: Propensity Score Matching

Dependent Variable:	Product Innovation		Product Innovation> 0	
	(1)	(2)	(3)	(4)
Exporting	0.062***		0.186***	
	(0.004)		(0.007)	
FDI		-0.061***		-0.1121***
		(0.006)		(0.009)
Constant	0.138***	0.190***	0.262***	0.355***
	(0.002)	(0.04)	(0.002)	(0.002)
Observations on Common Support	90,461	78,499	82,932	73,337

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Product innovation − the dependent variable measures new products as a share of total output. Columns 3 and 4 use a dummy as the outcome variable. The reported effects are the estimated average treatment effects on treated observations (ATT).
The Exporting and FDI variables indicate exporting and majority-ownership by foreign entities respectively. Section A.2 of the appendix describes the variables used to correct for self-selection.

This matching estimate of the treatment effects shows that export participation predicts an additional 6.2% of outputs that are new products (19.9% for exporters versus 13.8%

[15]The simple nearest-neighbor match suits this paper's purpose. The number of observations is large, with many firms in the control and treatment categories sharing similar observable attributes. Therefore, one expects counterfactuals that roughly approximate each tested firm-year. If the overlap between control and treatment items was worse or observations fewer, one could have considered kernel matching or other N-neighbor matching to average out the control observations used.

Unreported results using N-nearest neighbor matching yield results that are largely similar. Abadie and Imbens (2009) and Caliendo and Kopeinig (2008) explain the advantages of N-nearest neighbor matching over simple nearest neighbor matching.

for comparable non-exporting firms). Firms with majority foreign-ownership under-perform relative to their peers. New products account for 12.9% of their output, compared to 19.0% for Chinese-owned firms with similar propensities. Understandably, foreign-owned firms are larger and more likely to do R&D, so the innovation benchmark is set higher than for exporters.

To address the possibility that only foreign-owned exporters account for the estimated effects of exporting, I repeat the propensity score tests on the subset of the data that is foreign-owned only. (This gives 7,527 observations on the common support, much less than the 90,461 used in column 1 of Table 3). Among foreign-owned firms, exporters enjoy a product innovation advantage that is comparable but less than that in the full sample (5.0%); suggesting that this subset's average cannot account for all the export treatment effect in Table 3. (See Section A.3 for these results).[16] Section A.2 in the appendix supports these results by showing that the sample selected for matching is balanced in terms of the observed covariates, and graphically illustrates the common support on the propensity score for firms that received the export or foreign-ownership treatments.

Comparing the results from this set of tests with the baseline OLS estimates, the 6.0% difference obtained from the matching step is more than the 3.8% from the OLS regression for exporters. It is nice to see the two tests yield coefficients with the same sign.

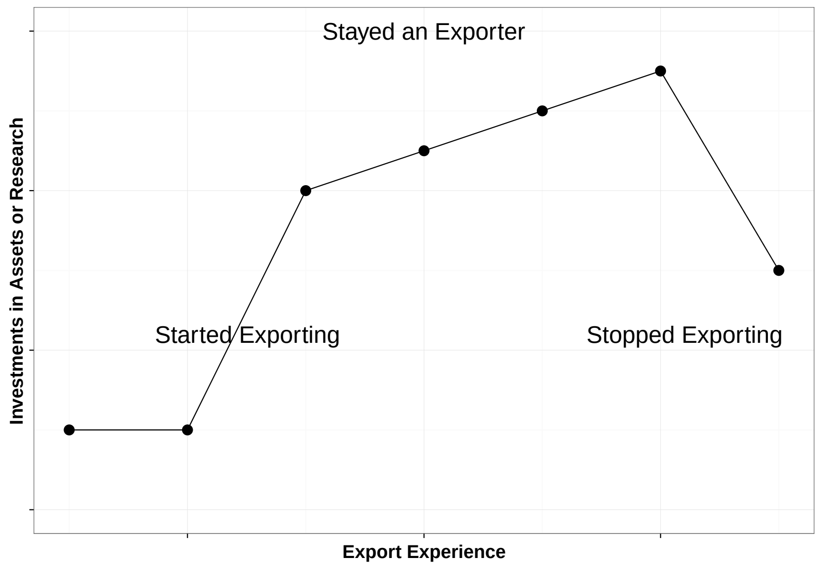
3.4 Learning Mechanisms for Product Innovation

Given the findings that link higher levels of product innovation to exporting, this section explores possible mechanisms that enable product innovation. The logic that drives the next steps is as follows: intangible factors associated with exporting or foreign ownership may drive the decision to create new products, but the act of creating new products must require measurable changes to the factors of production most relevant to product innovation. Examples of those tangible changes could be investments in R&D to develop or improve products. It could also be investments in equipment to change production processes and methods.

I focus on these two potential mechanisms: research and development spending could represent the homegrown dimension of innovation inputs. Aggregate R&D as a share of GDP in China was growing throughout this period. At the firm level, investing in R&D

[16]There may be lags before foreign ownership leads to innovation, as discussed in Guadalupe et al. (2012). Therefore, I run regressions that use the FDI variable lagged by one year. The estimated treatment effects are -0.040 and -0.108 for product innovation and the product innovation dummy respectively. The results are statistically significant and closely mirror the findings in 3.

Figure 1: Illustrative Export-Driven Innovation Pattern



This graph is purely illustrative for the expected changes to innovation inputs with export status. It does not use real data.

clearly indicates a commitment to learning, which could translate into product innovation. In the same vein, asset purchases could reflect technology diffusion through the acquisition of assets with embodied knowledge, as is well documented for China (Brahmbhatt and Hu, 2010; Augier et al., 2013). A large number of Chinese producers import their production equipment, which usually embody associated production methods (Woo, 2012).[17]

To the extent that exporting is causal to product innovation, it should also be causal to these changes in production, observed and unobserved. In other words, if firms learn to undertake actions like R&D necessary for innovation as they export, the observed measures of these mechanisms should increase when firms begin to export, grow as firms continue to export and decline for firms that stop exporting. Figure 1 illustrates this pattern of learning-by-exporting. (In contrast, the selection hypothesis would predict small increases on transition into the treatment, and no changes thereafter). Following the argument in De Loecker (2007), R&D and new assets could be mechanisms that firms learn as they export, and in learning, become more productive.

[17] Other causal drivers of product innovation may exist outside the two that are central to this section of the paper. The approach to estimating the causal relationship addresses the possibility of other unobserved causes.

Formally, for a set of mechanisms that lead to product innovation X:

$$X_{ist} = \gamma_s + \lambda_t + \beta S_{st} + \bar{\varepsilon}_{ist}, \tag{2}$$

where S represents the exporting or foreign ownership treatment status; γ helps to address selection - it is the average difference between exporters and non-exporters (or foreign vs. domestically owned firms). β is the parameter of interest, it measures the extent to which firm i changes X because its ownership or exporting status changed. X represents the set of causal factors like R&D, and investment in fixed capital. Firms may not report all elements of X in the data.

$\beta = E(X_{after,treated} - X_{before,treated} + X_{after,untreated} - X_{before,untreated})$ is the identifying assumption in (2), i.e. $E(\bar{\varepsilon}) = 0$. This is reasonable, especially if one includes firm fixed effects.

In other words, R&D spending and asset purchases should experience a positive shock right about when a firm starts to export, the positive trend should continue on a reduced scale for firms that keep exporting and one should see an incomplete reversal of the increased patterns of investment for firms that stop exporting. The reversal should be incomplete because those that stopped learned from their export experience.

Testing this idea is a regression model that extends the specification used by Bernard and Jensen (1999) and De Loecker (2007). The primary differences in this case are: (1) I test for innovation drivers, not productivity on the left hand side, and (2) I include lagged values of the dependent variable to reduce concerns about endogeneity.

Formally:

$$lnX_{it} = a + \beta_0 ln(X_{it-1}) + \beta_1 Start_{it} + \beta_2 Stay_{it} + \beta_3 Stop_{it} + \beta_4 Size_{it} + e_{it}, \tag{3}$$

where $Start$, $Stay$ and $Stop$ capture all the possible treatment status options for a firm in (3). For the exporting treatment, $Start$ indicates firms that do not export in year $t-1$ but export in year t and $Stay$ shows firms that export in year $t-1$ and continue to export in year t. $Stop$ flags firms that exported in year $t-1$, but failed to register exports in year t. X is a placeholder for the matrix of firm characteristics that include size, industry and location. To interpret the regression, one should consider that only observations in 2006-2007 are usable: of these, 4% of observations fit the *starting exports* category, 25% fall in the *Stay* category and 4% are observations corresponding to firm-years where exporting stopped. Firm-years unrelated to exporting make up the remaining 67% of observations.

Given a causal relationship between exporting or foreign ownership and R&D for example, one must still show R&D is causally linked to product innovation. Correlation would be sufficient if reverse causation were impossible. In this case, it is possible that firms undertake R&D or asset purchases after embarking on a course of product innovation for another reason.

Formally:

$$Product\ Innovation_{it} = \alpha_i + \alpha_2 X_{it} + \hat{\varepsilon}_{it}, \tag{4}$$

Firm fixed effects α_i help to identify the relationship in (4) as causal. (This approach also mitigates bias due to omitted elements of X that are firm specific). If $\alpha_2 > 0$ and $\beta > 0$, one could argue that the variables in X_{it} are the causal mechanisms through which exporters or foreign-owned firms undertake product innovation. The rest of this section focuses on estimating (3) and (4).

I rely on a Poisson pseudo-maximum likelihood specification for (2) as relatively few firms undertake research and development, and the variables by definition have lower bounds of zero. R&D expenses are greater than zero for only 83,176 of the 763,036 usable firm-year observations for this specification. These expenses are attributable to 45,340 firms. Even these firms do not spend on R&D in every year; (they account for 127,883 observations, which suggests that for them, R&D expense occurs in about 2 of 3 years). Asset purchases are more common - they are positive for 70% of observations with two consecutive firm-years, although they tend to be higher for exporting firms. Several papers shows that Poisson regression estimates can be useful, even when dependent variables are not count data (e.g. Silva and Tenreyro, 2011, 2006; Gourieroux et al., 1984).[18]

Table 4 presents some non-parametric comparisons before the regression exercises. It shows differences in exporting, R&D and asset purchases for firms that changed exporting or FDI status. Only 15,700 and 5,700 firms fit each of these categories, but those numbers are large enough to be instructive in this summary table format. As the dataset is a short 3-year panel, no distinction is made between firms that started exporting in 2006 or 2007. The table provides suggestive evidence of a strong relationship between the transition to exporting and product innovation, with exporting having the stronger relationship. 20% undertake product innovation in the year of exporting, compared to 10% for the same firms before exporting. (The comparable numbers are 4.4 and 5% for foreign-ownership). The

[18]There may be an argument for using a Tobit specification for this set of tests, however,one may not find consistent estimators in the presence of lagged variables and fixed effects. As shown in Arellano and Honoré (2001), the fixed effects do not enter linearly or multiplicatively into the model, as one expects for linear regressions.

Table 4: Changes at the Export and FDI Transitions

VARIABLES	Before Exporting	After Exporting	Before FDI	After FDI
	Group Averages			
Product Innovation	.049	.077	.044	.050
I(Product Innovation > 0)	.104	.206	.094	.106
R&D	475.93	773.75	464.47	632.10
I(R&D > 0)	.133	.165	.113	.127
Log(Original Asset Value)	8.858	9.084	9.333	9.518
I(Δ Original Asset Value > 0)	.762	.770	.785	.753
N	15726		5688	

share of output due to new products also increases, while an additional 3% of firms start spending on R&D in the year of exporting relative to year before exporting. About 12.7% of firms that received foreign capital undertake R&D; in the year before receiving foreign capital the fraction is 11.3% – so the incidence of R&D increases with foreign ownership, just not as much as with exporting.

Asset purchases were measured using the original purchase value of assets before depreciation, as recorded in the data.[19] The alternative –using changes in the net value of assets is problematic given the difficulty of accounting simultaneously for asset purchases, disposals and depreciation on old and new assets. Comparing the original purchase value of a firm's assets in one year with the prior year gives the lower bound of its assets purchases that year. The question of interest here is whether positive values of asset purchases are correlated with product innovation and exporting.

Table 5 shows that product innovation increases for firms with R&D and new assets, status notwithstanding.[20] The estimates use nearest-neighbor matching –the propensity to innovate was predicted using the same set of observable variables used to predict foreign-

[19]Say a hypothetical firm A owns a widget worth 100 Yuan in year 1. If it buys a second widget worth 150 Yuan in year 2, its original assets value increases to 250, even if the value of assets on the books is smaller due to depreciation. The main challenge with using this variable to measure asset changes is that when firms dispose of assets in the same year that purchase new ones, purchases are underreported by the value of the disposals. (If the firm sold the first widget at the same time that it upgraded to another, the reported value would be 150).

[20]Unreported OLS regressions that test the relationship between these innovation inputs and firm-level product innovation provide similar results for R&D, although the results obtained for asset acquisitions are not statistically significant. The propensity matching results reported in Table 5 address the concerns about selection bias –i.e. firms introducing new products tend to acquire fixed assets for the new production processes.

ownership and exporting status in Table 3. (However, exporting status and foreign-ownership status are both used as observables in this specification.) For columns 1 and 3, the value of asset acquisitions was an observable predictor of whether firms invested in R&D, (the $I(R\&D)$ treatment). For columns 2 and 4, R&D was used to predict whether firms acquire physical production capital, the $I(AssetPurchase)$ treatment.

Table 5: R&D and Asset Purchases Increase Product Innovation

	(1)	(2)	(3)	(4)
Dependent Variable:	Product Innovation		Product Innovation> 0	
	(1)	(2)	(3)	(4)
I(R&D)	0.136***		0.294***	
	(0.001)		(0.001)	
I(Asset Purchase)		0.008***		0.051***
		(0.003)		(0.004)
Constant	0.024***	0.154***	0.069***	0.318***
	(0.000)	(0.002)	(0.001)	(0.004)
Observations	357,341	59,578	357,341	59,578

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The product innovation measure represents the log of new products' value for a firm-year. Columns 3-4 use a dummy as the outcome variable. These are the $I()$ items are dummy variables that take the value of 1 if firms had non-zero R&D spending, or acquired physical production capital. Each of these two dummy variables is considered a 'treatment' that predicts whether firms undertake product innovation. The reported effects are the estimated average treatment effects on treated observations (ATT).

The treatment effects show that positive R&D spending predicts an additional 13.6% of outputs that are new products (16.0% for firms with R&D spending versus 2.4% for comparable firms without R&D spending). Firm-years that show positive physical asset acquisition in column 2 of Table 5 are also more likely to undertake product innovation. New products account for 16.2% of their output, compared to 15.4% for matched firms with no asset acquisitions.

Columns 2 and 4 suggest that purchasing fixed assets predicts higher levels and instances of product innovation, even if not as well as R&D. The estimated treatment effect for production asset acquisition is 0.8%, or 5% higher likelihood of any product innovation. Nevertheless, the results are statistically significant and positive - indicating that firms acquiring assets tend to do more product innovation. The propensity score matching estimates here address multiple measures of firm size, employee training, province and industry-year categories. (Given the findings in Augier et al. (2013) and Brahmbhatt and Hu (2010), which describe firms using the embodies knowledge in purchased physical capital to enable innovation, the effects of exporting/FDI on asset acquisition remains interesting as a possible source of product innovation).

Table 6 links exporting and foreign ownership to R&D and asset purchases. Column 1 shows R&D, while Column 2 shows asset purchases. The annual survey dataset reports both the depreciated and original or purchase values of fixed assets. Therefore, it is possible to track net asset purchases using their reported original values for fixed assets in 2006-2007. I use this data to estimate equation (3).[21]

Firms' patterns of spending on innovation inputs change as they start exporting. The PPML specification in Table 6 shows that R&D for the average firm increases by about 58% when a firm starts exporting and by 60% for firms that remain exporters. (To compute these, I use the average value of 0.92 for the R&D variable and apply the $e^{coeff-mean}$ transformation to the difference). That group in turn, invests more than firms that stop exporting. The firms that stop exporting still do better than those with no export record, having learned from their experience, their R&D spending is 50% above average. Capital purchase patterns do not follow the trend exactly, but remain broadly consistent: firms that start exporting invest more than the average non-exporter, those that remain exporters or stop exporting, invest less than the average non-exporter. Experienced exporters and firms that stop exporting invest in equipment at below-average rates for exporters, arguably because most investments required were made at the beginning of the export experience. Long run investment trends cannot be deduced from the three-year panel data. The size controls behave as expected, firms that are larger in terms of assets or employees also undertake more R&D. Large employers generally invest more in R&D and less in fixed asset purchases.

In contrast, firms that start FDI do not spend on R&D more than the average firm. Their asset purchases are larger than those of the average domestically owned firm, but the increase of 0.3% over the mean remains less than the 0.4% increased associated with starting exporting. (I compute these with the average value of 5.74 for asset purchases and apply the $e^{coeff-mean}$ transformation to the difference). After controlling for firm size and lagged values, R&D expense is actually 74% lower for firms that started to be majority foreign-owned.

[21] As described in the notes to Table 4, net asset purchases represent year-to-year differences between the original purchase value of physical assets. So for a firm with 20,000 yuan of assets at original purchase value in one year and 25,000 in the next year, one can infer asset purchases of 5,000 yuan, even if the net value of assets is lower than 25,000, due to depreciation.

Table 6: Innovation Drivers by Stage of Export/FDI Participation

	(1)	(2)	(3)	(4)
Dependent Variables:	Log(R&D)	Log(Asset Purchases)	Log(R&D)	Log(Asset Purchases)
Started_Exports	0.381***	0.176**		
	(0.122)	(0.076)		
Stayed_Exports	0.428***	-0.168***		
	(0.061)	(0.038)		
Stopped_Exports	0.262**	-0.127**		
	(0.116)	(0.059)		
Started_FDI			-0.412***	0.152**
			(0.123)	(0.073)
Stayed_FDI			-0.434***	0.112***
			(0.105)	(0.041)
Stopped_FDI			-0.383**	0.007
			(0.166)	(0.071)
Log(Assets)	1.055***	1.016***	1.068***	1.009***
	(0.029)	(0.018)	(0.029)	(0.018)
Log(Employees)	0.119***	-0.012	0.158***	-0.024
	(0.037)	(0.024)	(0.034)	(0.024)
Constant	-5.546***	-2.811***	-5.588***	-2.757***
	(0.266)	(0.254)	(0.257)	(0.249)
Observations	437,500	357,822	437,500	357,822
R-squared	0.674	0.507	0.687	0.495
Province FE	Y	Y	Y	Y
Ind.-Year FE	Y	Y	Y	Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the logged value of asset purchases or R&D undertaken in each firm-year. The main explanatory variables are firms' foreign-ownership or export status. I also use logged values of total assets and employee counts, as control variables that proxy for size. The PPML specification was selected to fit the non-negative dependant variables, given the categorical explanatory variables. Errors are clustered by firm.

The estimated effect of the change in ownership status is statistically significant. Similar patterns obtain for remaining majority foreign-owned or reverting from foreign-owned to domestic ownership. Asset purchases are higher than average - actually higher than for the comparable export status, but spending on R&D is less than average. The pattern of lower R&D spending by foreign-owned entities is consistent with the literature - multinationals generally prefer to keep R&D centralized where they have stronger intellectual property protection (Fernandes and Tang, 2012; Branstetter et al., 2006). In contrast, locally owned exporters generally do not have the option to outsource their R&D. Their spending on R&D and new assets therefore reflects their efforts to update production processes as they compete in global markets.[22]

The pattern of R&D growth experienced by these exporters may lend some credence to the Economist magazine's claim: Exporters in developing economies are staking their claim on the innovation terrain.

4 Robustness Checks

4.1 Learning with Corrected Biases

Bernard and Jensen (1999) did not need to prove that learning mechanisms work, unlike this paper. To address concerns that the regression coefficients in Table 6 are biased upwards because of self-selection, the next two paragraphs present the results of tests that use the propensity score matching method.

Table 7 presents results consistent with the findings of the OLS step. Each 'treatment condition' is tested separately. The control group was selected to match each treatment: Observations with the *Start* treatment were matched to others who were similarly not exporters in the previous period. *Stay* was matched against new exporters and those that had stopped exporting, while those with the *Stop* treatment were compared with firms that had no exporting history.

As in Table 6, firms that start exporting invest more in R&D and fixed production capital than their non-exporting peers. (1.00 for exporters vs. 0.864 for non-exporter peers). The estimates are statistically significant for both Exporting and FDI, but with opposite

[22] This pattern may be consistent with the foundational work of Vernon and Wells (1966), that with product innovation, most of the resources and R&D required are drawn from local sources. By that reasoning, R&D expenses may decline for affiliates of multinationals trying to replicate products using know-how from their home-countries.

Table 7: Matching Estimates by Stage of Export Participation

VARIABLES	Log(R&D)	Log(Asset Purchases)
Started_Exports	0.139***	0.193**
	(0.028)	(0.072)
Stayed_Exports	0.012	-0.031
	(0.023)	(0.059)
Stopped_Exports	-0.037	-0.092
	(0.024)	(0.070)
Started_FDI	-0.158***	0.047
	(0.045)	(0.114)
Stayed_FDI	-0.015	0.034
	(0.041)	(0.100)
Stopped_FDI	-0.098**	0.275**
	(0.043)	(0.116)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The reported effects are the estimated average treatment effects on treated observations (ATT). For these propensity score matching exercises, the counterfactual for each row was limited to comparable firm-years as follows: *Started_** was matched to observations not foreign-owned or an exporter, and *Stayed_** to observations with a history of exporting or foreign ownership, but currently not in a second consecutive year in that status. *Stopped_** was matched to either non-exporters or firms with no foreign-ownership in that year. The dependent variables are logged values of R&D and asset purchases (plus 1 to avoid losing zeros). The number of treated observations were 15,713, 110,260 and 17,100 respectively for Columns 1 of Exports. Columns 2 of that segment had 3,784, 35,947 and 5,211. The numbers vary by column because the match was limited to items on the common support. The matching variables include firm size, output per assets and employee, as well as 4-digit industries. Further detail on the mean outcomes for treated and untreated items, the control items on common support and balancing tests for the matching variables are available on request from the author.

signs. In the first year that a firm becomes majority foreign-owned it invests less in R&D than comparable Chinese-owned firms. This is consistent with Table 6, and supports the suggestion that when firms start exporting, they learn to do R&D. Chinese firms that become foreign-owned may actually reduce their R&D efforts if the parent company opts to locate R&D efforts elsewhere, to retain better control over intellectual property rights. While both sets of 'starters' out-invest peers in terms of fixed production capital, the estimates are only statistically significant for firms that started exporting.

Firms that remained as exporters do not appear to spend more on R&D than new exporters and firms that stopped exporting – the comparison group for this exercise. The difference for R&D is not statistically significant, as is the observed mean difference for assets purchases. Firms that remained majority foreign-owned, compared with new or formerly foreign-owned also do not register any statistically significant difference in their spending on R&D and asset purchases.

Firms that stop exporting invest less in R&D and new capital than other non-exporting peers. However, the difference is small enough that it is not statistically significant. This may imply that characteristics like output per-employee or other matching variables drive the learning suggested by Table 6. It does not invalidate the claim altogether, just how it is interpreted. Firms that changed from majority foreign ownership report a split pattern of estimated effects. While these firms spend less on R&D than comparable Chinese-owned firms, they spend more on asset purchases. Both estimates are statistically significant at the 95% level.

4.2 Other Empirical Specifications

Table 8 shows that the main results in the papers are robust to alternative specifications within the propensity score matching framework. The selection of matching observations may influence the estimated treatment effects, as shown in Smith and Todd (2005). Table 3 used nearest-neighbor matching, given the large number of observations and the quality of common support observed in the data, as documented in appendix section A.2. More advanced matching approaches include Mahalanobis distance matching (MDM) and coarsened exact matching (CEM). Mahalanobis distance matching selects matches treatment observations to observations that are closest in terms of the observed variables, where differences are weighted by the variance of each variable. The notable theoretical advantages of this approach are described in Rosenbaum and Rubin (1985). Coarsened exact matching, described in Iacus et al. (2012) and Blackwell et al. (2009), matches treatment observations within narrowly defined strata created from combinations of the observed variables. this approach has been shown to reduce imbalance, model dependence, estimation error and other threats to validity in making causal inferences.

Table 8: Estimated Treatment Effects Using MDM and CEM

	(1)	(2)	(3)	(4)
	Mahalanobis Distance Matching		Coarsened Exact Matching	
Exporting	0.039***		0.020***	
	(0.001)		(0.001)	
FDI		0.008***		-0.005**
		(0.001)		(0.002)
Constant	0.029***	0.039***	0.022***	0.026***
	(0.000)	(0.000)	(0.001)	(0.002)
Observations	760,567	759,567	72,396	12,764

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable is product innovation, measured as new products' share of total output. The reported effects are the estimated average treatment effects on treated observations (ATT). The Exporting and FDI variables indicate exporting and majority-ownership by foreign entities respectively. In sign and significance, the results are comparable to Table 3. Coarsened exact matching in columns 3 and 4 yields notably fewer observations on common support. Columns 1 and 2 use two-digit industries and provinces as controls, with Mahalanobis distance matching covariates that are identical to those in Table 3. Columns 3 and 4 use coarsened exact matching, with the same variables.

Table 8 provides results that are consistent with the conclusions of this paper. Tests using Mahalanobis distance matching resemble the preliminary findings in Table 2, with FDI having a small positive effect, but with the larger, statistically significant effect being due to exporting. Tests with coarsened exact matching yield results that are consistent with the propensity score matching results in Table 3, exporting leads to higher levels of product innovation, while FDI does not contribute to higher levels of product innovation, in comparison to firms with similar observables.

Furthermore, the definition of foreign capital excluded funds from Hong Kong, Macau and Taiwan (HMT) throughout this paper. This definition was motivated by the similarity of business cultures, technology and connections in the region.

Nevertheless, I show below in Table 9 that the coefficients of the OLS tests in Tables 2 and 6 would remain mostly unchanged if foreign capital were redefined to include funds from Hong Kong, Macau and Taiwan. (The implication is that the two categories of foreign capital sources in the data are not inherently associated with different propensities for product innovation). For the PSM tests, matching coefficients for both versions of the model are broadly similar, showing that firms increase R&D and asset purchases when they enter the export market, invest more as they remain exporters, and reduce the pattern if they stop exporting, but not to the level of firms that never exported.

Table 9 only indicates that the conclusions of this paper should not change, even if the definition of foreign capital had been more expansive from the start. In fact, I expect any other definition of foreign capital to enhance the contrast between the effects of trade and foreign investment presented in Tables 3 and 6.

Table 9: Comparing coefficients for FDI with and without HMT

	(1)	(2)	(3)	(4)	(5)	(6)
	Product Innovation			Product Innovation > 0		
Exporter	0.039***		0.044***	0.126***		0.145***
	(0.000)		(0.000)	(0.001)		(0.001)
FDI with HMT		-0.001	-0.019***		-0.007***	-0.065***
		(0.001)	(0.001)		(0.001)	(0.001)
Constant	0.029***	0.040***	0.031***	0.065***	0.101***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	760,777	760,777	760,777	762,883	762,883	762,883
R-squared	0.081	0.072	0.082	0.141	0.110	0.146

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The dependent variable in columns 1 - 3 is new product's share of total output, while columns 4 - 6 use a dummy that is 1 if new products represent a positive share of outputs. FDI with HMT is a categorical variable that switches from zero to 1 if more than 50% of ownership is from outside mainland China, Hong Kong, Macau and Taiwan (HMT). In sign and significance, the results are comparable to Table 2

The appendix includes tests of the match quality for all the propensity score-based tests in the previous section.

5 Conclusions

This paper compares the direct impacts of exporting and foreign ownership (FDI) on product innovation. FDI and export promotion are the two main channels that developing economies have adopted to lead private sector growth; hence the motivation to evaluate their relative merits in promoting product innovation. Firms with an interest in stimulating product innovation may also consider the same question as a matter of strategy.

Using propensity score matching methods and rich firm level data, this paper shows that exporting causes firms to engage in greater levels of product innovation, lending support to the 'learning-by-exporting' hypothesis (Bratti and Felice, 2012; Damijan et al., 2010; De Loecker, 2007). FDI does not give the same level of new product creation, either in terms of incidence or intensity. In some specifications, foreign ownership actually leads to less innovation and less spending on items like R&D. In a developing economy like China, the absence of a positive relationship between FDI and innovation may be due to foreign owners' efforts to protect intellectual capital by moving R&D abroad (Fernandes and Tang, 2012; Branstetter et al., 2006). Those firms could also be reducing innovation efforts in the developing-economy subsidiary to avoid effort duplication.

I further explore the causal nature of the relationship between exporting and innovation, through the use of potential innovation inputs like R&D and asset purchases, as R&D causally predicts new product innovation in this context. Exporting or foreign ownership may drive the decision to create new products, but the act of creating new products must require measurable changes to these or other innovation inputs. Estimates from that exercise indicate that firms that start exporting undertake more R&D and invest more in new production assets. These results also suggest that firms learn from exporting – firms that stop exporting spend more on R&D and new assets than the average non-exporter, even if less than new or continuing exporters. In all specifications, firms that change from Chinese to foreign ownership reduce R&D spending on average. Their asset purchases are higher than average, but less than the comparable number for new exporters.

These findings suggest that context may matter for whether foreign investment leads to product innovation. On the other hand, exporting consistently predicts higher levels of innovation efforts like R&D and better product innovation outcomes. In a context where a foreign owner only wants the low production cost of a location like China, foreign ownership may actually leads to lower levels of product innovation. The owners' priorities determines whether the firm undertakes costly innovation efforts.

Relating these findings to papers like Commander and Svejnar (2011) and Guadalupe et al. (2012) that find a positive relationship between product innovation and foreign ownership in European contexts holds the potential for additional work on how context, property rights and economic development influence technology transfer through ownership.

References

Abadie, A., Imbens, G. W., 2009. Matching on the Estimated Propensity Score. National Bureau of Economic Research (15301).

Aitken, B., Harrison, A., 1999. Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela. American Economic Review 89 (3), 605–618.

Amiti, M., Freund, C., 2010. The Anatomy of China's Export Growth. In: Feenstra, R. C., Wei, S.-J. (Eds.), China's Growing Role in World Trade. University of Chicago Press, pp. 35–56.

Arellano, M., Honoré, B., 2001. Panel Data Models: Some Recent Developments. Handbook of Econometrics 5, 3229–3296.

Augier, P., Cadot, O., Dovis, M., 2013. Imports and TFP at the Firm Level: The Role of Absorptive Capacity. Canadian Journal of Economics/Revue Canadienne d'Économique 46 (3), 956–981.

Aw, B. Y., Chung, S., Roberts, M. J., 2000. Productivity and Turnover in the Export Market: Micro-level Evidence from the Republic of Korea and Taiwan (China). World Bank Economic Review 14 (1), 65–90.

Aw, B. Y., Roberts, M. J., Xu, D. Y., 2008. R&D Investments, Exporting, and the Evolution of Firm Productivity. American Economic Review, 451–456.

Benhabib, J., Perla, J., Tonetti, C., 2014. Catch-Up and Fall-Back through Innovation and Imitation. Journal of Economic Growth 19 (1), 1–35.

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

Bernard, A. B., Redding, S. J., Schott, P. K., 2011. Multiproduct Firms and Trade Liberalization. Quarterly Journal of Economics 126 (3), 1271–1318.

Blackwell, M., Iacus, S., King, G., Porro, G., 2009. cem: Coarsened Exact Matching in Stata. Stata Journal 9 (4), 524.

Brahmbhatt, M., Hu, A., 2010. Ideas and Innovation in East Asia. World Bank Research Observer 25 (2), 177–207.

Branstetter, L. G., Fisman, R., Foley, C. F., 2006. Do Stronger Intellectual Property Rights Increase International Technology Transfer? Empirical Evidence from US Firm-Level Panel Data. Quarterly Journal of Economics 121, 321–349.

Bratti, M., Felice, G., 2012. Are Exporters More Likely to Introduce Product Innovations? The World Economy 35 (11), 1559–1598.

Broda, C., Weinstein, D. E., 2006. Globalization and the Gains from Variety. Quarterly Journal of Economics 121 (2), 541–585.

Caliendo, M., Kopeinig, S., 2008. Some Practical Guidance for the Implementation of Propensity Score Matching. Journal of economic surveys 22 (1), 31–72.

Castellani, D., Zanfei, A., 2006. Multinational Firms, Innovation and Productivity. Multinational Firms, Innovation and Productivity.

Clerides, S. K., Lach, S., Tybout, J. R., 1998. Is Learning by Exporting Important? Micro-dynamic Evidence from Colombia, Mexico, and Morocco. Quarterly Journal of Economics 113 (3), 903–947.

Commander, S., Svejnar, J., 2011. Business Environment, Exports, Ownership, and Firm Performance. Review of Economics and Statistics 93 (1), 309–337.

Damijan, J. P., Kostevc, C., Polanec, S., 2010. From Innovation to Exporting or Vice Versa? World Economy 33 (3), 374–398.

De Loecker, J., 2007. Do Exports Generate Higher Productivity? Evidence from Slovenia. Journal of International Economics 73 (1), 69–98.

De Loecker, J., 2013. Detecting Learning by Exporting. American Economic Journal: Microeconomics 5 (3), 1–21.

Desai, M. A., Foley, C. F., Hines Jr, J. R., 2004. The Costs of Shared Ownership: Evidence from International Joint Ventures. Journal of Financial Economics 73 (2), 323–374.

Djankov, S., Hoekman, B., 2000. Foreign Investment and Productivity Growth in Czech Enterprises. World Bank Economic Review 14 (1), 49–64.

Eckel, C., Neary, J. P., 2010. Multi-Product Firms and Flexible Manufacturing in the Global Economy. Review of Economic Studies 77 (1), 188–217.

Fernandes, A. P., Tang, H., 2012. Determinants of vertical integration in export processing: Theory and evidence from China. Journal of Development Economics 99 (2), 396–414.

Girma, S., Gong, Y., Görg, H., 2008. Foreign Direct Investment, Access to Finance, and Innovation Activity in Chinese Enterprises. World Bank Economic Review 22 (2), 367–382.

Girma, S., Gong, Y., Görg, H., 2009. What Determines Innovation Activity in Chinese State-Owned Enterprises? The Role of Foreign Direct Investment. World Development 37 (4), 866–873.

Girma, S., Gong, Y., Görg, H., Lancheros, S., et al., 2012. Foreign Ownership Structure, Technology Upgrading and Exports: Evidence from Chinese Firms. Kiel Institute for the World Economy Working Paper.

Gorodnichenko, Y., Svejnar, J., Terrell, K., 2010. Globalization and Innovation in Emerging Markets. American Economic Journal-Macroeconomics 2 (2), 194–226.

Gourieroux, C., Monfort, A., Trognon, A., 1984. Pseudo Maximum Likelihood Methods: Applications to Poisson Models. Econometrica, 701–720.

Guadalupe, M., Kuzmina, O., Thomas, C., 2012. Innovation and Foreign Ownership. American Economic Review 102 (7), 3594–3627.

Hering, L., Poncet, S., 2010. Market Access and Individual Wages: Evidence from China. Review of Economics and Statistics 92 (1), 145–159.

Hummels, D., Klenow, P., 2005. The Quality and Variety of a Nations Trade. American Economics Review 95 (3), 704–723.

Iacovone, L., Javorcik, B., Keller, W., Tybout, J., 2009. Walmart in Mexico: The Impact of FDI on Innovation and Industry Productivity. University of Colorado Working Paper.

Iacus, S. M., King, G., Porro, G., 2012. Causal Inference without Balance Checking: Coarsened Exact Matching. Political Analysis 20, 1–24.

Javorcik, B. S., 2004. Does Foreign Direct Investment Increase the Productivity of Domestic Firms? in Search of Spillovers Through Backward Linkages. American economic review, 605–627.

Keller, W., 2004. International Technology Diffusion. Journal of Economic Literature 42 (3), 752–782.

Kneller, R., Pisu, M., 2007. Industrial Linkages and Export Spillovers from FDI. World Economy 30 (1), 105–134.

Krugman, P., 1980. Scale Economies, Product Differentiation, and the Pattern of Trade. American Economic Review 70 (5), 950–959.

Lai, E. L.-C., 1998. International Intellectual Property Rights Protection and the Rate of Product Innovation. Journal of Development economics 55 (1), 133–153.

Leuven, E., Sianesi, B., 2012. PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. Statistical Software Components.

Lileeva, A., Trefler, D., 2010. Improved Access to Foreign Markets Raises Plant-Level Productivity For Some Plants. Quarterly Journal of Economics 125 (3), 1051–1099.

Lin, C., Lin, P., Song, F., 2010. Property Rights Protection and Corporate R&D: Evidence from China. Journal of Development Economics 93 (1), 49–62.

Madsen, J. B., 2008. Semi-Endogenous versus Schumpeterian Growth Models: Testing the Knowledge Production Function Using International Data. Journal of Economic Growth 13 (1), 1–26.

Rosenbaum, P. R., Rubin, D. B., 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. American Statistician 39 (1), 33–38.

Schott, P. K., 2008. The Relative Sophistication of Chinese Exports. Economic Policy 23 (53), 5–49.

Schumpeter, J. A., 1942. Capitalism, Socialism and Democracy. Routledge.

Segerstrom, P. S., 1991. Innovation, imitation, and economic growth. Journal of Political Economy, 807–827.

Silva, J. S., Tenreyro, S., 2006. The Log of Gravity. Review of Economics and Statistics 88 (4), 641–658.

Silva, J. S., Tenreyro, S., 2011. Further Simulation Evidence on the Performance of the Poisson Pseudo-Maximum Likelihood Estimator. Economics Letters 112 (2), 220–222.

Smith, J. A., Todd, P. E., 2005. Does matching overcome lalonde's critique of nonexperimental estimators? Journal of econometrics 125 (1), 305–353.

Sun, S., 2009. How Does FDI Affect Domestic Firms' Exports? Industrial Evidence. World Economy 32 (8), 1203–1222.

Vernon, R., Wells, L., 1966. International Trade and International Investment in the Product Life Cycle. Quarterly Journal of Economics 81 (2), 190–207.

Vogel, A., Wagner, J., 2010. Higher Productivity in Importing German Manufacturing Firms: Self-Selection, Learning from Importing, or both? Review of World Economics 145 (4), 641–665.

Woo, J., 2012. Technological Upgrading in China and India: What Do We Know? OECD Development Centre Working Papers (308).

Xiao, G., 2004. Peoples Republic of Chinas Round-Tripping FDI: Scale, Causes and Implications. Asia Development Bank Institute Discussion Paper 7.

Appendix A: Appendix

A.1 Variables used for propensity score matching

Firm size: Total assets for the firm. **Asset Productivity**: Total output per total assets, in logs. **Employee Productivity**: Total output per employee, in logs. **R&D**: Research and development expenses as a share of sales: this measure of innovation input is expected to correlate positively to exports as well as product innovation. **State Ownership - SOEs**: A categorical variable that indicates whether state, city or regional governments own the majority of a firm's capital. It should be inversely correlated with innovation. It may be positively correlated with exporting given that state owned entities tend to be larger than average. **Foreign Ownership**: The fraction of paid-up capital from foreign sources. Used only to predict exporting. **Export Intensity**: Exports as a fraction of sales. Used only to predict FDI. **Province**: A dummy for the firms' province. Factors related to this variable include proximity to foreign markets, ports, as well as the Special Economic Zones and Open Coastal Cities that were established to promote Chinese exports. **Industry**: The 445 industry groups aggregated at the US-equivalent of four-digit codes, represented as a categorical variable. **Age**: The difference between the reference year and the year the firm was established. To account for non-linearities in this variable's effect, I also include a squared age term. Employee Training: Employee training expenses divided by the total wage bill. Firms with high investments in employees' skills are expected to innovate more and export more. **Cash Flow**: Net cash flow from operations and finance as a share of total assets. Firms that are financially constrained are expected to have low to negative values of this variable. It also reflects the ease of access to finance, which is vital for exporting. **Employee Numbers**: A simple count of the number of employees **Vintage**: The ratio of the book value of equipment to their original purchase values. All firms in the sample are required to use the same accounting standards, so the measure provides a relatively uniform measure of capital equipment vintage.

A.2 Covariate Balancing and Common Support

The key variables are summarized in Table A1. This simple summary is consistent with the rest of the paper, showing higher levels of product innovation for exporters, Chinese-owned and foreign-owned alike.

Table A2 reports the standardized bias before and after matching for the results reported

Table A1: Summary of Key Variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
year	2006.08	0.813	2005	2007	763036
Product Innovation	0.04	0.163	0	1	760930
Exporting	0.274	0.446	0	1	763036
FDI	0.08	0.272	0	1	763036
FDI with HMT Capital	0.163	0.37	0	1	763036
Export Share of Sales	0.167	0.337	0	1	760992
Foreign Share of Ownership	0.085	0.262	0	1	763036
Asset Purchases Index	0.365	0.291	0	1	763036
State-Owned Dummy	0.088	0.283	0	1	763036
Started_Exporting	0.036	0.186	0	1	437841
Stayed_Exporting	0.252	0.434	0	1	437841
Stopped_Exporting	0.039	0.194	0	1	437841
Started_FDI	0.013	0.113	0	1	437841
Stayed_FDI	0.07	0.255	0	1	437841
Stop_FDI	0.012	0.109	0	1	437841
Age	9.282	9.104	1	126	763036
Log(Age)	1.898	0.806	0	4.836	763036
Employees	192.794	810.633	1	188151	763036
Log(Employees)	4.337	1.288	0	12.145	763036
R&D Expenses	454.727	16747.735	0	7142497	763036
Equipment Vintage	0.698	0.208	0	1	763036
Equipment (Original Value)	39782.204	532832.116	1	157000000	763036
Equipment (Current Value)	29484.101	355024.556	1	76589209	763036
Total Assets	82449.921	775616.848	1	154000000	763036
Log(Total Assets)	9.776	1.397	0	18.852	763036
Output	102839.952	908177.022	0	186000000	763036
New Product Value	12634.049	376061.876	0	110000000	763036
Sales	100776.006	898002.239	0	187000000	763036
Exports	22308.734	441338.881	0	181000000	763036
Paid up Capital	19685.688	156928.073	0	17512000	763036

in Table 3. The group averages for the variables used to predict exporting and FDI are generally within the 5% bias range that is considered reasonable (Caliendo and Kopeinig, 2008). This ranges in absolute terms from -0.2% for variable the output asset ratio to -8.8% for the foreign share of ownership. (The corresponding range for FDI is -0.4% and -4.4% for Employees and Assets respectively).

Table A2: Balancing Test for Propensity Score Matching Variables

Predictors of Exporting

	Means			t-test	
Variable	Treated	Control	%bias	t	$p > \|t\|$
Output/Total Assets	1.5738	1.5765	-0.2	-0.29	0.771
Output/Employees	6.1047	6.1443	-3.5	-4.48	0.000
Foreign Share of Ownership	.17867	.20366	-8.8	-8.93	0.000
State-Owned Dummy	.08919	.08761	0.5	0.72	0.471
Log(Total Assets)	11.54	11.522	1.1	1.34	0.181
Log(Employees)	5.5823	5.5187	4.6	5.86	0.000
Equipment Vintage	.65905	.66529	-3.3	-4.34	0.000
Log(R&D)	6.1893	6.1547	1.6	1.93	0.054
Employee Training	.01378	.01403	-0.4	-0.71	0.479
Log(Age)	2.2552	2.2174	4.6	5.97	0.000

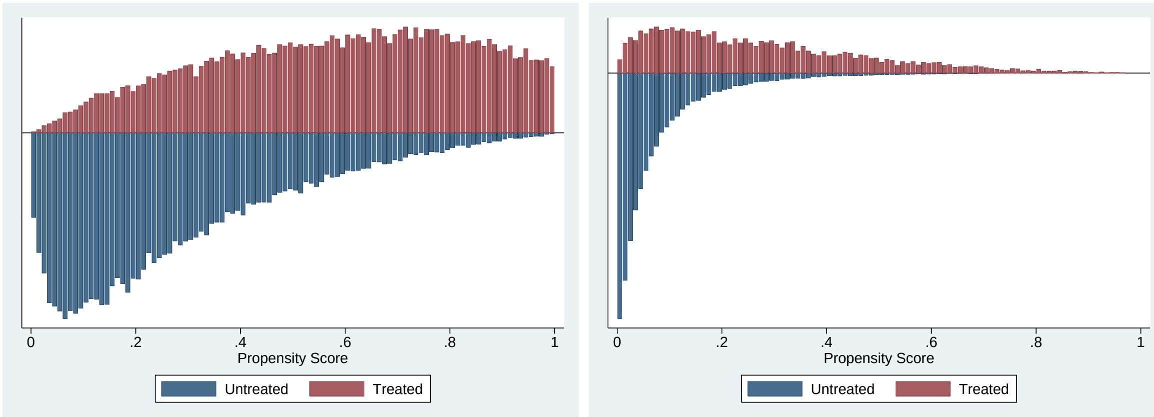
Predictors of Majority Foreign Ownership

	Means			t-test	
Variable	Treated	Control	%bias	t	$p > \|t\|$
Output/Total Assets	1.5869	1.6055	-1.5	-0.94	0.348
Output/Employees	6.4284	6.4654	-3.2	-1.85	0.064
Export Share of Sales	.38399	.37957	1.3	0.69	0.489
Log(Total Assets)	11.615	11.684	-4.4	-2.67	0.008
Log(Employees)	5.2847	5.2905	-0.4	-0.24	0.808
Equipment Vintage	.64691	.64471	1.2	0.72	0.473
Log(R&D)	6.1767	6.2185	-1.8	-1.10	0.271
Employee Training	.01099	.01165	-1.1	-1.22	0.221
Log(Age)	1.9825	1.9722	1.4	0.93	0.353

Please see descriptions of each variable at the beginning of this section of the appendix

The quality of common support for covariates can also be shown as a histogram of propensity scores for each of the firm categories. Figure A1 represents both Exporting and FDI categories' propensity scores. The upper histogram in red shows the distribution of propensity scores for exporters (or foreign-owned firms). As expected, this histogram falls

Figure A1: Graphing Covariate Match Quality



(a) Exporting (b) FDI.

to right of the lower or blue histogram of untreated observations. The firms that exports, or those that are foreign owned tend to have higher predicted probabilities of being exporters (or foreign-owned).

Tables A3 and A4 report the standardized bias before and after matching for the exporting and FDI results reported in Table 7. The matching between the control and treatment groups is excellent, with bias being less than 5% in all cases except for Output per employee and Foreign Share of Ownership for the Stay_Exporting variable and for 9 of the 28 tests for FDI.

A.3 Tests on Subset of Data: Foreign-Owned Firms Only

Do exporters undertake more product innovation? To ensure that this question is properly separated from the product innovation that is attributable to foreign-ownership, Table A5 reports the estimated effect of exporting on product innovation for the subset of firms that are foreign-owned. (Given the significant differences in the summary statistics from Table 1, comparing exporters within the subset of Chinese-owned firms appears unnecessary – the gap between exporters and non-exporters is smaller for foreign-owned firms). Like Table 3, this table uses propensity score matching estimates. The controls or counterfactuals for each observation are the N- most similar observations in terms of characteristics that predicted selection into the treatment.

Within the group of majority foreign-owned firms, exporters on average have an additional 5.0% of outputs that are new products. (14.3% for exporters versus 9.3% for comparable non-exporting firms). The difference is statistically significant, with a t-statistic of 2.77.

Table A3: Balancing Test for Propensity Score Variables: Transition Test I

Predictors of Started Exporting

	Means			t-test	
Variable	Treated	Control	%bias	t	$p > \|t\|$
Output/Total Assets	1.5281	1.5178	0.8	0.24	0.810
Output/Employees	5.925	5.9263	-0.1	-0.04	0.972
Foreign Share of Ownership	.13155	.13907	-3.0	-0.67	0.505
State-Owned Dummy	.09321	.09587	-0.9	-0.25	0.803
Log(Total Assets)	11.622	11.607	1.0	0.26	0.798
Log(Employees)	5.7027	5.6865	1.3	0.36	0.721
Equipment Vintage	.6641	.66567	-0.8	-0.24	0.811
Employee Training	.0156	.01577	-0.3	-0.10	0.918
Log(Age)	2.2718	2.2646	0.9	0.26	0.798

Predictors of Stayed Exporting

	Means			t-test	
Variable	Treated	Control	%bias	t	$p > \|t\|$
Output/Total Assets	1.5474	1.579	-2.7	-2.25	0.024
Output/Employees	5.9308	6.0291	-10.2	-7.75	0.000
Foreign Share of Ownership	.17727	.20722	-10.0	-6.44	0.000
State-Owned Dummy	.10083	.10293	-0.7	-0.55	0.584
Log(Total Assets)	11.995	12.026	-1.9	-1.45	0.146
Log(Employees)	6.1769	6.1311	3.6	2.76	0.006
Equipment Vintage	.62876	.62543	1.8	1.50	0.135
Employee Training	.01259	.01286	-0.7	-0.74	0.457
Log(Age)	2.4545	2.3972	7.5	6.07	0.000

Predictors of Stopped Exporting

	Means			t-test	
Variable	Treated	Control	%bias	t	$p > \|t\|$
Output/Total Assets	1.5485	1.5306	1.4	0.35	0.729
Output/Employees	5.8648	5.8697	-0.5	-0.12	0.908
Foreign Share of Ownership	.0759	.08364	-3.6	-0.75	0.453
State-Owned Dummy	.1368	.12554	3.3	0.80	0.423
Log(Total Assets)	11.375	11.417	-2.7	-0.64	0.519
Log(Employees)	5.5437	5.564	-1.7	-0.41	0.683
Equipment Vintage	.656	.65473	0.7	0.16	0.870
Employee Training	.01713	.01743	-0.6	-0.17	0.866
Log(Age)	2.3614	2.3585	0.4	0.09	0.928

Table A4: Balancing Test for Propensity Score Variables: Transition Test II

Predictors of Started FDI

Variable	Means Treated	Means Control	%bias	t-test t	$p > \|t\|$
Output/Total Assets	1.6976	1.6848	1.1	0.15	0.877
Output/Employees	6.1857	6.2	-1.6	-0.22	0.826
Export Share of Sales	.343	.3436	-0.2	-0.02	0.982
State-Owned Dummy	.07126	.08551	-4.4	-0.77	0.442
Log(Total Assets)	11.923	11.895	1.8	0.26	0.794
Log(Employees)	5.8305	5.8129	1.3	0.20	0.842
Equipment Vintage	.64612	.63734	4.8	0.70	0.481
Employee Training	.01038	.00969	1.6	0.61	0.544
Log(Age)	2.1074	2.175	-9.8	-1.60	0.110

Predictors of Stayed FDI

Variable	Means Treated	Means Control	%bias	t-test t	$p > \|t\|$
Output/Total Assets	1.6572	1.7246	-5.8	-2.06	0.040
Output/Employees	6.3125	6.4117	-10.1	-3.09	0.002
Export Share of Sales	.37451	.37824	-0.9	-0.31	0.755
State-Owned Dummy	.08289	.0575	8.5	3.21	0.001
Log(Total Assets)	11.947	12.094	-10.2	-3.26	0.001
Log(Employees)	5.7729	5.8381	-5.1	-1.68	0.093
Equipment Vintage	.60634	.60716	-0.4	-0.15	0.882
Employee Training	.01157	.00977	4.5	1.49	0.135
Log(Age)	2.1783	2.1604	3.3	1.06	0.288

Predictors of Stopped FDI

Variable	Means Treated	Means Control	%bias	t-test t	$p > \|t\|$
Output/Total Assets	1.63	1.6816	-4.3	-0.55	0.581
Output/Employees	5.9498	5.9698	-2.2	-0.28	0.783
Export Share of Sales	.33614	.38017	-12.6	-1.44	0.152
State-Owned Dummy	.11799	.14749	-8.4	-1.13	0.258
Log(Total Assets)	11.711	11.73	-1.2	-0.16	0.876
Log(Employees)	5.8332	5.8516	-1.4	-0.18	0.856
Equipment Vintage	.61518	.60384	6.0	0.77	0.444
Employee Training	.01034	.01078	-0.9	-0.22	0.825
Log(Age)	2.1231	2.1793	-8.4	-1.13	0.257

Table A5: Innovation by Exporter Status: Foreign-Owned Firms Only

Dependent Variable:	Product Innovation	Product Innovation> 0
	(1)	(2)
Exporting	0.044***	0.113***
	(0.007)	(0.011)
Constant	0.099***	0.186***
	(0.006)	(0.009)
Observations	7,527	7,527

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The product innovation measure represents new products as a share of total output. Columns 3 and 4 use a dummy as the outcome variable. The reported effects are the estimated average treatment effects on treated observations (ATT). The Exporting variable is a dummy that indicates firm-years with non-zero exports. Section A.2 describes the variables used to correct for self-selection.

Using the product innovation dummy as the outcome of interest yields a starker difference between exporters and non-exporters. The gap of 14% between these two subgroups is also statistically significant; 30% of foreign-owned exporters create new products while only 16% of comparable non-exporters do so.

As expected, the propensities for matched estimates were well balanced. Within the category of foreign-owned firms, exporters and non-exporters were similar in terms of size, location, employee numbers and other observed traits. The 7,527 observations on the common support, is smaller than the 90,461 used in column 1 of Table 3 largely because foreign-owned firms are less than 8.5% of the sample. Similar gains in product innovation for exporters are observed if the sample was chosen to be all firms with any level of foreign-ownership. I do not tabulate those results to avoid clutter.

In sum, even within the group of foreign-owned firms, exporters introduce more product innovations. This remains consistent this paper's conclusion that while foreign-ownership may lead to product innovation, the effect of exporting on product innovation is larger.

Table A6 repeats the exercise of estimating the treatment effect, but using other subsets of the data. Like Table A5, the first panel of the table tests for the effect of exporting on product innovation, using only non-exporters. The results follow the same pattern as the previous table. New products represent an additional 8% of the output of exporters, compared to non-exporters, among the class of firms that are not majority-foreign-owned. (Compare with 4% for the subset of foreign-owned firms). The probability of a new product innovation is also higher for firms that export, within this category.

Table A6: Innovation by Exporter/FDI Status: Data Subsets

Dependent Variable:	Product Innovation	Product Innovation> 0
	(1)	(2)
	Chinese-Owned Firms Only	
Exporting	0.080***	0.259***
	(0.002)	(0.004)
Constant	0.131***	0.266***
	(0.001)	(0.002)
Observations	74,875	74,875
	Exporting Firms Only	
FDI	-0.070***	-0.210***
	(0.005)	(0.007)
Constant	0.211***	0.509***
	(0.002)	(0.003)
Observations	29,787	29,787
	Non-Exporters Only	
FDI	-0.037***	-0.079***
	(0.006)	(0.009)
Constant	0.134***	0.265***
	(0.001)	(0.002)
Observations	40,734	40,734

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The product innovation measure represents new products as a share of total output. Column 2 uses a dummy as the outcome variable. The reported effects are the estimated average treatment effects on treated observations (ATT). The Exporting variable is a dummy that indicates firm-years with non-zero exports. The FDI variable is a dummy that indicates firm-years with majority foreign-ownership.

The second and third panel of Table A6 show the effect of majority foreign ownership (FDI) on product innovation. First, in the second panel, the subset of exporting firms only, one observes 7% lower share of output for new products for the firms that have FDI. A similar pattern, equally statistically significant, is obtained for the subset of the data that are not exporters. Firms that are not foreign-owned report higher levels and incidence of new product innovation that the matched foreign-owned firms with similar propensity scores. All these findings corroborate the results in the main body of the paper.

A.4 More Tests with FDI defined to include HMT

Table A7 shows that the coefficients in Table 7 of section 4 should remain largely unchanged if foreign capital was redefined to include funds from Hong Kong, Macau and Taiwan. In showing how firms change their investments in R&D and fixed assets as they become foreign-owned, keep that status or leave it, the estimates remain remarkably consistent with those of Table 7. Columns 1 and 2 reflect the values in Table 7 while the last two columns use the new definition of foreign ownership. Note that there are twice as many observations that are foreign-owned by this new definition, compared to the old. That is, firms in the first year of majority foreign ownership by this definition invest less in R&D than comparable Chinese-owned firms. One reason Chinese firms that become foreign-owned may reduce their R&D efforts is to avoid duplication of efforts by the foreign parent. It appears that foreign owners from Hong Kong, Taiwan and Macau are no more inclined to keep R&D in mainland China than other foreign owners. Similarly, firms that start majority foreign-ownership out-invest their peers in terms of fixed production capital. The estimates are not statistically significant, just like in Table 7.

For the firms that remain or stop being majority foreign-owned, the estimates in Table A7 are remarkably similar to estimates with the original foreign ownership definition. The one exception is that firms remaining foreign-owned in the new definition under-invest in R&D relative to comparable foreign-owned entities and the difference is statistically significant. In other words, the new definition does not help the argument in the literature that foreign ownership promotes innovation and innovation inputs like R&D.

In the same vein, Table A8 shows the effect of foreign ownership on product innovation, when foreign ownership is defined only to include wholly-foreign-owned firms. The comparison group for this test will be all firms with any level of Chinese ownership. The tests use a propensity score matching approach, following Tables 3 and A6.

The findings of lower product innovation by foreign-owned firms persists to this specification. In sum, Tables A7 and A8 suggests that the conclusions of this paper are robust to the definition of foreign capital.

Table A7: Comparing coefficients for FDI with and without HMT

FDI definition:	(without HMT)		(with HMT)	
VARIABLES	Log(R&D)	Log(Asset Purchases)	Log(R&D)	Log(Asset Purchases)
Started_FDI	-0.158***	0.047	-0.155***	0.052
	(0.045)	(0.114)	(0.040)	(0.111)
Stayed_FDI	-0.015	0.034	-0.067**	-0.055
	(0.041)	(0.100)	(0.033)	(0.093)
Stopped_FDI	-0.098**	0.275**	-0.124***	0.202*
	(0.043)	(0.116)	(0.043)	(0.116)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: HMT stands for Hong Kong, Macau and Taiwan. The estimates in Columns 3 and 4 use foreign ownership definitions that include capital from these sources outside the Chinese mainland. Columns 1 and 2 replicate the results in Table 7. The propensity score matching approach also follows the pattern in that table, the counterfactual for each row was limited to comparable firm-years as follows: *Started_FDI* was matched to observations not foreign-owned, *Stayed_FDI* to observations in the first year of foreign ownership or that was majority foreign-owned in the previous year, *Stopped_FDI* was matched to firms no foreign-owned in that year. The dependent variables are logged values of R&D and asset purchases (plus 1 to avoid losing zeros). The number treated observations were 6,753, 66,902 and 5,635 respectively for Columns 3. Columns 4 had 1,647, 21,373 and 1,470. The numbers vary by column because the match was limited to items on the common support.

Table A8: Innovation by FDI Status: Wholly Foreign Owned Firms

Dependent Variable:	Product Innovation	Product Innovation> 0
	(1)	(2)
Wholly FDI	-0.059***	-0.143***
	(0.004)	(0.007)
Constant	0.162***	0.355***
	(0.001)	(0.002)
Observations	72,025	72,025

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Product innovation – the dependent variable measures new products as a share of total output. Column 2 uses a dummy as the outcome variable. The reported effects are the estimated average treatment effects on treated observations (ATT).
The FDI variables indicate exclusively foreign ownership.