Firm productivity and importing: Evidence from Chinese manufacturing firms

Jabbour, Liza; Elliott, Robert; Zhang, Liyun

DOI:
10.1111/caje.12226

Citation for published version (Harvard):
Jabbour, L, Elliott, R & Zhang, L 2016, 'Firm productivity and importing: Evidence from Chinese manufacturing firms', *Canadian Journal of Economics/Revue Canadienne d`Economique*, vol. 49, no. 3, pp. 1086-1124. https://doi.org/10.1111/caje.12226

Firm productivity and importing: Evidence from Chinese manufacturing firms

Robert J R Elliott

Liza Jabbour

Liyun Zhang

University of Birmingham

Abstract. This paper investigates various aspects of the relationship between firm productivity and importing for a large sample of Chinese firms between 2002 and 2006 making a distinction between the origin, variety, skill and technology content of imports. Employing a random effects Probit model and a propensity score matching with difference-in-differences (PSM-DID) approach and treating imports as endogenous in our measure of total factor productivity (TFP) (De Loecker, 2007), we test the self-selection and learning-by-doing hypotheses. Our results show evidence of a bi-directional causal relationship between importing and productivity. Although importing firms tend to be more productive before entering the import market, once they start importing firms experience significant productivity gains for up to two years following entry. We also find evidence of learning effects following the decision to import which is stronger when import starters source their products from high-income economies, import a wider variety of products, and import products with a higher skill and technology content. A number of robustness checks confirm the learning effects of importing on TFP growth.

JEL classification: F14, O4

The authors would like to thank the Editor John Ries, Farid Toubal, Facundo Albornoz and two anonymous referees for their helpful comments. Financial support from ERSC grant RES-000-22-3959 is gratefully acknowledged. High Performance Computing Cluster of University of Birmingham(BlueBEAR) is also acknowledged for the IT support for the econometric estimation of this paper.
Corresponding author: Liza Jabbour, l.jabbour@bham.ac.uk

1. Introduction

In an increasingly globalized world, the relationship between firm performance and the extent to which a firm is internationalized is subject to ever greater scrutiny from academics and policy makers. In recent years, the general trend has been for firms to export to and import from an ever increasing number of countries and in ever greater volumes. The internationalization of firms is especially important for developing and newly industrialising countries that continue to pursue an export-led growth strategy and remain dependent to a large extent on exports for future growth and employment. A recent example is China where the common perception is that the rapid growth over the last two decades has been driven by exports to the West. However, less well documented are the benefits to Chinese firms from the process of importing raw materials and intermediate inputs from abroad.[1]

The motivation for this paper is to investigate how engagement with global trade (importing and exporting) impacts firm performance and how this is influenced by firm productivity, size, ownership, the variety of imported inputs, the skill and technology content of imported products and where a firm sources its inputs. Central to our analysis is an investigation of the causal relationship between productivity and importing. That is to say, whether more productive firms decide to import (self-selection hypothesis) or whether those firms that start importing increase their productivity (learning-by-doing hypothesis). Our data consist of a large sample of Chinese manufacturing firms between 2002 and 2006. We chose to study China and the period immediately after China's 2001 entry into the WTO for two reasons. First, because of China's increasingly important role in the global economy and second, because this period represents the beginning of the transition of Chinese firms from relatively low skilled assembly tasks to more high technology and high value added production. It is therefore useful to understand the role of imports in this transition process.

The existing literature has tended to concentrate on the determinants of export participation categorizing firms into exporters and non-exporters (Roberts and Tybout 1997; Baldwin and Gu 2004; Ruane and Sutherland 2005; Lileeva and Trefler 2010) and on the causal relationship between exporting and productivity (Girma, Greenaway and Kneller 2004; Arnold and Hussinger 2005; Wagner 2007). Studies specific to China have also tended to concentrate on exporting and include Kraay (1999), Du and Girma (2007),Yang and Mallick (2010), Lu, Lu and Tao (2010), Sun and Hong (2011) and Yi and Wang (2012). A feature of these papers is that they have tended to ignore importing even though we know that a large number of exporters also import. Likewise, a significant number of non-exporters source significant levels of raw materials and intermediate inputs from abroad. Therefore, if importing increases the propensity of a firm to export, then ignoring import activity will upwardly bias the estimated premia associated with exporting.

Perhaps surprisingly, research on importing is still fairly limited certainly compared to the number of studies on exporting. Previous research on firm importing behaviour includes Halpern, Koren and Szeidl (2005), HKS; MacGarvie (2006); Kugler and Verhoogen (2009); Castellani, Serti and Tomasi (2010), CST; Kasahara and Lapham (2013) and shows that characteristics of importers tend to be similar to those export in that importers are larger (generally larger than exporters), more productive and more capital-intensive than non-importers. In terms of productivity, a positive and significant productivity differential between importing and non-importing firms has been found by HKS (2005) and Andersson, Loof and Johansson (2008),

[1]Between 2000 and 2010 China's trade balance increased from USD24.1 billion to over USD181.51 billion. Imports during this period increased from USD225 billion to USD1,396.24 billion while exports rose from USD249.2 billion to USD1,577.75 billion over the same period (China Statistical Yearbook 2013).

ALJ. Research into the impact of importing on Chinese firms is more limited with the exception of working papers by Manova and Zhang (2009) and Feng, Li and Swenson (2012), FLS. Finally, in a related literature, a small number of studies have examined the performance of both exporting and importing firms (Bernard, Jensen and Schott 2005; Bernard, Jensen, Redding and Schott 2007; Kasahara and Rodrigue 2008; Muuls and Pisu 2009; Aristei, Castellani and Franco 2013) and find that two-way traders outperform non-traders and one-way traders (firms that only export or import) in terms of productivity and size.

Studies that investigate the direction of causality between productivity and importing, to the best of our knowledge, are limited to McCann (2009), Vogel and Wagner (2010) and Augier, Cadot and Dovis (2013), ACD. ACD (2013) study Spanish firms and find an insignificant productivity effect of switching to importing, although when firms both import and have a large share of skilled labour there is some evidence of a learning effect from the use of imported intermediates suggesting an absorptive capacity effect. Vogel and Wagner (2010) use German manufacturing firm data and find some evidence for self-selection of more productive firms into importing but no support for the learning effect of importing on productivity. Finally, McCann (2009) uses the Irish Census of Industrial Production to study productivity gains from international trade and finds that becoming an exporter significantly increases total factor productivity (TFP) but for firms that become importers there is no such effect.

The contribution of this paper is three-fold. First, to the best of our knowledge, this is the first paper to investigate the causal relationship between importing and firm productivity for Chinese manufacturing firms. Our approach is to merge Chinese industrial enterprise survey data with transaction-level customs data to provide a uniquely rich dataset from which to analyse the international activity of Chinese manufacturing firms. The comprehensive nature of the data means we are able to examine various aspects of the import performance relationship. More precisely, we control for the impact of firm's initial productivity, size, and ownership structure. We also distinguish imported inputs by their skill and technology content, country of origin and the number of imported varieties. Second, we measure productivity using a relatively new measure of TFP using a modified algorithm by De Loecker (2007) where firm import status is considered endogenous and introduced to all stages of the estimation procedure. This allows us to control for simultaneity and selection bias and allows for different market structures, demand conditions and factor markets for importing and non-importing firms. The introduction of import status as an additional state variable in the production function means the import status has a dynamic effect on the evolution of productivity.[2] Third, our methodological approach is to combine propensity score matching with difference-in-differences (PSM-DID) techniques to examine the relationship between firm productivity and importing behaviour using narrowly defined 2-digit industries in the matching mechanism. Such an approach means that we can control for unobserved firm level heterogeneity more effectively. It is only because our data include such a large number of firms that we have sufficient sample size to match firms at levels of detail to allow us to address questions previously overlooked.

Before we describe our methodology in detail we briefly rehearse the arguments for the self-selection hypothesis and learning-by-doing hypothesis, usually discussed from an exporting perspective, in an importing context. The self-selection argument is that firms that want to start importing have to incur sunk costs which include the costs associated with the search for information on possible inputs (for example, to find out which foreign firms in which countries can supply the required inputs), learning to navigate often complex customs procedures and having to understand tax and trade credit regulations (ALJ 2008; CST 2010). Additional fixed costs may include quality inspection costs and those transport costs incurred by importers (ALJ

[2]A similar approach has been employed by Van Biesebroeck (2005) and Kasahara and Rodrigue (2008).

2008; Kasahara and Lapham 2013). The self-selection hypothesis assumes that only highly productive firms can afford to incur these costs and the additional risks associated with trade and hence profit from importing. One may therefore expect firms to improve their productivity before entering into the process of importing.

In contrast, the learning-by-doing hypothesis argues that it is the very act of engaging in import activity with which firms are able to access products or inputs at lower prices, a broader range of inputs, or inputs of better quality than are available in the domestic market that helps to drive productivity growth (HKS 2005; Muuls and Pisu 2009). It is hypothesised that importing firms are able to extract knowledge and learn about the technology embodied in the imported inputs which may eventually contribute to improved production efficiencies at home (ALJ 2008; CST 2010). The learning-by-importing hypothesis also argues that access to foreign markets is a source of international technology transfer as firms can adopt advanced manufacturing technologies from their trading partners and engage in more product innovation at lower costs both of which boost firm-level productivity (Blalock and Veloso 2007; Goldberg, Khandelwal, Pavcnik and Topalova 2009, GKPT; Topalova and Khandelwal 2011). The other benefit of importing is that new foreign inputs increase the ability of firms to manufacture new varieties or improve the quality of existing varieties.[3]

Our main finding is of a bi-directional causal relationship between firm productivity and importing for Chinese manufacturing firms. That is to say, more productive firms self-select into the import market but that this process of importing also further enhances firm productivity. Our PSM-DID results are broadly consistent and robust to a battery of robustness checks. In contrast to McCann (2009), Vogel and Wagner (2010) and ACD (2013) we find that Chinese firms appear to have the capacity to absorb new technologies and production techniques from the high-income economies and do learn from importing which leads to a subsequent improved productivity. We also find that of all new import starters, the strongest learning effect is generally experienced by those firms with initially low levels of productivity. In terms of origins of imports, we find that new importers who import from high income countries experience greater productivity gains than those that import from lower income countries. Our results also indicate that the extent of learning by importing is positively linked to the skill and technology content of imported products and to the number of imported varieties.

The remainder of this paper is organized as follows. Section 2 presents our identification strategy and estimation methodology. Section 3 describes the data and the construction of our dataset, followed by Section 4 which reports and discusses our results. Section 5 presents a number of robustness checks and finally Section 6 concludes.

2. Empirical Methodology

2.1. Identification Strategy

Our methodological approach is to employ a random-effects (RE) Probit and propensity score matching with difference-in-differences (PSM-DID) techniques to identify the direction and magnitude of any causal effects between importing and firm productivity.

First, in order to test the self-selection into importing hypothesis, we estimate the propensity

[3]In a related literature, recent empirical studies have found that imported intermediate inputs and/or a decline in input tariffs are associated with significant productivity gains, quality upgrading and increased exports (Amiti and Konings 2007; Kasahara and Rodrigue 2008; Acharya and Keller 2009; GKPT 2010;Amiti and Khandelwal 2013; Bas and Strauss-Kahn 2014).

of a firm entering the import market by estimating the following Probit model:

$$Pr(START_{it}=1)=\phi(age_{i(t-1)},wage_{i(t-1)},TFP_{i(t-1)},\\ pregrowth_{it},EXP_{i(t-1)},size_{i(t-1)},ownership_{i(t-1)},D_r,D_j,D_t) \tag{1}$$

where *Pr* denotes the predicted probability of firm *i* starting to import at time t, and $\phi(.)$ is the normal cumulative distribution function. $START_{it}$ is a dummy variable which equals 1 if firm *i* begins to import at time *t* and zero otherwise. Firm characteristics such as age, average employee wages, TFP, past productivity growth rate ($pregrowth$), export status, size and ownership are included in the estimation. Taking into account the past productivity growth rate is important if it is autocorrelated over time (Girma, Kneller and Pisu 2007). If we fail to control for past productivity growth, we would mistakenly attribute a causal effect to importing on post entry productivity growth as it could be that firms that start importing were already on a permanently different growth trajectory and this is what is captured by the switch. A full set of region dummies (D_r), industry dummies (D_j) and year dummies (D_t) are also included to capture location, industry and time effects respectively. All time-variant explanatory variables are lagged by one year in order to mitigate simultaneity concerns. We expect a positive and significant effect of TFP on firms' propensity of entering the import market.

The second part of our identification strategy is to discover whether there is any change in a firm's productivity growth following entry into an import market, i.e., the learning-by-doing effect. We define y_{it} as firm *i*'s TFP at time *t* and $y_{i(t+s)}$ as the productivity *s* period(s) later ($s \geq 0$). The causal effect of importing on productivity of firm *i* at *t+s* can be identified by looking at the difference:

$$y^1_{i(t+s)} - y^0_{i(t+s)} \tag{2}$$

where the superscripts denote import behaviour which is equal to 1 if a firm imports at *t* and zero otherwise. Hence $y^0_{i(t+s)}$ represents the productivity of firm *i* at period *t+s had* it not participated in import markets since time *t*.

The fundamental evaluation problem is that only one of the two outcomes of (2) is observable. For example, if $y^1_{i(t+s)}$, is observed for firm *i*, then $y^0_{i(t+s)}$, the counter-factual outcome, is not observed. This means a direct estimation of the individual treatment effect is not possible. Hence, we need to calculate the population average treatment effect (ATE) which is the difference in the expected outcomes of participants and non-participants where:

$$ATE = E[y^1_{i(t+s)} - y^0_{i(t+s)}] \tag{3}$$

In order to identify differences in firm productivity after a firm begins to import we focus on the import starters. The average productivity effect that import starters would have experienced if they had not previously imported, i.e., the average treatment effect on the treated (ATT), is given by:

$$ATT = E[y^1_{i(t+s)} - y^0_{i(t+s)}|START_{it}=1]\\ = E[y^1_{i(t+s)}|START_{it}=1] - E[y^0_{i(t+s)}|START_{it}=1] \tag{4}$$

Likewise, the counter-factual which is the average productivity of new importers, $E[y^0_{i(t+s)}|START_{it} = 1]$, is not observed. However, as Heckman, Ichimura and Todd (1998), HIT point out, the average productivity of an appropriate control group of non-import starters, i.e., $E[y^0_{i(t+s)}|START_{it} =$

0], can be used as a substitute. Hence, Equation (4) can be rewritten as:

$$ATT = E[y^1_{i(t+s)}|START_{it} = 1] - E[y^0_{i(t+s)}|START_{it} = 0] \tag{5}$$

To select a valid control group we employ a matching approach. The purpose of matching is to pair each import starter with a similar (ideally, identical) firm that has never entered the import market. The first step is to estimate the probability of a firm starting to import (or the propensity score) on the basis of a set of observable characteristics as described in Equation (1).

With the estimated propensity scores, the next step is to check that propensity scores are balanced across treated and control groups. Following Imbens (2004), De Loecker (2007) and Garrido, Kelley, Paris, Roza, Meier, Morrison and Aldridge (2014), GKPRMMA, we split the sample into *k* equally spaced intervals of the propensity scores and test within each interval whether the mean propensity score is equivalent in the treatment and comparison groups. If it is not equivalent, we split the interval into smaller blocks and test again. We continue this process until equality holds for every interval. After the propensity score is balanced within blocks across the treated and control groups, we check for the balance of each observed covariate within blocks of the propensity score. If the balance test is rejected, covariates included in the propensity score estimation can be modified, for example by recategorizing variables or including higher order terms or splines of the variables.[4]

After creating a balanced propensity score, we match the import starters with a group of non-importing firms so that the estimated propensity score of a non-importing firm is as close as possible to that of a new importer. Several matching algorithms have been developed, e.g. nearest neighbour matching, calliper and radius matching, kernel matching and stratification matching.[5] We adopt kernel matching and we impose the common support condition by dropping the importing starters whose propensity scores are higher than the maximum or lower than the minimum of those persistent non-importers. In kernel matching, each treated firm is given a weight of one and control firms are weighted by the distance in propensity score from the treated firm within a range, i.e., bandwidth, of the propensity score. Kernel matching maximizes precision as more information is used than other matching algorithms by retaining the sample size as only observations outside the range of common support are discarded (GKPRMMA, 2014). The choice of bandwidth is important which leads to a tradeoff between bias and variance (Silverman 1998; GKPRMMA, 2014).[6] High bandwidth values yield a smoother estimated density function, therefore leading to a better fit and a decreasing variance between the estimated and the true underlying density function. However, bias arises from selecting a wide bandwidth as potentially interesting and important features of the population regression function may be smoothed away in response to the weakness of common support (Caliendo and Kopeinig 2008). Too large a bandwidth will include control firms quite different

[4]For example, the continuous size variable e.g. log of employment can be replaced with categorized dummy variables in this case.

[5]Although all matching estimators construct the differences between the outcome of a treated individual and outcomes of units from the control group, they vary in terms of how the neighbourhood for the treated individual is defined, how the weights are assigned to these neighbours and how the common support problem is handled. Each has its own advantages and disadvantages. See Caliendo and Kopeinig (2008) for a discussion on these issues and practical guidance for the implementation of propensity score matching.

[6]There is large existing literature and continuing research on the important issue of how to select the bandwidth. For more discussion on the choices between a constant bandwidth and a varying bandwidth, algorithms of bandwidth selectors such as cross-validation method and data-driven plug-in method, see Park and Marron (1990); Sheather and Jones (1991); Park and Turlach (1992); Brockmann, Gasser and Herrmann (1993); Fan and Gijbels (1995); Jones, Marron and Sheather (1996); Frolich (2005).

from the treated firm. Taking these concerns into account and aiming for an unbiased estimate given the large sample size of our data (presented in the next section), we choose a small bandwidth of 0.01.[7]

Rather than matching across the entire manufacturing sector (GGK 2004, Vogel and Wagner 2010), our matching is performed separately for each 2-digit industry of the manufacturing sector within each year.[8] In this way we create control groups within narrowly defined industries in the same year. This is important as firms in different industries face different technological and market conditions and the marginal effects of such variables on the propensity to enter the import market of these firms may differ substantially between different industries. Similarly, if matching is not done within a year, an import starter in the treatment year can be matched with a control firm in *any* year. Our large sample size allows us to achieve what we believe is the best practice.

Having constructed the control group of firms (*C*) that are similar to the treated firms (*T*) by propensity score matching, we use a difference-in-differences (DID) methodology to estimate the causal effect of importing on productivity.

A DID estimator first measures the difference in productivity before and after entry into the import market for importing firms conditioned on past performance and a set of dummy variables. However, such differences in productivity cannot exclusively be attributed to importing behaviour as post-entry productivity growth might be caused by factors that are contemporaneous with entry into the import market. The second step is to difference the differences obtained for the import starters with the corresponding difference for non-importing firms. Since DID estimates the difference before treatment it removes the effects of common shocks and hence provides a more accurate estimate.

As Blundell and Costa Dias (2000, p.438) point out, a non-parametric approach that combines propensity score matching with difference-in-differences has the potential "…to improve the quality of non-experimental evaluation results significantly". Hence, we combine PSM with DID such that the selection on unobservable determinants can be allowed when the determinants lie on separable firm and /or time-specific components of the error-term. Hence, imbalances in the distribution of covariates between the treated and control groups account for varying unobserved effects influencing importing and productivity. Our PSM-DID estimator based on a sample of matched firms is therefore given by:

$$ATT^{PSM-DID} = \frac{1}{N_T}\sum_{i\in T}[\Delta y_{i(t+s)} - \sum_{j\in C} w_{ij}\Delta y_{j(t+s)}] \tag{6}$$

where N_T is the number of treated units (firms that start to import) on the common support, Δy_i is the difference in productivity before entry into the import market and s years after entry of treated firm *i*, Δy_j is the difference in productivity of control firm *j* between *t* and *t+s* and w_{ij} is the weight placed on the control firm *j* in the construction of the estimated expected counterfactual outcome for treated firm *i*, determined by the propensity score matching algorithm, $\sum_{j\in C} w_{ij} = 1$. As matching is always performed at time t when a firm starts importing, $\Delta y_{i(t+s)}$ presents the productivity growth s periods after the decision to start importing compared to the year before the entry to import market.

[7] We also try an alternative bandwidth of 0.06 as a robustness check.

[8] We create a bin for each industry-year category and add the estimated propensity score to ten times the bin number, creating large wedges in propensity scores between bins to force the matching to be within bins.

2.2. *Assessing the Propensity Score Matching Quality*

An important step in the PSM approach is to assess the quality of matching. We perform several balancing tests suggested in the literature to assess the quality of our propensity score matching (e.g. Rosenbaum and Rubin, 1985; Smith and Todd, 2005; Caliendo and Kopeinig, 2008; Austin, 2009). We first compare the situation before and after the matching and check if any differences in means of the observable characteristics for firms from treatment and control groups remain after conditioning on the propensity score. Differences between both groups are expected before matching, but these differences should be reduced significantly after matching. A formal two-sample *t*-test between the treated and control groups for each variable is performed to ensure that no significant bias exists.[9]

The second test is to examine the standardized difference (SD) (or % bias) in treated and control samples for all variables used in the PSM. The lower the standardized difference, the more balanced the treated and control groups will be in terms of the variable being considered. Standardized difference for comparing means between groups are computed as follows. For continuous variables, the standardized difference is defined as:

$$SD = 100\frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{S_T^2+S_C^2}{2}}} \tag{7}$$

where $\bar{X}_T$ and $\bar{X}_C$ denote the sample mean of the variable X in treated and control groups, respectively, while S_T^2 and S_C^2 denote the sample variance of the variable in treated and control groups, respectively.

For dichotomous variables, the standardized difference is defined as:

$$SD = 100\frac{\hat{P}_T - \hat{P}_C}{\sqrt{\frac{\hat{P}_T*(1-\hat{P}_C)+\hat{P}_C*(1-\hat{P}_C)}{2}}} \tag{8}$$

where $\hat{P}_T$ and $\hat{P}_C$ denote the mean of the dichotomous variable P in treated and control groups, respectively.

Unlike *t*-tests, the standardized difference is not influenced by sample size. Thus, the use of the standard difference allows us to compare the balance in measured variables between treated and the control in the matched sample with those in the unmatched sample (Austin, 2009). There are no formal criteria specified in the literature for when a standardized difference is considered too large. Rosenbaum and Rubin (1985) suggest that a value of 20% of standardized difference is large. We follow ACD (2013) and GKPRMMA (2014) and use the same criteria.

Also as Sianesi (2004) suggests, we reestimate the propensity score on the matched sample and compare the pseudo-R^2s before and after matching. The pseudo-R^2 indicates how well the variables X explain the participation probability. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore the pseudo-R^2 should be fairly low. Furthermore, we also perform a likelihood- ratio test on the joint insignificance of all variables in the Probit model. The test should be rejected before matching and should be not rejected after matching.

[9] Caution needs to be paid if using *t*-tests to check the balance of covariates. Because the goal of matching is to ensure balance within a sample, the larger population from which the sample was drawn is not a concern. Moreover, *t*-tests are affected by sample size and might not be statistically significant even in the presence of covariate imbalance (Ho, Imai, King and Stuart 2007; Austin 2009; GKPRMMA, 2014).

3. Data and Descriptives

3.1. Data

The data used in this paper are drawn from two sources. The firm-level production data are from the Annual Survey of Industrial Enterprises provided by the National Bureau of Statistics of China (NBS) and the transaction-level trade data are provided by the Department of Customs Trade Statistics, the General Administration of Customs of China. We use data from both sources for the period 2002 to 2006.

The NBS data cover all state-owned industrial enterprises and non-state-owned industrial enterprises with annual sales of greater than 5 million Chinese Yuan (RMB).[10] According to the NBS industry classification, industrial enterprises refer to enterprises that operate in the mining and quarrying sector, manufacturing sector or in the production and supply of power, gas and water. The NBS survey is the primary source for the construction of numerous aggregate statistics used in the China Statistical Yearbooks. The NBS data include the firm's identification (tax code) and basic information such as year founded, location, ownership type, employment, China industrial classification (CIC) code and principle products.[11]

The ownership structure of firms is organized according to the shares of capital from different types of investors: domestic firms and foreign-funded firms. We group the domestic firms into state-owned enterprises (*SOE*), collectively-owned enterprises (*COLLECTIVE*) and private enterprises (*PRIVATE*). Foreign-funded enterprises are split into two groups, firms with over 25% of their capital controlled by Hong Kong, Macau and Taiwan (HMT) owned parents and firms with over 25% of capital controlled by foreign investors (*FOREIGN*) excluding HMT firms. In terms of size, we group our sample into three categories: *LARGE*, *MEDIUM* and *SMALL*.[12] We also group firms into one of three geographical regions, *EAST*, *CENTRAL* and *WEST*. The East includes the coastal area and is the most developed whilst the West is the least developed and covers a vast geographical area.

Trade data record all import and export transactions with non-zero values that enter or exit through Chinese customs. Each observation represents a shipment and contains detailed information on the time of the transaction (month and year), type of trade (import/ export), exporting/importing firm identifier, ownership type, product traded (8-digit HS code and name), value, quantity, unit, destination country (of the exported commodities) / country of origin (of the imported products), type of trade (ordinary trade, processing trade, compensation trade, consignment, etc.) and finally mode of transport.

We concentrate only on manufacturing firms (CIC13-43) and we restrict our analysis to those firms that participate in the survey for the whole period.[13] We first link the firms covered in the surveys over the period and select the firms by their IDs and names.[14] Our next step is to

[10]The official USD and RMB exchange rate between 2002 and 2004 was 8.277, 8.194 in 2005 and 7.973 in 2006 (World Development Indicators, World Bank). Hence, the threshold for inclusion in the dataset is equivalent to annual sales of between USD600,000 and USD627,000.

[11]The data also provide information on more than 50 financial variables from the accounting statements, including capital, assets, liabilities, creditors equity, gross output, industrial value-added, sales, income, profits, investment, value of exports, current / accumulated depreciation, the wage bill and R&D expenses.

[12]We follow the classification standard provided by NBS: Small firms are those with less than 300 employees or 30 million RMB in sales or 40 million RMB in total assets, medium sized firms are those with between 300 and 2,000 employees and between 30 million and 300 million RMB in sales and between 40 million and 400 million RMB in total assets and large firms are those with more than 2,000 employees and 300 million RMB or more in sales and 400 million RBM or more in total assets.

[13]GGK (2004) and Arnold and Hussinger (2005) use similar rule in their data construction.

[14]Brandt, Biesebroeck and Zhang (2012), BBZ, use the same survey data for the period 1998 to 2007. Our

match the survey data with the trade data. Since the survey and trade data use different coding systems for the firm identifier, we cannot merge datasets by firm identification codes alone. Hence, we match using a number of common variables in both datasets, e.g., firm name, registration place and year of the establishment. Following BBZ (2012), we exclude observations with incomplete records or negative values of key variables such as firm age, assets, real capital stock, number of employees, output, value-added and total wages. We also drop abnormal observations if any of the following are found to be negative: net of total assets and fixed assets; net of total assets and current assets; net of total liability and current liability; net of current depreciation and accumulated depreciation. Our final sample is a balanced panel for the period 2002 to 2006, covering 43,618 firms and corresponds to 218,090 firm-year observations. Table A1 of Appendix A provides a list of our variables and definitions.

Finally, to measure TFP we use the De Loecker (2007) approach which is an extension of Olley and Pakes (1996). Because the ownership structure of a firm may influence input decisions, ownership dummies are included in the production function. Furthermore, since firms in different industries have different factor inputs and input prices, we estimate the production function for each 2-digit industry separately rather than doing this for the entire manufacturing sector. See Appendix B for a description of how we calculate TFP following the De Loecker (2007) method. Table B1, in Appendix B, presents the coefficients from the TFP estimation.

3.2. The Internationalisation of Chinese Firms

In this section we describe the characteristics of Chinese firms and the extent to which they engage in international trade. The firm heterogeneity and exporting literature has shown that, broadly speaking, exporters are larger, more productive, more capital- and skill-intensive and pay higher wages than non-exporters. These studies have tended to focus only on firm exporting status and categorized firms into two mutually exclusive groups, i.e., exporters and non-exporters, ignoring any import activity. However, a large number of exporters also import at the same time. Similarly, there will be a number of non-exporters who also import. Firms that export and import at the same time may perform rather differently from those that only export and ignoring import activities may lead to an upward bias in the estimated export premia. Likewise, ignoring exports may bias the impact of importing on productivity. In order to get a better picture of the international activities of the Chinese manufacturing firms, we divide our sample into four categories: exporter-only (firms that export but do not import), importer-only (firms that import but do not export), two-way traders (firms that both export and import) and non-traders (firms that neither export nor import).

First, we examine the number of firms in each category and their average output. Table 1 documents the participation of Chinese manufacturing firms in international trade. On average, between 2000 and 2006, around 70% of firms are classified as non-traders. Of the other 30%, more than half (around 17%) import and export and of the rest 7% export only and 6% import only.[15] When we consider average output, two-way traders are the largest, followed by importers, exporters and finally non-traders whose output is one-quarter that of two-way traders.

method is similar to theirs except that they first link firms over time with IDs and then match firms that might have changed their IDs as a result of restructuring, merger or acquisition using other information such as firm's name, address, industry, etc. They point out that only 4% of all matches are constructed using information of the firm other than IDs. As we use both IDs and names for matching, the fraction we exclude is small. Further details on our matching procedure are available from the authors upon request.

[15] Although we are looking at SOEs and relatively large firms with annual sales greater than 5 million RMB we still find similar participation rates to those found in ALJ (2008) for Swedish manufacturing firms, Muuls and Pisu (2009) for Belgium firms and Vogel and Wagner (2010) for German manufacturing firms.

Hence, although non-traders are about 70% of the total sample, their output accounts just about 40% of total output. In contrast, two-way traders make up just 17% of total firms yet contribute to more than 40% of total output. Similar patterns are observed for individual years.

In Table 2 we compare the characteristics of firms in each trade group. Three observations stand out. First, firms that participate in international trade tend to be larger, more productive, more capital intensive and pay higher wages than non-traders. Second, among trading firms, two-way traders also tend to be larger, more productive, capital intensive and pay higher average wages than one-way traders. Third, differentiating between importers and exporters, we find that importer only firms outperform exporter only firms. These findings are in line with CST (2010) and Vogel and Wagner (2010) although CST (2010) find that importer only firms are the most capital intensive of the four groups while we find importer only firms come in a close second to the two-way traders but are still more capital intensive than exporters-only and non-traders.

Apart from the premia of importers compared to non-traders and only-exporters, we are also interested in understanding whether differences exist among importers in terms of where they source their imports, the skill and technology intensity of these inputs and the number of different varieties of inputs that a firm imports. Table 3 compares several characteristics of importers of different groups. First, we follow the classification by the World Bank and categorise the importers into two groups based on the origin of their imports.[16] One group consists of those firms that import from high income economies and the other group with firms that import only from non-high income economies. Compared to firms that import only from non-high income economies, those that import from high-income economies tend to be older, larger, more skill intensive (paying higher wages to employees) and more productive, with larger means for labour productivity and TFP mesaured by both the De Loecker (2007) and Levinsohn and Petrin (2003) methods. Second, we differentiate importers by the skill and technology content of their imported goods.[17] Perhaps not surprisingly, firms that import high and medium skill and technology intensive products are also found to be older, larger, more skill intensive and more productive than those that import low skill and technology intensive products. Finally, we group importers by the numbers of their imported varieties.[18] Likewise, firms importing two or more varieties are older, larger, more skill intensive and more productive than those that import only one variety.

[16] For a list of countries classified as high income see http://data.worldbank.org/about/country-classifications/country-and-lending-groups#High_income

[17] The classification of HS 6-digit products for skill and technology intensity is available from United Nations Conference on Trade and Development (UNCTAD) Database. See http://www.unctad.info/en/Trade-Analysis-Branch/Data-And-Statistics/Other-Databases/.

[18] Following Broda and Weinstein (2006), Arkolakis, Demidova, Klenow and Rodriguez-Clare (2008), Khandelwal (2010), Chen and Ma (2012) and Martin and Mejean (2014), we define a variety as an HS 6-digit product imported from a country. The intuition is that a same HS product imported from US is considered to have different technology or labour input from that imported from Mexico. In this way, they are counted as different varieties.

TABLE 1
Export and import participation of Chinese manufacturing firms

	Trade status							
Year	Only-exporters		Only-importers		Two-way traders		Non-traders	
	No. of firms (% of total)	Avg output (% of total)	No. of firms (% of total)	Avg output (% of total)	No. of firms (% of total)	Avg output (% of total)	No. of firms (% of total)	Avg output (% of total)
2002	2,438	72.62	2,768	127.03	6,907	198.77	31,524	54.59
	5.59	4.89	6.34	9.71	15.83	37.90	72.24	47.51
2003	2,858	73.40	2,663	145.34	7,382	244.12	30,734	65.86
	6.55	4.74	6.10	8.75	16.92	40.74	70.43	45.76
2004	3,302	73.85	2,712	163.67	8,015	277.18	29,608	70.94
	7.57	4.87	6.21	8.86	18.37	44.35	67.85	41.93
2005	3,680	98.04	2,580	195.79	8,072	312.43	29,305	81.92
	8.43	6.23	5.91	8.73	18.50	43.57	67.16	41.47
2006	4,012	93.01	2,511	238.18	7,762	356.05	29,352	93.66
	9.19	5.75	5.75	9.22	17.79	42.62	67.26	42.40
2002-2006	16,290	83.77	13,234	172.71	38,138	280.09	150,523	73.05
	7.47	5.39	6.07	9.02	17.48	42.18	68.99	43.41

NOTES: Only-exporters refer to firms that export but do not import. Only-importers refer to firms that import but do not export. Two-way traders are firms that both export and import while non-traders are those that neither export nor import. Average output is measured in millions of RMB using industry deflators.

TABLE 2

Trade status and firm characteristics for Chinese manufacturing 2002-2006

	Firm characteristics						
Trade status	No. of firms (% of total)	employment	total sales	labour productivity	TFP_DL	capital intensity	wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-Traders	150,489	4.877	10.044	3.817	6.294	3.530	2.274
	(69.00)	(1.03)	(1.18)	(0.99)	(1.02)	(1.21)	(0.55)
Only-exporters	16,282	5.250	10.462	3.787	6.504	3.542	2.374
	(7.47)	(1.03)	(1.12)	(0.92)	(0.96)	(1.16)	(0.50)
Only-importers	13,225	5.548	10.840	3.961	6.779	3.825	2.648
	(6.06)	(1.15)	(1.33)	(1.20)	(1.12)	(1.50)	(0.63)
Two-way traders	38,094	5.711	11.108	4.005	6.929	3.964	2.678
	(17.47)	(1.17)	(1.39)	(1.12)	(1.16)	(1.29)	(0.61)
All firms	218,090	5.091	10.310	3.857	6.450	3.625	2.375
	(100.00)	(1.12)	(1.30)	(1.02)	(1.08)	(1.25)	(0.59)

NOTES: Column (1) gives the numbers of observations of each trade group and their shares to the total respectively. Columns (2) - (7) provide the means and standard deviations (in parentheses) of corresponding firm characteristics for each group of firms. All indicators of firm characteristics are in logs. Labour productivity refers to value-added per employee, TFP_DL is total factor productivity estimated following De Loecker (2007) method. Capital intensity is capital per employee and average wage is wage per employee.

TABLE 3
Characteristics of Chinese importers 2002-2006

	No. of firms (% of total)	age	employment	wage	labour productivity	TFP_DL	TFP_LP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
a) Origin of imported products							
High-income economies	30,139	2.300	5.749	2.862	4.403	7.257	7.359
	(80.12)	(0.56)	(1.23)	(0.63)	(1.10)	(1.15)	(1.17)
Non-high-income economies	7,527	2.204	5.460	2.572	3.980	6.744	6.830
	(19.98)	(0.56)	(1.12)	(0.53)	(1.07)	(1.06)	(1.07)
b) Skill and technology content of imported products							
High and medium skill and technology	29,792	2.290	5.737	2.867	4.413	7.248	7.351
	(79.10)	(0.56)	(1.23)	(0.63)	(1.10)	(1.16)	(1.18)
Low skill and technology	7,874	2.245	5.517	2.565	3.963	6.801	6.883
	(20.90)	(0.56)	(1.10)	(0.53)	(1.03)	(1.03)	(1.04)
c) Number of imported varieties							
One variety	7,683	2.257	5.512	2.571	3.993	6.796	6.893
	(20.40)	(0.60)	(1.10)	(0.52)	(0.99)	(1.02)	(1.04)
Two or more varieties	29,983	2.287	5.737	2.863	4.402	7.246	7.346
	(79.60)	(0.55)	(1.23)	(0.63)	(1.12)	(1.16)	(1.16)

NOTES: Column (1) gives the numbers of observations of each group and their shares to the total respectively. Columns (2)-(7) provide the means and standard deviations (in parentheses) of corresponding firm characteristics. All indicators of firm characteristics are in logs.

4. Empirical Results

The descriptive evidence suggests that productivity for Chinese manufacturing firms differs by the type of participation in international markets. However, the existence of productivity differentials may be due to other factors related to firm productivity. Hence, the next step in our empirical investigation is to estimate the extent of any productivity premia controlling for the productivity related factors. The productivity premia for traders are estimated by regressing *TFP* on a set of dummy variables including trade status (non-traders are omitted as the reference group). The estimating equation is given by:

$$TFP_{it} = \alpha + \beta_1 EXPonly_{it} + \beta_2 IMPonly_{it} + \beta_3 EXP/IMP_{it} + \gamma X_{it} + \varepsilon_{it} \qquad (9)$$

where *i* and *t* represent firm and year respectively, *EXPonly* (*IMPonly*) is a dummy variable that equals 1 if a firm exports (imports) but does not import (export), and 0 otherwise; *EXP/IMP* is a dummy for a firm that both exports and imports and 0 otherwise; *X* is a vector of control variables (including firm size, ownership, firm age, employees' average wages, industry, region and year dummies). Finally, ε is the error term.

Table 4 presents the productivity premia for Chinese firms between 2002 and 2006 for TFP measured by both the De Loecker (2007) method and the more traditional Levinsohn and Petrin (2003) method. The coefficients on the three trade status dummies are positive and highly significant (at the 1% level) and show that compared to non-traders, firms that trade enjoy higher productivity levels controlling for a set of firm characteristics. However, the degree of the productivity premia differs across the three groups. Two-way traders enjoy the largest productivity premia, followed by firms that only import. Firms engaged in exporting only have the smallest premia. To put these results in context, firms that both import and export are 24.86% (100[exp(0.222)-1]) more productive than non-traders. The productivity advantage of firms that import only over non-traders is 16.88 percent (100[exp(0.156)-1]), double that of exporters only who have a premia over non-traders of 8.11 percent (100[exp(0.078)-1]). Our results are consistent with the descriptive evidence in Table 2 and are in line with findings from Muuls and Pisu (2009) for Belgian firms, Vogel and Wagner (2010) for German manufacturing firms, CST (2010) for the Italian manufacturing industry and Kasahara and Lapham (2013) for Chilean manufacturing plants. The results indicate that importing correlates with high productivity for the Chinese manufacturing firms. We now move on to explore the causation between importing and productivity.

4.1. Self-selection into Importing

The next stage is to apply a RE Probit model to test the self-selection into importing for Chinese manufacturing firms. The probability of starting to import is regressed on a set of firm characteristics and other controlled variables as specified in Equation (1) and the results are presented in Table 5 where Column (1) displays the coefficients and Column (2) the average marginal effects (AME).[19] Past export experience is found to have a highly significant effect on firms' decision to enter the import market. Firm that exported in the previous year are found to have a 3% higher likelihood of starting to import in the current period. The importance of experience

[19]The average marginal effects of continuous variables are computed by $AME = \frac{1}{n}\sum_{i=1}^{n}\phi(X_i'\beta)\beta$ and dummy variables by $AME = \frac{1}{n}\sum_{i=1}^{n}[\Phi(X_i'\beta|X_j = 1) - \Phi(X_i'\beta|X_j = 0)]$, where $\Phi(.)$ is the standard normal cumulative distribution function and $\phi(.)$ is the standard normal density function.

TABLE 4
Productivity premia for Chinese firms 2002-2006

Dependent variable: TFP*it*		
	TFP_De Loecker	TFP_LP
EXPonly	0.078***	0.084***
	(0.008)	(0.008)
IMPonly	0.156***	0.158***
	(0.009)	(0.009)
EXP/IMP	0.222***	0.224***
	(0.007)	(0.007)
SMALL	-0.474***	-0.482***
	(0.006)	(0.006)
LARGE	0.346***	0.367***
	(0.012)	(0.012)
FOREIGN	0.438***	0.426***
	(0.015)	(0.016)
HMT	0.370***	0.359***
	(0.015)	(0.015)
COLLECTIVE	0.299***	0.290***
	(0.014)	(0.014)
PRIVATE	0.343***	0.335***
	(0.013)	(0.014)
age	0.069***	0.073***
	(0.005)	(0.005)
wage	0.283***	0.281***
	(0.003)	(0.003)
Constant	5.806***	5.813***
	(0.025)	(0.025)
Observations	218,090	218,090

NOTES: Standard errors in parentheses. Region, indusrty and year dummies included. *** indicates significance at 0.01.

is revealed by the negative coefficient on firm age. TFP, labour force skills (proxied by average wages of employees) and firm size are significant determinants of the probability of entering into import market. Larger and more productive firms and those with more skilled labour are more likely to start to import. Ownership is also found to be an important factor. Compared to SOEs (the reference group), foreign owned firms (including HMT owned) and private firm are more likely to start to import. Our main variable of interest is TFP. After controlling for other firm characteristics, firms that start to import are already more productive however, they are not necessarily on a different productivity growth trajectory. As time-varying independent variables are lagged one year, these results show a causal effect of importing and TFP for Chinese manufacturing firms: more productive firms self-select into importing.[20]

4.2. Learning by Importing

As described in Section 2, when matching firms in our PSM-DID procedure, we ensure that the propensity score is balanced and covariates are balanced within blocks of the propensity score across treatment and control groups. Three matching estimators are applied and after matching we test the reliability of the matching using several methods. Tables A2 and A3 in Appendix A present the results of our balancing tests to assess the quality of matching. Statistics from standardized differences, *t*-tests, mean and median biases, pseudo-R^2s likelihood-ratio tests between unmatched and matched sample indicate that the quality of our PSM are satisfied. After assuring the matching to be satisfactory we proceed to make a comparison between the treated and control groups. Our PSM-DID results are presented in Table 6. The PSM-DID results provide the causal effect of importing on TFP where the ATTs can be interpreted as percentage changes in TFP. Results from Gaussian Kernel matching with bandwidth of 0.01 are presented in panel (a).[21] The ATTs for the entry year and up to two years after starting to import are all positive and statistically significant (at the 1% level), suggesting a positive effect of importing on productivity.[22] Our results suggest that import market entrants have 10.9% higher TFP growth than matched non-importers in the year of entry. New importers also appear to experience steady and increasing productivity growth for the first two years after entry. In the year after entry, new importers have a 13.5% higher TFP growth which increases to 17.1% two years after entry. These results suggest a strong learning by importing effect for Chinese firms.

Results form two other matching estimators are also presented in Table 6 with one-to-one matching in panel (b) and nearest neighbours matching with the number of neighbours of five in panel (c). Results are similar to those obtained from Kernel matching. Since Kernel matching uses all the observations within the common support and thus maximizes precision, we use Kernel estimator for the rest of the matching estimation results described below.

First we consider the impact of firm heterogeneity in terms of initial productivity levels on learning-by-importing. In the context of exporting, Lileeva and Trefler (2010) show how the

[20]Our results are robust to the estimation of a RE Probit model of entry where we control for size using a continuous variable measured as log of the number of employees.

[21]Following Silverman (1998); HIT(1997), we also tried a bandwidth of 0.06 and the results are presented in Table A4 in Appendix A. We compare the results with those previously obtained using a bandwidth of 0.01 (Panel (a) in Table 6) and find that the ATTs are slightly higher with bandwidth 0.01, but the standard errors are very similar for both choices of bandwidth.

[22]We do not look at the ATT for the pre-entry year as the quality of matching indicates no significant difference between the matched import starters and non-importers before the treatment. We are not able to look at the effects on TFP of importing three or more years after the entry due to the relatively short period of our sample.

TABLE 5
Self-selection into importing for Chinese manufacturing firms

	(1)	(2)
	RE Probit	AME
EXP	0.740***	0.041***
	(0.019)	(0.001)
age	-0.021	-0.001
	(0.015)	(0.001)
wage	0.163***	0.009***
	(0.018)	(0.001)
TFP	0.102***	0.006***
	(0.012)	(0.001)
pregrowth	-0.027*	-0.001*
	(0.014)	(0.001)
MEDIUM	0.328***	0.018***
	(0.025)	(0.001)
LARGE	0.568***	0.031***
	(0.068)	(0.004)
FOREIGN	0.684***	0.038***
	(0.057)	(0.003)
HMT	0.582***	0.032***
	(0.056)	(0.003)
COLLECTIVE	-0.059	-0.003
	(0.062)	(0.003)
PRIVATE	0.264***	0.015***
	(0.054)	(0.003)
EAST	0.159***	0.009***
	(0.034)	(0.002)
WEST	-0.041	-0.002
	(0.052)	(0.003)
Constant	-3.875***	
	(0.117)	
Observations	106,354	106,354
log likelihood	-11,460	

NOTES: Standard errors in parentheses. Industry and year dummies included.
All time varying variables are lagged one year. *** and * indicate significance at 0.01 and 0.1 respectively.

TABLE 6
Importing and productivity for Chinese manufacturing firms: PSM-DID estimates

	s=0	s=1	s=2
Outcome variable: year-to-year productivity growth rate			
a) Gaussian Kernel matching			
ATT	0.109***	0.135***	0.171***
	(0.013)	(0.018)	(0.024)
N (control)	93,523	62,174	30,808
N (treated)	3,034	2,265	1,429
b) One-to-one matching			
ATT	0.129***	0.167***	0.176***
	(0.019)	(0.024)	(0.033)
N (control)	93,523	62,174	30,808
N (treated)	3,034	2,265	1,429
c) Nearest neighbours matching			
ATT	0.118***	0.138***	0.166***
	(0.014)	(0.019)	(0.025)
N (control)	93,523	62,174	30,808
N (treated)	3,034	2,265	1,429

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

interaction between investment in R&D and access to foreign markets leads to heterogeneous responses of firms to improved market access. Testing their theoretical framework using Canadian data, they show that productivity gains of new exporters depend negatively of the initial productivity of firms. Also in the context of exporting, De Loecker (2013) shows a U-shaped relationship between learning-by-exporting and initial productivity.

Our results are presented in Table 7. Panels (a) and (b) examine firms with TFP at the sample mean or above in the initial year and those below. New importers from both groups learn from participation in imports market as ATTs are positive and significant (at 1% level). New importers whose TFP are below the sample mean have 10.7% higher TFP growth than the matched non-importers at the year of entry and keep a high TFP growth after the entry (14.7% and 19% higher for their first and second years of import market participation). New importers whose TFP is at sample mean or above show a 12.2% higher TFP growth at the year they start importing and their TFP growth rate is 13.3% and 15.9% higher than the control group. Hence, although firms that have a TFP below the mean initially have a slightly smaller productivity growth rate than those who have mean or above TFP at the entry year, these new importers display a stronger learning effect from importing afterwards as their TFP growth rates are higher in the first and second year after entry. Panels c) and d) compare firms of the first and fourth quartiles of initial TFP and confirm the result that the initially lower productive firms exhibit higher learning-by-importing effects.

TABLE 7
PSM-DID estimates by TFP levels

	s=0	s=1	s=2
a) Below mean TFP			
ATT	0.107***	0.147***	0.190***
	(0.021)	(0.029)	(0.038)
N (control)	55,910	37,168	18,442
N (treated)	1,276	918	543
b) Mean and above TFP			
ATT	0.122***	0.133***	0.159***
	(0.018)	(0.023)	(0.032)
N (control)	37,303	24,783	12,226
N (treated)	1,758	1,347	885
c) 1st quartile of TFP			
ATT	0.106***	0.131***	0.185***
	(0.035)	(0.050)	(0.065)
N (control)	26,650	17,582	8,655
N (treated)	27,174	371	218
d) 4th quartile of TFP			
ATT	0.135***	0.119***	0.140***
	(0.026)	(0.033)	(0.042)
N (control)	17,200	11,395	5,670
N (treated)	1,008	789	538

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

We also investigate whether the origin of imports has an impact on the magnitude of the learning effect. If Chinese firms import the majority of their inputs from high income economies one might expect that importers will show higher productivity gains as they are able to learn from exposure to sellers in high income markets. However, these inputs are likely to be more expensive. The PSM-DID results are presented in Table 8. Firms that start importing experience productivity gains at entry and after regardless of the origin of their imports. However, firms that start to import from high income economies display stronger learning effects compared to those starting to import only from non-high income economies.

TABLE 8
PSM-DID estimates by origins of imports

	s=0	s=1	s=2
a) High-income economies			
ATT	0.120***	0.141***	0.176***
	(0.016)	(0.022)	(0.030)
N (control)	93,568	62,222	30,856
N (treated)	2,000	1,501	984
b) Non-high-income economies			
ATT	0.082***	0.103***	0.117***
	(0.024)	(0.030)	(0.040)
N (control)	91,582	61,522	30,563
N (treated)	859	630	370

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

We also test whether the effect of importing on TFP growth depends on the skill and technology content of imported products. We classify the firms into two groups based on the skill and technology intensity of their imported goods. The PSM-DID estimates are presented in Table 9. ATTs for both groups are positive and highly significant for all three periods (at the 1% significance level, except for firms importing low skill and technology intensive products one year after the entry where the effect is only significant at the 10% level.) However, the magnitude of the learning from importing effect differs between the two groups. For firms that import high and medium skill and technology intensive products, the TFP growth is 11.9% higher for the import starters at the year of their entry compared to the control firms. These new importers maintain a steady TFP growth after entry with 15.5% and 17% higher TFP growth rate for the first and second year compared to the matched non-importers. For firms that import only low skill and technology intensive products, new importers have a 8.1% higher TFP growth than the control group at the year of entry into import markets. One year after entry, these new importers still have a 5.1% higher TFP growth than the matched non-importers, but only one-third of the growth rate of the new importers who source high and medium skill and technology intensive products. Two years after entry, new entrants importing only low skill and technology intensive products have 12.3% higher TFP growth than the control group, but this is still about 5% lower than firms that import high and medium skill and technology intensive products. Hence, although all new importers experience productivity growth in the year of entry to imports market, firms that import more skill and technology intensity products are found to learn more from importing. Our results highlight that the quality of imported products and the technology content of imports are important drivers of the magnitude of the learning effect.

Finally, we test the impact of the variety of imported inputs on the learning from importing effect. Results are presented in Table 10. New importers are found to display higher TFP growth at entry year and two years afterwards regardless of the number of varieties imported.

TABLE 9
PSM-DID estimates by skill and technology intensity of imports

	s=0	s=1	s=2
a) High and medium skill and technology intensive products			
ATT	0.119***	0.155***	0.170***
	(0.017)	(0.022)	(0.030)
N (control)	92,449	62,152	30,826
N (treated)	1,878	1,425	936
b) Low skill and technology intensive products			
ATT	0.081***	0.051*	0.123***
	(0.023)	(0.031)	(0.039)
N (control)	90,948	60,360	29,431
N (treated)	919	661	392

NOTES: Standard errors in parentheses. *** and * indicate significance at 0.01 and 0.1.

New entrants who import only one variety show a 6.5% higher TFP growth at the entry year and 8.6% and 9.3% for first and second year after entry than the control group of non importers. However, starters that import two or more varieties have much higher TFP growth rates, compared to the group of matched non-importers, with 13.1%, 13.4% and 16.1% higher TFP growth rates than the matched non-importers at entry year, first and second year after the entry respectively.[23]

TABLE 10
PSM-DID estimates by the variety of imported inputs

	s=0	s=1	s=2
a) one variety			
ATT	0.071***	0.098***	0.111***
	(0.018)	(0.024)	(0.035)
N (control)	93,453	62,271	30,842
N (treated)	1,448	1,023	570
b) two varieties or more			
ATT	0.124***	0.141***	0.175***
	(0.020)	(0.026)	(0.033)
N (control)	93,707	62,251	30,878
N (treated)	1,411	1,018	784

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

5. Robustness Checks

In this section we perform a number of robustness checks. We start by examining whether the impact of importing on productivity varies for firms with different ownership structures. Compared to domestic firms, a much higher proportion of foreign and HMT owned firms import. Our data show that firms with foreign capital and private firms are more likely to import than state-owned firms. The results are presented in Table 11. Except for collective firms, all other four types of firms show the learning effect of importing on TFP. However, the extent of the learning effect varies among different ownership categories. For foreign-owned firms, import starters have a 11.1% higher TFP growth than the group of matched non-importing firms in the year of entry. The TFP growth rate for these new entrants drops to 10.7% and then increases to 19.1% two years after entry. A similar but bigger learning effect is found for HMT new importers with the TFP growth rate for 16.2%, 18.4% and 21.1% for entry year, one year and two years after the entry.

It is interesting to note that although only a small number of SOEs start to import, in the year of entry, these new import entrants do not experience significant TFP growth. However, in the years following entry these SOE new entrants enjoy a big increase of their TFP growth with 26.4% and 43.7% for first year and second year after the entry. For private firms, new importers have a rate of TFP growth that is 10.4% higher than that of matched non-importers in

[23] We apply a PSM-DID approach with multiple treatments (Lechner, 2001, 2002) where the treatments are as follows: non-importers, import starters with one variety and import starters with two or more varieties. Within our sample, 50% of starters import one variety and 75% of starters import three or less. Results from a multinomial logistic estimation are presented in Table A5 in the Appendix. Results comparing import starters with two or more varieties and import starters with one variety are available from the authors upon request.

the year of entry. The gap continues to grow in the first and second years after entry to 13.8% and 18.1% respectively.

TABLE 11
PSM-DID estimates by ownership

	s=0	s=1	s=2
a) FOREIGN			
ATT	0.111***	0.107***	0.191***
	(0.034)	(0.041)	(0.051)
N (control)	5,753	3,908	1,978
N (treated)	728	596	418
b) HMT			
ATT	0.162***	0.184***	0.211***
	(0.030)	(0.037)	(0.050)
N (control)	9,960	6,659	3,321
N (treated)	801	630	389
c) PRIVATE			
ATT	0.104***	0.138***	0.181***
	(0.018)	(0.027)	(0.038)
N (control)	57,574	37,847	18,675
N (treated)	1,327	918	539
d) SOE			
ATT	0.119	0.264**	0.437**
	(0.092)	(0.027)	(0.175)
N (control)	3,270	1,914	1,346
N (treated)	78	52	44
e) COLLECTIVE			
ATT	0.047	-0.054	-0.053
	(0.077)	(0.111)	(0.163)
N (control)	9,970	7,218	3,226
N (treated)	97	68	38

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

We also investigate whether the learning effect differs by firm's size. The results are reported in Table 12. For large firms the ATTs are not significant at usual levels in the year of entry and up to two years after entry. The ATTs for medium and small firms are all positive and significant suggesting a strong and positive learning effect for medium and small sized new importers. A 10.2% higher TFP growth is observed for small new importers at the entry and 10.7 % the year following the entry and 13% two years after. The ATTs for medium firms are 7.5%, 16.7 % and 17.8 % at entry year, one year and two years after the entry.

We also test the treatment effect of importing on productivity using an alternative TFP measure by Levinshon and Petrin (2003).[24] The results are presented in Table 13 and estimates of the ATTs are very close to those with TFP_DL as reported in Table 6.

Furthermore, as import entrants may exit from the imports market at some point during

[24]The correlation between TFP estimated by De Loecker (2007) and that by Levinsohn and Petrin (2003) is 0.994.

TABLE 12
PSM-DID estimates by firm size

	s=0	s=1	s=2
a) SMALL			
ATT	0.102***	0.107***	0.130***
	(0.017)	(0.022)	(0.030)
N (control)	81,658	54,493	27,102
N (treated)	2,013	1,499	915
b) MEDIUM			
ATT	0.075***	0.167***	0.178***
	(0.024)	(0.033)	(0.045)
N (control)	11,234	7,285	3,523
N (treated)	923	688	453
c) LARGE			
ATT	0.001	0.107	0.089
	(0.092)	(0.120)	(0.178)
N (control)	442	316	176
N (treated)	92	72	54

NOTES: Standard errors in parentheses and *** indicates significance levels at 0.01.

TABLE 13
PSM-DID estimates with TFP_LP

	s=0	s=1	s=2
ATT	0.111***	0.138***	0.177***
	(0.014)	(0.018)	(0.025)
N (control)	93,522	62,173	30,807
N (treated)	3,034	2,265	1,429

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

the period, we test the learning effect excluding the exiters and also test whether these import exiters ever learn from importing. Results for the sample excluding exiters are presented in Table 14 and for the sample of exiters only in Table 15. Firms that start importing during our sample and continue being active in imports market exhibit a 11% higher TFP growth rate than the matched non-importers at the year they start importing. These firms continue to show a big increase of TFP growth after entry with 19.7% and 24.8% for first and second subsequent years. Compared with the results obtained for the whole sample which include firms that start importing and stop during the sample period (see results from Table 6 in the previous section), continuous new importers experience higher TFP growth since they start importing and up to two years after their entry.

When we look at firms that start importing and stop during the sample, the new importers still have about 10% higher TFP growth than the matched non-importers after entry. Compared with the results for the whole sample (Table 6) and the sample of surviving import starters (Table 14), these import starter-exiters show the smallest TFP growth rates compared to the control group for the three years after entry.

TABLE 14
PSM-DID estimates excluding import exiters

	s=0	s=1	s=2
ATT	0.110***	0.197***	0.248***
	(0.018)	(0.028)	(0.037)
N (control)	92,772	61,420	30,054
N (treated)	1,668	899	514

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

TABLE 15
PSM-DID estimates for import starter-exiters

	s=0	s=1	s=2
ATT	0.105***	0.008***	0.104***
	(0.019)	(0.022)	(0.029)
N (control)	61,960	61,960	30,804
N (treated)	1,366	1,366	915

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

As the decision to import is likely to relate to the decision to export and thus all or part of the productivity growth of the firms may be due to the learning from exporting rather than from importing, We have performed an extra robustness check where we estimate the learning by importing effects on a sample of importers only. We perform our PSM-DID for importers only by dropping observations that export during the sample period. Results are presented in Table 16. Focusing on the sample without exporters, the new importers are still found to have a 9% higher TFP growth than the matched non-importers at the year of entry and 10.8% and 13.1% higher for the first and second year after entry.

We have also performed PSM-DID estimation based on placebo treatments. From the sample of non-importers, we drew a random sample of firms (we chose a 5% proportion of the

TABLE 16
PSM-DID estimates for non-exporters

	s=0	s=1	s=2
ATT	0.009***	0.108***	0.131***
	(0.031)	(0.042)	(0.051)
N (control)	77,537	51,168	25,703
N (treated)	622	414	253

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

total sample) that we then considered to be import starters and implemented our PSM-DID estimator to compare their productivity growth to the matched control firms (Huber, Lechner and Wunsch, 2013). We simulated this process 200 times and we found no significant learning effects resulting from the placebo treatment.[25]

So far we have been examining the treatment effects of importing using PSM method. Matching algorithms frequently omit a significant proportion of the population when comparison groups are being constructed, thus limiting the ability to generalize from the results. An alternative approach is recommended to adjust for confounding by using estimated propensity scores to construct weights for individual observations (Hirano, Imbens and Ridder, 2003; Lunceford and Davidian, 2004; Curtis, Hammill, Eisenstein, Kramer and Anstrom, 2007). As a final robustness check, we estimate the treatment effects using inverse probability weighting (IPW). IPW estimators use weighted averages of the observed outcome variable to estimate means of the potential outcomes. Each weight is the inverse of the estimated probability that an individual receives a treatment level.

Results are reported in Table 17. The average treatment effect among the import starters on TFP growth rate is 10.6% at the year of entry to import market, which increases to 13.7% and 17.5% one and two years after entry. The results are almost identical to our main results obtained by Gaussian Kernel matching (Panel (a) of Table 6).

TABLE 17
Productivity and importing: treatment effects by IPW

	s=0	s=1	s=2
ATET	0.106***	0.137***	0.175***
	(0.012)	(0.016)	(0.022)
POM	0.022***	0.104***	0.140***
	(0.007)	(0.009)	(0.014)
Observations	97,128	64,994	32,793

NOTES: ATET is the average treatment effect among the treated while POM is the potential-outcome mean. Standard errors in parentheses and *** indicates significance at 0.01.

[25]Results are not reported due to limited space and available from the authors upon request.

6. Conclusions

In this paper we have examined various aspects of the relationship between firm performance and international trade concentrating on the little explored relationship between importing and productivity. This paper presents an empirical analysis of the causal effects between productivity and importing using RE Probit model and propensity score matching with difference-in-differences approaches. Using Chinese manufacturing firm-level data we observe bi-directional causality between importing and productivity. Generally speaking, more productive firms self-select into the imports market and after import-market entry on average firms experience productivity gains. However, these gains are not evenly distributed.

Our results show that compared to the matched non-importing firms, learning effects are stronger for firms that initially had lower productivity. The origin, quality and variety of imported products is also important. We find that import starters that source their inputs from high income economies have larger productivity gains than those that start to import only from non-high income economies. Furthermore, we find that new importers who import medium and high skill and technology intensive products and import more varieties of inputs display stronger learning effects.

Our finding of strong supporting evidence of learning-by-importing for Chinese manufacturers, in contrast to the results of Vogel and Wagner (2010) for German manufacturers and ACD (2013) for Spanish firms, may be because developed countries have long been exposed to foreign competition and had access to global import markets. However, in China's case, joining the WTO in 2001 marked a step change in the international opportunities available to Chinese firms. At this time, firms from China were more likely to be some distance from the technological frontier meaning Chinese firms would have been exposed to considerable learning opportunities from the use of superior inputs because of existing gaps in technology and product quality between them and potential new trading partners.

Our results have potentially important policy implications. First, because Chinese manufacturing firms appear to benefit from importing, China could derive additional productivity gains from further trade liberalization and might want to consider promoting trade liberalisation alongside continued export promotion. Recent senior trade delegations from China to the West and the subsequent highly publicised deals make it clear that China is interested in importing high quality intermediate inputs and attracting further foreign direct investment. Our result that indigenous firms and small- and medium-sized firms exhibit high productivity growth as they learn from importing means that government support to help these firms break into the imports markets and overcome potentially large sunk costs could be beneficial. Examples include lowering barriers to importing by providing more information on sources of intermediate inputs, lowering tariffs and arranging for such firms to attend overseas trade fairs and similar events and possible support mechanisms that policy makers could employ.

References

Acharya, R. C., and W. Keller (2009) "Technology transfer through imports." *Canadian Journal of Economics* 42(4), 1411–48

Amiti, M., and A. K. Khandelwal (2013) "Import Competition and Quality Upgrading." *The Review of Economics and Statistics* 92(2), 476–90

Amiti, M., and J. Konings (2007) "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *The American Economic Review* 97(5), 1611–38

Andersson, M., H. Loof, and S. Johansson (2008) "Productivity and International Trade-Firm Level Evidence from a Small Open Economy." *Review of World Economics* 144(4), 774–801

Aristei, D., D. Castellani, and C. Franco (2013) "Firms' exporting and importing activities: is there a two-way relationship?" *Review of World Economics* 149(1), 55–84

Arkolakis, C., S. Demidova, P. J. Klenow, and A. Rodriguez-Clare (2008) "Endogenous Variety and the Gains from Trade." *American Economic Review* 98(2), 444–50

Arnold, J. M., and K. Hussinger (2005) "Export Behavior and Firm Productivity in German Manufacturing: A Firm-Level Analysis." *Review of World Economics* 141(2), 219–43

Augier, P., O. Cadot, and M. Dovis (2013) "Imports and TFP at the firm level: the role of absorptive capacity." *Canadian Journal of Economics* 46(3), 956–81

Austin, P. C. (2009) "Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples." *Statistics in Medicine* 28(25), 3083–107

Baldwin, J. R., and W. Gu (2004) "Participation in Export Markets and Productivity Performance in Canadian Manufacturing." *Canadian Journal of Economics* 36 (3), 634–57

Bas, M., and V. Strauss-Kahn (2014) "Does importing more inputs raise exports? Firm-level evidence from France." *Review of World Economics* 150(2), 241–275

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2007) "Firms in International Trade." *Journal of Economic Perspectives* 21(3), 105–30

Bernard, A. B., J. B. Jensen, and P. K. Schott (2005) "Importers, Exporters, and Multinationals: A Portrait of Firms in the U.S. that Trade Goods." *NBER Working Paper No. 11404*

Blalock, G., and F. Veloso (2007) "Imports, Productivity Growth, and Supply Chain Learning." *World Development* 35 (7), 1134–51

Blundell, R., and M. Costa Dias (2000) "Evaluation Methods for Non-Experimental Data." *Fiscal Studies* 21(4), 427–68

Brandt, L., J. V. Biesebroeck, and Y. Zhang (2012) "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics* 97(2), 339–51

Brockmann, M., T. Gasser, and E. Herrmann (1993) "Locally Adaptive Bandwidth Choice for Kernel Regression Estimators." *Journal of the American Statistical Association* 88(424), 1302–09

Broda, C., and D. E. Weinstein (2006) "Globalization and the Gains from Variety." *The Quarterly Journal of Economics* 121(2), 541–85

Caliendo, M., and S. Kopeinig (2008) "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys* 22(1), 31–72

Castellani, D., F. Serti, and C. Tomasi (2010) "Firms in International Trade: Importers and Exporters Heterogeneity in Italian Manufacturing Industry." *The World Economy* 33(3), 424–57

Chen, B., and H. Ma (2012) "Import Variety and Welfare Gain in China." *Review of International Economics* 20(4), 807–20

Curtis, L. H., B. G. Hammill, E. L. Eisenstein, J. M. Kramer, and K. J. Anstrom (2007) "Using Inverse Probability-Weighted Estimators in Comparative Effectiveness Analyses With Observational Databases." *Medical Care* 45(10), 103–07

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

——— (2013) "Detecting Learning by Exporting." *American Economic Journal: Microeconomics* 5(3), 1–21

Du, J., and S. Girma (2007) "Finance and Firm Export in China." *Kyklos* 60(1), 37–54

Fan, J., and I. Gijbels (1995) "Data-Driven Bandwidth Selection in Local Polynomial Fitting: Variable Bandwidth and Spatial Adaptation." *Journal of the Royal Statistical Society. Series B (Methodological)* 57(2), 371–94

Feng, L., Z. Li, and D. L. Swenson (2012) "The Connection between Imported Intermediate Inputs and Exports: Evidence from Chinese Firms." *NBER Working Paper No. 18260*

Frolich, M. (2005) "Matching estimators and Optimal Bandwidth Choice." *Statistics and Computing* 15, 197–215

Garrido, M. M., A. S. Kelley, J. Paris, K. Roza, D. E. Meier, R. S. Morrison, and M. D. Aldridge (2014) "Methods for Constructing and Assessing Propensity Scores." *Health Services Research* 49(5), 1701–20

Girma, S., D. Greenaway, and R. Kneller (2004) "Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms." *Review of International Economics* 12(5), 855–66

Girma, S., R. Kneller, and M. Pisu (2007) "Do exporters have anything to learn from foreign multinationals?" *European Economic Review* 51(4), 993–1010

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2009) "Trade Liberalization and New Imported Inputs." *American Economic Review: Papers and Proceedings* 99(2), 494–500

——— (2010) "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India." *The Quarterly Journal of Economics* 125 (4), 1727–67

Halpern, L., M. Koren, and A. Szeidl (2005) "Imports and Productivity." *Centre for Economic Policy Research Discussion Paper No. 5139*

Heckman, J. J., H. Ichimura, and P. E. Todd (1997) "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *The Review of Economic Studies* 64(4), 605–654

——— (1998) "Matching as an Econometric Evaluation Estimator." *Review of Economic Studies* 65(2), 261–94

Hirano, K., G. W. Imbens, and G. Ridder (2003) "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score." *Econometrica* 71(4), 1161–89

Ho, D. E., K. Imai, G. King, and E. A. Stuart (2007) "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference." *Political Analysis* 15(3), 199–236

Huber, M., M. Lechner, and C. Wunsch (2013) "The performance of Estimators Based on the Propensity Score." *Journal of Econometrics* 175(1), 1 – 21

Imbens, G. W. (2004) "Nonparametric estimation of average treatment effects under exogeneity: a review." *Review of Economic and Statistics* 86(1), 4–29

Jones, C., J. Marron, and S. Sheather (1996) "A Brief Survey of Bandwidth Selection for Density Estimation." *Journal of the American Statistical Association* 91(433), 401–07

Kasahara, H., and B. Lapham (2013) "Productivity and the Decision to Import and Export: Theory and Evidence." *Journal of International Economics* 89(2), 297–316

Kasahara, H., and J. Rodrigue (2008) "Does the Use of Imported Intermediates Increase Productivity? Plant-level Evidence." *Journal of Development Economics* 87(1), 106–18

Khandelwal, A. K. (2010) "The long and short (of) quality ladders." *Review of Economic Studies* 77(4), 1450–76

Kraay, A. (1999) "Exports and Economic Performance: Evidence From a Panel of Chinese Enterprises." *Revue d'Economie du Developpement* 1(2), 183–207

Kugler, M., and E. Verhoogen (2009) "Plants and Imported Inputs: New Facts and an Interpretation." *American Economic Review: Papers & Proceedings* 99(2), 501–07

Lechner, M. (2001) "Identification and estimation of causal effects of multiple treatments under the conditional independence assumption." In M. Lechner and F. Pfeiffer, eds., *Econometric Evaluation of Labour Market Policies*, volume 13 of *ZEW Economic Studies*, pp. 43–58, Physica-Verlag HD

——— (2002) "Some practical issues in the evaluation of heterogeneous labour market programmes by matching methods." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 165(1), 59–82

Levinsohn, J., and A. Petrin (2003) “Estimating Production Functions using Inputs to Control for Unobservables.” *Review of Economic Studies* 70(2), 317–41

Lileeva, A., and D. Trefler (2010) “Improved Access to Foreign Markets Raises Plant-level Productivity For Some Plants.” *Quarterly Journal of Economics* 125(3), 1051–99

Lu, J., Y. Lu, and Z. Tao (2010) “Exporting behavior of foreign affiliates: Theory and evidence.” *Journal of International Economics* 81(2), 197–205

Lunceford, J. K., and M. Davidian (2004) “Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study.” *Statistics in Medicine* 23(19), 2937–60

MacGarvie, M. (2006) “Do firms learn from international trade?” *The Review of Economics and Statistics* 88 (1), 46–60

Manova, K., and Z. Zhang (2009) “China’s Exporters and Importers: Firms, Products and Trade Partners.” *NBER Working Paper No. 15249*

Martin, J., and I. Mejean (2014) “Low-wage country competition and the quality content of high-wage country exports.” *Journal of International Economics* 93(1), 140–52

McCann, F. (2009) “Importing, Exporting and Productivity in Irish Manufacturing.” *Working Papers No.200922, School Of Economics, University College Dublin*

Muuls, M., and M. Pisu (2009) “Imports and Exports at the Level of the Firm: Evidence from Belgium.” *The World Economy* 32(5), 692–734

Olley, S., and A. Pakes (1996) “The dynamics of productivity in the telecommunications equipment industry.” *Econometrica* 64(6), 1263–98

Park, B. U., and J. S. Marron (1990) “Comparison of Data-Driven Bandwidth Selectors.” *Journal of the American Statistical Association* 85(409), 66–72

Park, B. U., and B. A. Turlach (1992) “Practical Performance of Several Data Driven Bandwidth Selectors.” *Computational Statistics* 7, 251–70

Roberts, M. J., and J. R. Tybout (1997) “The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs.” *American Economic Review* 87(4), 545–64

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

Ruane, F., and J. Sutherland (2005) “Export performance and destination characteristics of Irish manufacturing industry.” *Review of World Economics* 141(3), 442–59

Rubin, D. (2001) “Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation.” *Health Services & Outcomes Research Methodology* 2, 169–88

Sheather, S. J., and M. C. Jones (1991) “ A Reliable Data-Based Bandwidth Selection Method for Fernel Density Estimati.” *Journal of the Royal Stat* 53(3), 683–90

Sianesi, B. (2004) "An evaluation of the Swedish system of active labour market programmes in the 1990s." *Review of Economics and Statistics* 86(1), 133–55

Silverman, B. (1998) *Density Estimation for Statistics and Data Analysis*. London: Chapman & Hall/CRC

Smith, J. A., and P. E. Todd (2005) "Rejoinder." *Journal of Econometrics* 125(1), 365–75

Sun, X., and J. Hong (2011) "Exports, Ownership and Firm Productivity: Evidence from China." *The World Economy* 34 (7), 1199–215

Topalova, P., and A. Khandelwal (2011) "Trade Liberalization and Firm Productivity: The Case of India." *Review of Economics and Statistics* 93(3), 995–1009

Van Biesebroeck, J. (2005) "Exporting Raises Productivity in Sub-Saharan Manufacturing Plants." *Journal of International Economics* 67(2), 373–91

Vogel, A., and J. Wagner (2010) "Higher Productivity in Importing German Manufacturing Firms: Self-selection, Learning from Importing, or Both?" *Review of World Economics* 145(4), 641–65

Wagner, J. (2007) "Exports and Productivity: A Survey of the Evidence from Firm Level Data." *The World Economy* 30(1), 60–82

Yang, Y., and S. Mallick (2010) "Export Premium, Self-selection and Learning-by-Exporting: Evidence from Chinese Matched Firms." *The World Economy* 33(10), 1218–40

Yi, J., and C. Wang (2012) "The decision to export: Firm heterogeneity, sunk costs, and spatial concentration." *International Business Review* 21 (3), 766–81

Appendix A

TABLE A1
Definition of variables

Variable	Definition
EXP	a binary variable which equals 1 if a firm had positive exports and 0 otherwise
EXPonly	a binary variable which equals 1 if a firm had positive exports and no positive imports and 0 otherwise
IMP	a binary variable which equals 1 if a firm had positive imports and 0 otherwise
IMPonly	a binary variable which equals 1 if a firm had positive imports and no positive exports and 0 otherwise
EXP/IMP	a binary variable which equals 1 if a firm had both positive exports and positive imports and 0 otherwise
START	a binary variable which equals 1 if a firm starts importing and 0 otherwise
age	log of a firm's age: the report year minus the founded year of a firm
wage	log of average wage of employees of a firm (ratio of total wage bill to the number of employees)
TFP_DL	total factor productivity of a firm estimated by the method of De Leocker(2010)
TFP_LP	total factor productivity of a firm obtained from estimation of the semi-parametric approach of Levinsohn and Petrin (2003)
employment	log of the number of employees of a firm
pregrowth	difference of TFP between the year when a firm starts importing and 1 year before the entry
SOE	a dummy which equals 1 if a firm is state-owned and 0 otherwise
COLLECTIVE	a dummy which equals 1 if a firm is collectively-owned and 0 otherwise
PRIVATE	a dummy which equals 1 if a firm is private-owned and 0 otherwise
FOREIGN	a dummy which equals 1 if a firm with over 25% share of capital from foreign investors and 0 otherwise
HMT	a dummy which equals 1 if a firm with over 25% share of capital from Hong Kong, Taiwan or Macao investors and 0 otherwise
SMALL	a size dummy which equals 1 if a firm is a small firm and 0 otherwise.
MEDIUM	a size dummy which equals 1 if a firm is a medium firm and 0 otherwise.
LARGE	a size dummy which equals 1 if a firm is a large firm and 0 otherwise.
EAST	a region dummy which equals 1 if a firm is located in the East of China and 0 otherwise.
CENTRAL	a region dummy which equals 1 if a firm is located in Central area of China and 0 otherwise.
WEST	a region dummy which equals 1 if a firm is located in the West of China and 0 otherwise.

TABLE A2
Balancing test from Gaussian Kernel matching (I)

Variables	Sample	Mean		%bias	% reduction in |bias|	t-test	
		Treated	Control			t-stat	p>|t|
EXP	Unmatched	0.54348	0.10300	106.7		95.42	0.000
	Matched	0.51945	0.49818	5.2	95.2	1.66	0.098
age	Unmatched	2.23260	2.26410	-4.7		-2.93	0.003
	Matched	2.30490	2.30740	-0.4	92.2	-0.17	0.867
wage	Unmatched	2.51520	2.28360	42		28.53	0.000
	Matched	2.52760	2.50580	4	90.6	1.58	0.115
TFP_DL	Unmatched	6.72950	6.31000	41.5		28.79	0.000
	Matched	6.79170	6.74860	4.3	89.7	1.64	0.100
pregrowth	Unmatched	0.14409	0.10481	5.7		3.08	0.002
	Matched	0.14409	0.13141	1.8	67.7	0.74	0.460
MEDIUM	Unmatched	0.26651	0.10813	41.5		33.99	0.000
	Matched	0.27554	0.26493	2.8	93.3	0.93	0.352
LARGE	Unmatched	0.02529	0.00637	15.2		15.36	0.000
	Matched	0.02999	0.02790	1.7	88.9	0.49	0.626
FOREIGN	Unmatched	0.25857	0.05871	56.9		55.27	0.000
	Matched	0.22808	0.20636	6.2	89.1	2.05	0.040
HMT	Unmatched	0.28365	0.11151	44.3		36.43	0.000
	Matched	0.27324	0.27876	-1.4	96.8	-0.48	0.630
COLLECTIVE	Unmatched	0.04202	0.17560	-43.9		-24.16	0.000
	Matched	0.04120	0.04746	-2.1	95.3	-1.19	0.236
PRIVATE	Unmatched	0.38921	0.58947	-40.9		-27.64	0.000
	Matched	0.43045	0.43725	-1.4	96.6	-0.53	0.594

NOTES: Reported are the means of variables for treated and control firms for unmatched and matched sample together with the together with the %bias (SD), % reduction in |bias| and t-tests in matched sample compared to those in unmatched sample.

TABLE A3
Balancing test from Guassian Kernel matching (II)

Sample	Psuedo R2	LR chi2	p>chi2	Mean Bias	Median Bias	B	R	%Var
Unmatched	0.204	5518.09	0.000	17.5	8.5	150.1*	1.12	50
Matched	0.002	14.88	1.000	0.7	0	9.9	0.91	0

NOTES: B is the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group and R is the ratio of treated to (matched) non-treated variances of the propensity score index. Rubin (2001) recommends that B be less than 25 and that R be between 0.5 and two for the samples to be considered sufficiently balanced. An asterisk is displayed next to B and R values that fall outside those limits.

TABLE A4
Gaussian Kernel matching with bandwidth 0.06

	s=0	s=1	s=2
ATT	0.085***	0.099***	0.125***
	(0.013)	(0.017)	(0.022)
N (control)	93,523	62,174	30,808
N (treated)	3,034	2,265	1,429

NOTES: Standard errors in parentheses and *** indicates significance at 0.01.

Appendix B

Total Factor Productivity Estimation

In this paper we measure TFP using the De Loecker (2007) approach. As in the standard Olley and Pakes (1996) model, a firm is assumed to be risk-neutral and to maximize its expected value of both current and future profits. The production function is set up as the follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \tag{B.1}$$

where *i* and *t* denote firm and time, y, *k* and *l* are the logs of output as measured by value added, capital input and labor input respectively, ω is the transmitted productivity shock which impacts the firm's decision rules and η is an i.i.d component which is uncorrelated with input choices.

At the beginning of every period, the firm makes the following decisions. First, it makes a discrete decision to continue its operation or exit by comparing the continuation value with a one-time sell-off value. Secondly, conditional on staying in operation, it decides the level of labour input (*l*) and investment (*i*). Capital is accumulated according to the law of motion $k_{it} = (1-\delta)k_{it} + i_{it}$ and it is assumed that investment in the current period becomes productive the next period.

The demand for investment is a function of the firm's capital *k* and productivity ω:

$$i_{it} = i_t(k_{it}, \omega_{it}) \tag{B.2}$$

Compared to firms that do not import, importing firms have some advantages, including the ability to access intermediate inputs that are not produced domestically to access better quality intermediate inputs and to potentially purchase intermediate-inputs at lower prices. Besides, past import status may have an impact on the evolution of productivity and importing materials may bring plants into close contact with foreign suppliers in developed countries, which may have a learning effect (Kasahara and Rodrigue 2008). As a result, importing firms face different market structures and factor prices when the exiting and investment decisions are made. The investment function now depends on the additional state variable of import status.

$$i_{it} = i_t(k_{it}, \omega_{it}, IMP_{it}) \tag{B.3}$$

where IMP_{it} is a dummy of import status of firm i in time t.

As investment is a control on a state variable, it is costly to adjust and researchers often come across data with a substantial observations of 0 investment. To circumvent the problem

TABLE A5
Factors associated with the number of imported varieties

	(1)	(2)
	One variety	Two or more varieties
EXP	2.253***	1.518***
	(0.060)	(0.061)
age	-0.091*	0.052
	(0.048)	(0.048)
wage	0.279***	0.600***
	(0.057)	(0.054)
TFP	0.205***	0.340***
	(0.037)	(0.036)
pregrowth	-0.032	-0.099**
	(0.045)	(0.046)
MEDIUM	0.623***	0.883***
	(0.075)	(0.071)
LARGE	0.959***	1.437***
	(0.222)	(0.171)
FOREIGN	1.252***	2.236***
	(0.196)	(0.188)
HMT	1.121***	1.719***
	(0.191)	(0.185)
COLLECTIVE	-0.087	-0.193
	(0.215)	(0.227)
PRIVATE	0.553***	0.810***
	(0.185)	(0.181)
EAST	0.410***	0.397***
	(0.113)	(0.121)
WEST	-0.097	0.008
	(0.176)	(0.177)
Constant	-8.265***	-10.788***
	(0.378)	(0.384)
Observations	97,252	97,252
Log likelihood	-12,078	-12,078

NOTES: The base outcome is 0 imported variety. Column (1) reports the coefficients for importing one variety and Column (2) two and more varieties using maximum-likelihood multinomial logistic models. Industry and year dummies included. All time varying variables are lagged one year. Standard errors in parentheses. *** indicates significance at 0.01.

of firms with 0 investment, Levinsohn and Petrin (2003) suggest a modification of the Olley and Pakes (1996) approach by using intermediate inputs (m), such as materials or energy usage, instead of investment, as a proxy variable to recover the unobserved firm productivity. Since intermediate inputs are not typically state variables and it is less costly to adjust intermediate inputs they may respond more fully to productivity shocks. Equation (B.3) then becomes:

$$m_{it} = m_t(k_{it}, \omega_{it}, IMP_{it}) \tag{B.4}$$

We can invert this demand function to obtain the productivity shock ω_{it} as given by:

$$\omega_{it} = \omega_t(k_{it}, m_{it}, IMP_{it}) \tag{B.5}$$

Substituting ω_{it} with (B.5) to the production function in (B.1), we have:

$$y_{it} = \beta_0 + \beta_l l_{it} + \phi_t(k_{it}, m_{it}, IMP_{it}) + \eta_{it} \tag{B.6}$$

where $\phi_t(k_{it}, m_{it}, IMP_{it}) = \beta_k k_{it} + \omega_t(k_{it}, m_{it}, IMP_{it})$.

In the first stage, OLS can be used to obtained a consistent estimate of β_l from Equation (B.6) by substituting a third-order polynomial in the three variables, k_{it}, m_{it} and IMP_{it}, to approximate $\phi_t(.)$. Estimation is done industry by industry, adding the ownership and year dummies to capture the ownership and time effects.

In the second stage, the capital coefficient β_k is estimated as the follows.

To correct the selection bias, the survival decision depends on import status through the productivity shock and through the capital accumulation process. If we define the indicator function χ_{it} to be equal to 1 if firm i continues in operation at t and 0 if it exits, then the survival probability is determined on the information set J at time t by:

$$\begin{aligned}
& Pr\{\chi_{i(t+1)} = 1 | J_{it}\} \\
= \; & Pr\{\omega_{i(t+1)} \geq \underline{\omega}_{i(t+1)}(k_{i(t+1)}, IMP_{it}) | \underline{\omega}_{i(t+1)}(k_{i(t+1)}, IMP_{it}), \omega_{it}\} \\
= \; & \psi\{\underline{\omega}_{i(t+1)}(k_{i(t+1)}, IMP_{it}), \omega_{it}\} \\
= \; & \psi_{it}(k_{it}, m_{it}, IMP_{it}) \equiv P_{it}
\end{aligned} \tag{B.7}$$

We assume that productivity follows a first order Markov process:

$$\omega_{i(t+1)} = E[\omega_{i(t+1)} | \omega_{it}, IMP_{it}, \chi_{i(t+1)} = 1] + \xi_{i(t+1)} \tag{B.8}$$

where $\xi_{i(t+1)}$ is the innovation in productivity for the next period which depends on current productivity and import status and survival in the next period.

Now consider the expectation of $y_{i(t+1)} - \beta_l l_{i(t+1)}$ conditional on information at t and survival:

$$\begin{aligned}
& E[y_{i(t+1)} - \beta_l l_{i(t+1)} | k_{i(t+1)}, \chi_{i(t+1)} = 1] \\
= \; & \beta_0 + \beta_k k_{i(t+1)} + E[\omega_{i(t+1)} | \omega_{it}, IMP_{it}, \chi_{i(t+1)} = 1] \\
\equiv \; & \beta_k k_{i(t+1)} + g(\omega_{i(t+1)}, \underline{\omega}_{it})
\end{aligned} \tag{B.9}$$

Provided the density of $\omega_{i(t+1)}$ conditional on ω_{it} is positive in a region, $\omega_{i(t+1)}$, $\omega_{i(t+1)}$ can be written as a function of P_{it} and ω_{it} from the survival equation in (B.7). We then can write $g(.)$ as a function of P_{it} and ω_{it}.

Substituting P_{it} and ω_{it} into $g(.)$, we have the following from Equation (B.1):

$$\begin{aligned} & y_{i(t+1)} - \beta_l l_{i(t+1)} \\ = \;& \beta_0 + \beta_k k_{i(t+1)} + E[\omega_{i(t+1)}|\omega_{it}, IMP_{it}, \chi_{i(t+1)} = 1] + \xi_{i(t+1)} + \eta_{it} \\ = \;& \beta_0 + \beta_k k_{i(t+1)} + g(P_{it}, \omega_{it}) + \xi_{i(t+1)} + \eta_{it} \end{aligned} \tag{B.10}$$

Using $\omega_{it} = \phi_t(k_{it}, m_{it}, IMP_{it}) - \beta_k k_{it}$ from (B.6), we rewrite the first three terms of the right-hand side of Equation (B.10) as a function of $\phi_t - \beta_k k_{it}$ and P_{it}:

$$y_{i(t+1)} - \beta_l l_{i(t+1)} = \beta_0 + \beta_k k_{i(t+1)} + g(P_{it}, \phi_{it} - \beta_k k_{it}) + \xi_{i(t+1)} + \eta_{it} \tag{B.11}$$

A consistent estimate of β_k is obtained by running nonlinear least squares on Equation (B.11) by substituting the coefficient on labor β_l obtained from the first stage, as well as the survival probability P_{it} estimated from Equation (B.7). As in the first stage of the estimation procedure, the function $g(P_{it}, \phi_{it} - \beta_k k_{it})$ is approximated using a higher order polynomial expansion in P_{it} and $(\phi_{it} - \beta_k k_{it})$.

TABLE B1
Coefficients from TFP Estimations

CIC code	13	14	15	16	17	18	19	20	21	22
ln(labour)	0.233***	0.157***	0.240***	0.095	0.225***	0.268***	0.250***	0.245***	0.213***	0.226***
	(0.011)	(0.014)	(0.017)	(0.068)	(0.006)	(0.008)	(0.008)	(0.017)	(0.019)	(0.013)
ln(capital)	0.039***	0.057***	0.037***	0.131***	0.045***	0.048***	0.062***	0.061***	0.043***	0.035***
	(0.008)	(0.011)	(0.013)	(0.049)	(0.005)	(0.006)	(0.008)	(0.012)	(0.014)	(0.009)
IMP	-0.058**	-0.049	0.033	-0.102	-0.017	-0.011	-0.022	-0.043	-0.019	-0.041
	(0.027)	(0.032)	(0.042)	(0.151)	(0.013)	(0.014)	(0.019)	(0.037)	(0.037)	(0.029)
Obs in Stage 1	11,774	5,946	3,412	255	21,996	14,481	7,005	3,283	2,620	7,858
CIC code	23	24	25	26	27	28	29	30	31	32
ln(labour)	0.238***	0.256***	0.224***	0.184***	0.144***	0.285***	0.197***	0.212***	0.186***	0.297***
	(0.014)	(0.013)	(0.029)	(0.007)	(0.016)	(0.027)	(0.017)	(0.008)	(0.006)	(0.015)
ln(capital)	0.033***	0.028***	0.101***	0.043***	0.051***	0.106***	0.053***	0.048***	0.034***	0.064***
	(0.011)	(0.010)	(0.023)	(0.006)	(0.013)	(0.022)	(0.015)	(0.007)	(0.005)	(0.012)
IMP	-0.019	-0.039	0.084	-0.001	0.066*	-0.124**	-0.015	-0.001	0.016	-0.050
	(0.034)	(0.025)	(0.084)	(0.018)	(0.035)	(0.063)	(0.034)	(0.018)	(0.020)	(0.053)
Obs in Stage 1	6,260	4,268	1,290	19,726	5,779	1,446	3,227	12,641	20,106	4,634
CIC code	33	34	35	36	37	39	40	41	42	43
ln(labour)	0.226***	0.202***	0.190***	0.145***	0.183***	0.179***	0.193***	0.161***	0.262***	0.269***
	(0.017)	(0.008)	(0.007)	(0.011)	(0.010)	(0.008)	(0.009)	(0.014)	(0.011)	(0.020)
ln(capital)	0.039***	0.058***	0.036***	0.037***	0.063***	0.051***	0.057***	0.044***	0.049***	0.024
	(0.012)	(0.007)	(0.005)	(0.008)	(0.008)	(0.007)	(0.009)	(0.013)	(0.010)	(0.060)
IMP	-0.001	-0.020	0.016	0.042*	0.017	-0.038*	-0.004	-0.023	-0.037	-0.192
	(0.047)	(0.020)	(0.016)	(0.024)	(0.022)	(0.020)	(0.025)	(0.035)	(0.028)	(0.225)
Obs in Stage 1	4,569	13,740	19,567	10,105	12,241	13,716	11,656	5,784	5,314	1,552

NOTES: Standard errors in parentheses. *** , ** and * denote significance at 1%, 5% and 10% respectively.