

Import and Innovation: Evidence from Chinese Firms

Zhiyuan Chen , Jie Zhang , Wenping Zheng

PII: S0014-2921(17)30033-8
DOI: [10.1016/j.euroecorev.2017.02.008](https://doi.org/10.1016/j.euroecorev.2017.02.008)
Reference: EER 2962

To appear in: *European Economic Review*

Received date: 17 February 2017
Accepted date: 21 February 2017

Please cite this article as: Zhiyuan Chen , Jie Zhang , Wenping Zheng , Import and Innovation: Evidence from Chinese Firms, *European Economic Review* (2017), doi: [10.1016/j.euroecorev.2017.02.008](https://doi.org/10.1016/j.euroecorev.2017.02.008)

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.



Import and Innovation: Evidence from Chinese Firms^{*}

Zhiyuan Chen[†], Jie Zhang[‡], Wenping Zheng[§]

8th Feb, 2016

Abstract

This paper investigates the relationship between imports and innovation by importing firms. We first construct a theoretical model in which imports stimulate innovation through cost-reducing knowledge spillovers. We then employ a combined micro dataset of Chinese manufacturing firms to estimate the effects of imported intermediates on the firm's R&D investment. The dataset allows us to construct firm-year level instruments for importing and exporting that are uncorrelated with the innovation decision of the firm. Our estimations find that: (1) importing intermediates tends to increase importing firms' R&D intensity; and that (2) exporting also increases importing firms' R&D intensity. Examining the channels through which importing affects innovation, we find that importing from high-income sources has a greater impact on innovation. High-tech firms tend to experience greater increases in innovation intensity, as do private firms. Our results are supported by a series of robustness checks.

Keywords: imports, exports, R&D intensity

JEL classification: F14, F61, O31

^{*} We are grateful to John Riew and Han Hong for their constructive comments on earlier versions of this paper. We are also immensely grateful to Marc Henry, Fu Xin, and Maoliang Bu for helping us with editing the manuscript. Comments from the editor, the associate editor and two anonymous referees are gratefully acknowledged. Zhang gratefully acknowledges funding from National Natural Science Foundation of China (Grant No. 41371139), and MOE project of Key Research Institute of Humanities and Social Sciences at Universities (Grant No. 15JJD790035). Zheng gratefully acknowledges support from the Outstanding Innovative Talents Cultivation Funded Programs 2015 of Renmin University of China. All remaining errors are ours.

[†] Department of Economics, Pennsylvania State University. Email: zxc5109@psu.edu.

[‡] Corresponding author, Institute of China's Economic Reform and Development, Renmin University of China. Email: zhangjie0402@ruc.edu.cn; tel: +86 10 62515100; fax: +86 10 82509097.

[§] School of Economics, Renmin University of China. Email: wenpingzheng@ruc.edu.cn.

1. Introduction

China's continuous economic rise has attracted worldwide attention. Along with its economic upsurge, the Chinese economy has exhibited a noteworthy feature: the concurrent expansion of import value and steady growth in R&D intensity. China's import value, which has grown from 0.13 trillion USD to 1.95 trillion USD over the last 3 decades, has been the second largest in the world for over 6 years. Meanwhile, the R&D intensity¹ has risen from 0.23% in 1995 to 1.15% in 2012, making China one of the few developing countries with an R&D intensity above 1%.

Observing the simultaneous rise of import value and R&D intensity, one may speculate that imports may enhance R&D intensity. In this paper, we formalize this prediction by showing that importing materials from technologically advanced economies can stimulate indigenous firms' innovative activities through cost-reducing knowledge spillovers. Although a large body of research has shown that imported intermediate goods enhance firms' productivity², the relationship between imports and innovative activities has been studied much less. One exception is the work of Bøler et al. (2015), which shows that R&D and international outsourcing are complementary activities. With less expensive R&D, firms tend to increase R&D investment as well as imports, which ultimately contributes to the reduction of production costs both at the micro and the macro levels. Instead of investigating the complementary relationship between imports and R&D investment, we focus on one direction, that is, on the mechanism through which importing stimulates innovative activities. Specifically, we concentrate on the effect of knowledge spillovers on R&D cost reductions. Using a dataset of Chinese manufacturing firms, we find that imports have a positive impact on innovation.

China's innovation activity has benefited greatly from the open policy that was established in the late 1980s. Foreign direct investment (FDI) has been well documented as a contributor to China's regional innovation capacity and patent surge (Fu, 2008; Hu and Jefferson, 2009). Moreover, importing has spurred Chinese firms' incremental innovation by creating competitive pressure³ (Lu and Ng, 2012). Yet the corresponding papers, which focus on the influence of competitive pressure on innovation, have neglected to consider that firms can innovate at a lower cost by learning from the technology embodied in imported materials from advanced economies.

This study aims to fill a gap in the existing literature by directly linking firms' import behavior with their innovation activity. We first construct a theoretical model to illustrate that imports can stimulate innovation through cost-reducing knowledge spillovers. Our model has three defining characteristics: first, it includes firm heterogeneity as in the Melitz model (Melitz, 2003); second, it incorporates firms' innovative behavior as in Atkeson and Burstein (2010); and third, it considers the decision to import, which enables us to analyze the impact of imports on firms' investment in innovation.

Our model is different from the "trapped factor" model of Bloom et al. (2013). In their model, labor and capital are "trapped" factors in that workers have some firm-specific human capital and capital has firm-specific adjustment costs. When import competition from low-wage countries

¹ R&D intensity is measured by the ratio of R&D expenditure to GDP, which is calculated by using the R&D expenditure of all industrial firms recorded by China's National Bureau of Statistics (NBS).

² Most of these studies focus on developing countries: López and Yadav (2010) on Chilean plants, Goldberg et al. (2008) on India, and Halpern et al. (2015) on Hungarian manufacturing firms.

³ This phenomenon is also found in other countries. Teshima (2008) has found evidence that a reduction of import tariff has increased Mexican firms' R&D investment; Gorodnichenko et al. (2010) have found a positive correlation between trade liberalization and innovation using data from 27 emerging economies.

removes the market for a firm's current products, these trapped factors become useless within the firm. This decreases the shadow value of these factors as inputs into innovation or the production of new goods, which ultimately lowers the opportunity cost of innovation. This leads firms to invest more in research to create new goods. In contrast, we focus on knowledge spillovers incurred by importing materials from foreign countries. In our model, knowledge diffusion increases importing firms' knowledge accumulation and reduces their innovation costs, which in turn enhances their returns on innovation.

To examine the relationship between imports and innovation, we combine the Chinese Manufacturing Firms Database and the China Customs Trade Database from 2000 to 2006. This matched dataset has two features. First, it contains firm-level R&D expenditures⁴, which allows us to use R&D intensity as a measure of innovation⁵. R&D has been suggested to be a more representative indicator of innovation than patents because it measures firms' independent innovation investment. In China, innovative firms are reluctant to apply for patents because the protection of intellectual property rights has been weak (Hu and Jefferson, 2009). This makes patent applications a particularly unsuitable indicator of innovation by Chinese firms. In addition, R&D intensity is consistent with our model's prediction that imports influence innovation intensity rather than innovation volume or outcomes, such as patents. Second, the dataset includes detailed information on firms' importing status, such as the category of each imported product and its source. This information allows us to open the "black box" of an import bundle to analyze the effect of imported intermediates on innovation. Moreover, we can use records of import sources to conduct an in-depth investigation of the underlying mechanism.

To address potential endogeneity problems, we construct instruments for importing and exporting at the firm-year level. Following Hummels et al. (2014), we employ the exchange rate and world export supply as instruments for intermediates imports, and the exchange rate and world import demand as instruments for exports. Because China has experienced a significant tariff reduction after joining the World Trade Organization (WTO) (Lu and Yu, 2015), we also use the import tariff as an instrument for the importing of intermediate inputs.

Our main findings are that (1) importing of intermediates increases the importing firms' R&D intensity and that (2) exporting also tends to increase their R&D intensity. Examining the channels through which importing can affect innovation, we find that importing from high-income sources has a greater positive impact on innovation and that high-tech firms and private firms experience a greater gain in innovation intensity.

This study makes the following contributions to the existing literature. First, it contributes to the literature on trade and technology. A large body of literature has documented the critical role of trade in stimulating technological change, although the mechanism varies from market size and knowledge diffusion, to competition in the product market. However, most existing theories on firms' participation in international trade and innovation that originate from Melitz (2003) emphasize exporting behavior. Existing literature on the influence of imports mostly focuses on

⁴ R&D expenditures refer to the real expenditure of surveyed units on their R&D activities, including the direct expenditure on R&D activities, the indirect expenditure of management and services on R&D activities, the expenditure on capital construction and material processing by others, excluding the expenditure on production activities, and fees transferred to cooperating and entrusted agencies on R&D activities.

⁵ Of course, employing this measurement raises some concerns. [Gorodnichenko et al. \(2010\)](#) have noted that R&D is an input rather than an output of innovation. They argue that R&D may fail to capture the feature of innovation in emerging economies where most firms are engaged in imitation and adaptation.

productivity rather than innovation—the major source of productivity growth⁶. To our knowledge, our paper is one of the few that looks directly at the effect of imports value on innovation intensity from the firm-level perspective. This study, combined with the existing literature on exporting and innovation, provides a more complete picture of the welfare effect of trade liberalization.

Second, we find that knowledge spillovers play an important role in enhancing innovation intensity by distinguishing between high-income sources and low-income sources. Although the relationship between the number of export destinations, firms' characteristics, and resulting trade gains are extensively explored (Eaton et al. 2004; Eaton et al. 2011; De Loecker, 2007; Manova and Zhang, 2012), import sources and their impacts on firms' performance has not been thoroughly investigated. By separating import sources into high-income and low-income groups, we find that importing from high-income sources tends to have a larger marginal effect on innovation investment. The result is robust to alternative classification methods for high-income and low-income countries.

Third, this study is complementary to recent empirical and theoretical studies that have documented how Chinese import competition (or “China Shock”) has induced manufacturing firms' technical changes in the US and EU⁷. Whereas the previous literature has revealed that importing from low-income countries like China has spurred technological upgrades of firms operating in developed economies, we find that importing from high-income sources contributes to knowledge accumulation, as firms are able to study the more advanced technology embedded in foreign materials as well as foreign sellers' organizational and operational ideas. Overall, this helps us refine the picture of a global trading system in which Chinese firms learn from advanced technology through imitation and second-hand innovation, and technology-leading countries preserve the comparative advantage of producing technology-intensive products by shifting resources to create new products.

Finally, our study also provides a method for finding instruments for Chinese firms' decisions on importing and exporting at the firm-year level. A growing body of literature investigates the impact of participation in international trade on Chinese firms' performance. However, the endogeneity of firms' decisions to import and/or export is a common issue in these studies. Our study, which adapts the idea of Hummels et al. (2014) to match China's economic background, provides a feasible approach for constructing instruments for importing and exporting.

The remainder of the paper is structured as follows. Section 2 builds a simple model to illustrate how imports can stimulate innovation through cost-reducing the knowledge spillovers embedded in imported materials. Section 3 briefly describes the data sources and data-processing procedures. In Section 4, we introduce the specifications of our empirical models and the process of constructing instruments. In Section 5, we report the instrumental estimation results, which include a preliminary analysis and further investigation of certain channels. Section 6 provides a series of robustness checks. The last section concludes.

⁶ Halpern et al. (2015) have explored this topic theoretically by considering an import-augmented production function. The pioneering empirical work of Amiti and Konings (2007) has documented the productivity-enhancing effect of imported intermediate inputs. Using detailed firm-level data from India, Goldberg et al. (2008) have found that having access to a wider range of new imported inputs contributes to the expansion of domestic firms' product scope. López and Yadav (2010) have documented the spillover effects caused by imported intermediates for Chilean manufacturing plants.

⁷ See Bloom et al. (2013) for a concise literature review of the related empirical literature.

2. Model

2.1 Demand

Following the classic literature on monopolistic competition (Dixit and Stiglitz, 1977), we assume a representative consumer with a constant elasticity of substitution (CES) utility function over a continuum of horizontally differentiated varieties indexed by i :

$$U = \left(\int_{i \in \Omega} q(i)^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}} \quad (1)$$

where the mass of available varieties belongs to a set Ω . θ is the elasticity of substitution between any pair of goods; we assume $\theta > 1$. Let p_i index the price of variety i , and R be the aggregate expenditure of consumers (R also represents the market size); the demand of variety i is derived as follows:

$$q(p) = \frac{R}{P} \left[\frac{p}{P} \right]^{-\theta} \quad (2)$$

where $P = \left(\int_{i \in \Omega} p(i)^{1-\theta} di \right)^{\frac{1}{1-\theta}}$ is the price index which is dual to (1). Let Q be the consumption index with $Q \equiv U$, then the aggregate expenditure can be written as $R = PQ = \int_{i \in \Omega} r(i) di$, where

$$r = R \left[\frac{p}{P} \right]^{1-\theta} \quad (3)$$

is the spending on variety i .

2.2 Production and Innovation Investment

2.2.1 Production

A continuum of active firms exists, each producing a distinct variety i . The production of final goods requires two factors: labor and intermediates. Labor is supplied domestically, whereas a firm can use domestic and foreign intermediates. Foreign intermediates exhibit increasing return to scale⁸. Let $d^m \in \{0,1\}$ denote the firm's decision to import; d^m is equal to 1 for an importer and 0 otherwise. To import, a firm has to pay a per-period fixed cost f_m . There is also a fixed cost f for production that is common to all firms. Both f and f_m are measured in units of labor. The production technology is given by

$$q = \varphi \left(x_h^{\frac{\rho-1}{\rho}} + d_m x_m^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho\alpha}{\rho-1}} l^{1-\alpha} \quad (4)$$

where φ is the firm's specific productivity, x_h represents the intermediates produced in the home-country, x_m is the imported foreign variety, $\alpha \in (0,1)$ is the share of intermediate inputs in total inputs, and $\rho > 1$ is the elasticity of substitution between foreign and domestic

⁸ This assumption is widely used in endogenous growth models where long-term economic growth stems from an increased variety of intermediates. See Ethier (1982) and Romer (1987) for example.

intermediates.

A country's intermediates are produced with labor as the only input. Hence $x_h = l_h$, where l_h is the labor used to produce intermediate x_h . The market for intermediate goods is competitive; therefore, the price of domestic intermediate goods is equal to the wage rate ω . We normalize $\omega \equiv 1$ for the sake of simplicity. To use one unit of foreign intermediate inputs, a firm must pay $\tau > 1$ units of labor because of transport cost. Hence under perfect competition, the price of imported intermediates is τ .

2.2.2 Innovation investment

Following Atkeson and Burstein (2010), we assume that all firms have access to step-by-step innovation technology. One successful innovation increases the firm's productivity from φ to $\chi\varphi$, where $\chi > 1$ is a constant. Each firm has to choose the probability of success, which is denoted as $\mu \in (0,1)$. μ can also be interpreted as the innovation intensity. The cost of innovation is a function of innovation intensity and of the value of imported intermediates, which is specified as follows:

$$n(\mu, x_m) = h(\mu) g(x_m) \quad (5)$$

where $h'(\cdot) \geq 0$ and $h''(\cdot) < 0$ for all firms⁹. We also assume that $h(0) = 0$, and that $\lim_{\mu \rightarrow 1} h'(\mu) = \infty$. Under this assumption, no firm will choose the probability of success to be 1. $g' < 0$ and $g'' \leq 0$; $g(\cdot)$ is a decreasing function so that imports generate a positive externality that reduces the cost of innovation. For expositional purposes, we assume $g(x_m) = 1 - \beta x_m$, where β can be understood as a parameter of the firm's ability to absorb knowledge from the importing source; a larger β implies a more significant impact of imports on reducing the cost of innovation. β is a random variable with a distribution with support $[\underline{\beta}, \bar{\beta}]$; the distribution is time invariant, independent across periods, and common to all firms. The current value of β is realized at the beginning of this period. After the realization of β , firms make the decision to import. We also assume $x_m \in (0, 1/\beta)$ to guarantee that the innovation cost is positive.

2.3 Decision to import

To better understand the impact of imports on innovation investment, we first need to consider the decision to import. Let $v(\varphi, \beta)$ be the value of incumbent firms, $v_a(\varphi, \beta)$ be the firm value if no imports occur, and $v_m(\varphi, \beta)$ be the firm value when a firm decides to import. It follows that

$$v(\varphi, \beta) = \max_{d_m \in \{0,1\}} \{v_a(\varphi), v_m(\varphi, \beta)\} \quad (6)$$

Define the one-period profit functions as follows:

⁹ For example, $h(\mu) = \eta_1 \mu + \eta_2 \mu^2$, where $\eta_1 > 0$ and $\eta_2 > 0$.

$$\begin{aligned}\Pi_a(\varphi) &= \max_{\{x_h, l, p\}} \{pq(p) - x_h - l - f\}, \\ \Pi_m(\varphi) &= \max_{\{x_h, x_m, l, p\}} \{pq(p) - x_h - \tau_\mu x_m - l - f - f_m\}\end{aligned}$$

where $\tau_\mu \equiv \tau - \beta h(\mu)$ is the adjusted price of importing foreign intermediates for the positive externality caused by knowledge spillovers. We assume that $\tau_\mu \in [\underline{\tau}, \tau]$, and that $\underline{\tau}$ is large enough to guarantee that the problem has meaningful bounded solutions. Combining (2) to solve the standard profit maximization problem yields the following:

$$\Pi_a(\varphi) = \Delta \varphi^{\theta-1} - f, \quad (7)$$

$$\Pi_m(\varphi, \mu, \beta) = \Delta (1 + \tau_\mu^{1-\rho})^{\frac{(\theta-1)\alpha}{\rho-1}} - f - f_m \quad (8)$$

where $\Delta \equiv \frac{R}{\theta} \left[\frac{\theta-1}{\theta} \alpha^\alpha (1-\alpha) P \right]^{\theta-1}$ is a constant that is exogenous to the firm's decisions to produce and import. Note that the linear assumption for knowledge spillovers yields a simple expression for the profit function when importing. The positive externality from importing reduces the importing cost from τ to τ_μ . Moreover, the optimal importing value (if the firm imports) can be expressed as

$$x_m(\varphi, \mu, \beta) = \Delta_m (1 + \tau_\mu^{1-\rho})^{\frac{(\theta-1)\alpha}{\rho-1}+1} \tau_\mu^{-\rho} \varphi^{\theta-1} \quad (9)$$

where $\Delta_m \equiv \alpha(\theta-1)\Delta$. Then we can express $v_a(\varphi)$ and $v_m(\varphi, \beta)$ as

$$v_a(\varphi) = \max_\mu \{ \Pi_a(\varphi) - h(\mu) + \delta E_{\beta'} [\mu v(x\varphi, \beta') + (1-\mu)v(\varphi, \beta')] \} \quad (10)$$

$$v_m(\varphi, \beta) = \max_\mu \{ \Pi_m(\varphi, \mu, \beta) - h(\mu) + \delta E_{\beta'} [\mu v(x\varphi, \beta') + (1-\mu)v(\varphi, \beta')] \} \quad (11)$$

where β' is the parameter delineating the firm's ability to absorb knowledge from importing in the subsequent period.

The firm chooses to import if and only if $v_m(\varphi, \beta) > v_a(\varphi)$. In our formulation, the decision to import depends on two factors: the first factor is the productivity, which affects the profit in current period; the second is the knowledge spillover effect: with larger β , the firm can enjoy more knowledge spillovers that potentially reduce the innovation cost, which stimulates innovation in the current period and increases expected firm value in the future. However, if we want to obtain a precise cut-off rule for the decision to import, we need further assumptions on the marginal return of innovation, $E_{\beta'} [v(x\varphi, \beta') - \beta v(\varphi, \beta')]$. For example, if we assume

$E_{\beta'} [v(x\varphi, \beta') - \beta v(\varphi, \beta')]$ is non-decreasing in φ , there exists a cut-off productivity level φ^*

above which firms choose to import. For the purpose of our paper, we do not go into much details about this, and simply keep in mind that both φ and β affect the firm's decision to import.

2.4 Equilibrium innovation investment

2.4.1 Equilibrium innovation investment for non-importers

When no importing occurs, the first-order condition of (10) with respect to μ gives

$$h'(\mu_a) = \delta E_{\beta'} [v(\chi\varphi, \beta') - v(\varphi, \beta')] \quad (12)$$

which determines the equilibrium innovation investment, μ_a , for non-importing firms. The right-hand side of the above equation is the expected marginal return of innovation, which is determined by the discount rate and the expected increase in firm value induced by step-by-step innovation. Equation (12) indicates that the marginal cost of innovation is equal to its marginal benefit.

2.4.2 Equilibrium innovation investment for importers

Based on the analysis in Subsection 2.3, firms choose to import if φ is large enough. Using (11), the first-order condition with respect to μ is

$$h'(\mu_m) = \delta E_{\beta'} [v(\chi\varphi, \beta') - v(\varphi, \beta')] + \frac{\partial \Pi_m(\varphi, \mu_m, \beta)}{\partial \mu}, \quad (13)$$

where μ_m represents the equilibrium innovation investment. Equation (13) also equates the marginal cost to the marginal benefit of innovation. The right-hand side can be regarded as the marginal return of innovation for importers. Apart from the expected increase in firm value,

another term, $\frac{\partial \Pi_m(\varphi, \mu_m, \beta)}{\partial \mu}$, is the marginal effect of innovation on current profit. Under

the specific linear assumption for the cost-reducing effect of importing, importing reduces the innovation cost in a way similar to reducing the price of imported intermediates¹⁰. From equation

(9), we can write x_m^* as $x_m^* = x(\varphi, \mu_m, \beta)$.

From the discussion above, we can see that productivity plays a very important role in understanding the relationship between imports and innovation. First, it affects the decision to import, which has an impact on the decision to innovate. Second, it also affects the expected revenue generated by innovation. In particular, the marginal return on innovation has two parts:

$\delta E_{\beta'} [v(\chi\varphi) - v(\varphi)]$ and $\frac{\partial \Pi_m(\varphi, \mu_m, \beta)}{\partial \mu}$; both depend on φ ¹¹.

2.4.3 The impact of imports on innovation intensity

¹⁰ This result would not change if we abandoned the assumption of linear representation for the knowledge spillover effect.

¹¹ In our setting, $v(\chi\varphi) - v(\varphi)$ cannot be a constant except when there is no innovation input.

We are now ready to analyze the relationship between import value and innovation intensity. In our model, a firm has to make decisions on both imports and innovation investment; they are determined simultaneously in equilibrium. On one hand, a firm chooses to import if the expected positive externality from foreign materials is large enough so that innovation can trigger a large increase in current and future profits. On the other hand, a firm chooses to increase its investment in innovation if the import value is large enough to generate sufficient positive externality so that increasing the innovation investment is profitable. To understand the influence of imports on innovation, we examine the exogenous changes that directly affect importing, but not R&D investment. For this purpose, we evaluate the consequence of a decrease in τ , given φ and β are fixed. The following proposition summarizes the result.

Proposition 1. *For importers, given φ and β , importing intermediates stimulates innovation: an exogenous decrease in τ increases the import value, which in turn increases R&D intensity.*

Proof. First, from (8) we can show that

$$\frac{\partial \Pi_m(\mu, \varphi, \beta)}{\partial \mu} = \Delta \alpha (\theta - 1) \beta h'(\mu) \left(1 + \tau_\mu^{1-\rho}\right)^{\frac{(\theta-1)\alpha}{\rho-1}} \tau_\mu^\rho \varphi^{\theta-1},$$

Consider two different importing costs τ_1 and τ_2 , where $\tau_1 > \tau_2$. When reducing τ_1 to τ_2 , we know from (9) that the firm will increase x_m if the innovation intensity is fixed at the original level, which implies $\tau_{\mu_1} > \tau_{\mu_2}$. Then, the marginal effect of innovation on current profits will increase, as $\frac{\partial \Pi_m(\mu, \varphi, \beta)}{\partial \mu}$ is decreasing in τ_μ . This increase will cause the marginal cost of innovation to be smaller than the marginal benefit of innovation. Therefore, the firm will increase the innovation investment to maximize its firm value. Hence $\mu_{m1} < \mu_{m2}$.

□

Note that our prediction for the impact of import value on innovation depends on the condition that φ and β are fixed. Different import values are caused by different importing costs (τ). If we were to compare the innovation investment across firms with different productivity levels, we would need to make additional assumptions because our model shows productivity affects both the decision to import and the perceived marginal return of innovation. This observation is critical to conducting our empirical analysis. To detect the impact of imports on innovation, we have to address the following: first, the reverse causality between imports and innovation and, second, the endogeneity of productivity. We will discuss in greater detail the approach that we use to tackle these two issues.

3. Data Description

This study uses two main sources of firm-level data. The first database is the Chinese Manufacturing Firms Dataset (CMFD), which is compiled by China's National Bureau of Statistics (NBS) and covers 2000 to 2006. This dataset includes both State Owned Enterprises (SOEs) and non-SOEs with annual sales no less than five million *Renminbi* (equivalent to approximately 700,000 US dollars). These firms account for 98% of export manufacturing. The NBS of China requires firms to provide details of their operations and financial statistics, such as firm sales, export value, employment, and total assets. In total, the dataset includes more than 100 financial variables listed in the major accounting sheets of all these firms. Most importantly, it contains information on each firm's annual R&D expenditures that, combined with data on annual sales and total assets, can be used to construct R&D intensity as a proxy for innovation intensity.

Although the CMFD contains rich firm-level information, it does not include detailed information on firms' participation in international trade. This leads us to employ the China Customs Trade Data (CCTD), which are collected by China's General Administration of Customs. This dataset contains detailed information on all the monthly merchandise transactions that passed through China customs between 2000 and 2006. The information includes firm identifiers, eight-digit HS product codes, the relevant customs regime (ordinary trade, processing trade, or other forms of trade), transaction quantities, values, import sources and export destinations, and modes of transportation. We add this monthly data to the yearly data for every recorded firm.

To merge these two datasets, we synthesize existing procedures to improve matching efficiency. The detailed data-processing procedures are presented in the data appendix. The final CMFD used in our investigation contains 589,853 firms with 1,082,985 observations from 2000 to 2006. The final number of matched observations is 109,148. Compared to the matching results of Wang and Yu (2012), who use the same data source from 2002 to 2006, our matching procedure has a higher efficiency in terms of the import and export value of the matched sample. In their results, the share of export (import) value of the matched firms in the CCTD dataset is 47.0% (37.6%), whereas ours is 58.1% (51.6%). The matched sample gives us firm-level information on imports and exports, which allows us to identify a firm's trading status.

Throughout our discussion, we focus on manufacturing firms with two-digit industry codes ranging from 13 to 43. The code-industry correspondence table is presented in the data appendix. We exclude processing firms from our estimation sample because processing firms that import tariff-free inputs for manufacturing face more serious financial constraints (Manova and Yu, 2012), and are unwilling to innovate. Including processing firms in our regression would have caused biased estimations of the impact of imports on innovation. Nonetheless, as a robustness check, we use different standards to classify processing firms. Section 6 presents the estimation results in detail.

4. Model specification and identification

4.1 Model specification

To test the prediction of our model, we estimate following econometric model:

$$RD_{i,j,k,o,t} = \alpha IMP_{i,j,k,o,t} + \beta EXP_{i,j,k,o,t} + \gamma TFP_{i,j,k,o,-1} + X'_{i,j,k,o,t} \theta + \lambda_j + \lambda_k + \lambda_o + \lambda_t + \varepsilon_{i,j,k,o,t} \quad (14)$$

where $RD_{i,j,k,o,t}$ is the R&D intensity for firm i in three-digit industry j , province k , ownership structure o , and year t ; $IMP_{i,j,k,o,t}$ is the firm import intensity, $EXP_{i,j,k,o,t}$ is the firm export intensity. Although our theoretical model does not explicitly include the decision to export, discerning the impact of exports is not difficult in our analysis. Specifically, exporting increases profits when the productivity is high enough. In turn, this rise in profits increases the expected marginal benefit of innovation, which makes the firm more innovative. Throughout our estimation, we use two scaling approaches to measure all the intensity variables: (1) using sales as the scaling variable and denoting the related intensity variables with the superscript a ; that is, RD^a , IMP^a and EXP^a ; and (2) using total fixed assets as the scaling variable, and denoting the related intensity variables by superscript b , i.e., RD^b , IMP^b and EXP^b . Using these two categories of variables is a robustness check. To address the potential endogeneity problem caused by missing variables, we also include a firm's pre-sample productivity, denoted as $TFP_{i,j,k,o,-1}$. This acts as a control for firm-level heterogeneity¹². $X'_{i,j,k,o,t}$ is a vector of various firm characteristics including firm age, the logarithm of the number of employees, the logarithm of capital intensity, firm leverage, and firm collateral; λ_j is the three-digit industry fixed effect, capturing all the time-invariant industrial effects; λ_k is the province fixed effect, controlling for all time-invariant province characteristics including provincial policy differences and geographical features; λ_o is the ownership structure fixed effect, capturing all the time-invariant ownership structure characteristics; λ_t is the time effect, capturing all common yearly shocks, such as macroeconomic shocks; and finally, $\varepsilon_{i,j,k,o,t}$ is the error term. To address possible heteroskedasticity and serial correlation, we use heteroscedasticity-robust standard errors clustered at the city level¹³.

As we have observed from our dataset, the distribution of R&D intensity accumulates near zero (see Figure 1). The truncation feature of the R&D observations may cause bias in our estimations if we use the ordinary least squares estimator. To address this concern, we use the Tobit model to conduct the truncated regression on $RD > 0$.

Figure 1 here

Another important concern is the endogeneity of decisions to import and export. Identifying the effect of imports and exports on innovation requires that, conditional on all controls, $IMP_{i,j,k,o,t}$ and $EXP_{i,j,k,o,t}$ are not correlated with $\varepsilon_{i,j,k,o,t}$. However, this condition is likely to be violated because importing and exporting are related to firm-level characteristics. Moreover, according to our model, a simultaneity problem exists because importing is also affected by R&D investment. This requires us to isolate the changes in imports that are not caused by variations in R&D investment. To this end, we construct instruments that are correlated with a firm's imports and exports but are not (1) correlated with the error term once we control for firm-level characteristics or (2) affected by R&D investment.

4.2 Instruments construction

¹² Specifically, we employ the approach proposed by Olley and Pakes (1996) to estimate firm-level productivity. Similar to Brandt et al. (2012), we estimate coefficients of capital and labor for each manufacturing industry. Then we calculate productivity for each firm.

¹³ We also attempt to cluster the standard errors at the provincial level or at the industry-year level; all our results are robust to these changes.

This section discusses instrument construction. Our goal is to construct instruments that are only correlated with imports and exports at the firm-year level but that are not correlated with innovative activities. Following Hummels et al. (2014) and considering the trade liberalization after China's accession to the WTO in 2002, we employ import tariffs, exchange rates, and world export supply as the instruments for imports of intermediate inputs. We use the exchange rate and world import demand as the instruments for exports¹⁴.

4.2.1 Variables construction

A. Import tariff Import tariffs have been used as an instrument for import shocks or demand shocks or trade liberalization in a large body of literature on international trade, especially for developing countries that have experienced an episode of trade liberalization (Pavcnik, 2002; Bustos, 2011; Topalova and Khandelwal, 2011). In the case of China, import tariffs have sharply decreased since its accession to the WTO. As discussed in Lu and Yu (2015), the tariff reduction can be regarded as exogenous for the following reasons. First, the accession process is lengthy and the results were quite uncertain before 2001; Chinese firms had no opportunity to adjust their imports and innovation investment until the enactment of a real tariff reduction in 2002. Second, the tariff reduction on all products must follow the WTO agreement. Therefore, the tariff reduction affects all industries. As supporting evidence, in our data we find that industries under more protection have received greater tariff reductions since the WTO accession. In addition, China was not a recipient of the most-favored-nation (MFN) treatment prior to its accession to the WTO; joining the WTO has unpredictable consequences for firms. Even after its accession to the WTO, China still faced non-tariff barriers: a typical case is Multi-Fiber Arrangement (MFA) quotas on Chinese textile exports, which were not removed until January 2005 (Upward and Wang, 2016). According to our merged dataset, the weighted average value of tariffs declined from 6.90% in 2001 to 2.77% in 2006 for all importers, and from 6.30% in 2001 to 2.60% in 2006 for non-processing importers. The exogenous decrease in tariffs, which is correlated to importing and/or exporting activities, makes the weighted average tariff a plausible instrument for imports and/or exports. Specifically, we construct the variable for the import tariff at the firm-product-year level, $tariff_{c,p,t}$ for product p from country c at year t .

B. WES and WID Following Hummels et al. (2014), we define the world export supply (WES), $WES_{c,p,t}$, as country c 's total supply of product p to the global market, minus its supply to China in year t . We construct this variable using BACI world bilateral trade data at HS six-digit product level¹⁵. $WES_{c,p,t}$ captures variations in comparative advantage that arise from changes in product price, product quality, or variety for the exporting country. Similarly, world import demand (WID), $WID_{c,p,t}$, is country c 's total purchases of product p from the world market, minus its imports from China at year t . According to this construction, an increase in $WID_{c,p,t}$ can be caused by shocks to demand or a weakening of the comparative advantage in terms of product p in country c . The

¹⁴ Due to having limited access to the transport cost used in Hummels et al. (2014), we are only able to construct instruments for import and export costs, which rely on the ratio of export F.O.B. price to import C.I.F. price that is obtained from the CEPII Trade Unit Values database. However, the instruments for trade cost are not always significant in the first-stage regression, perhaps because of the rapid growth of imports and exports during the sample period. Trade liberalization explains the volatility of imports and exports better than transport costs.

¹⁵ BACI is the World trade database developed by the CEPII at a high level of product disaggregation; details of this database can be found at http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=1.

summary statistics suggests a notable increase in the averages of *WES* and *WID* over the sample period.

C. Exchange rate China has experienced a regime reform of its exchange rate from “fixed peg arrangement” to “managed floating”. During our sample period, the most significant reform occurred when the regime of managed floating was promoted in 2005. In the period from 2001 to 2006, we can find significant exchange rate volatility. Other than the direct effect of exchange rate reforms, the recent literature has elucidated the third-country effect on bilateral exchange rate (Berg and Mark, 2015). Before 2005 the *Renminbi* (Chinese currency) had been pegged to the US dollar, which implies a change in the bilateral exchange rate between the US dollar and a third currency could still cause the floating of the bilateral exchange rate between *Renminbi* and that specific currency. As shown in Figure 2, the bilateral exchange rates between the US dollar and AUD, CAD, CHF, EUR, and GBP have undergone mild depreciation after a period of appreciation. By contrast, the exchange rate between USD and JPY fluctuated considerably during 1999-2007. Hence, we still consider the exchange rate as an important factor that affects a firm’s decision to import.

Figure 2 Here

The weighted average of real exchange rate is calculated as follows. We first use the yearly average nominal exchange rate from the World Development Indicators Database, and transform all the exchange rates in terms of US dollars. For each country c in year t , we define the exchange rate between China and country c as the exchange rate between currency c and US dollars divided by the bilateral exchange rate between the *Renminbi* and the US dollar. Let $EX_{c,t}$ be the exchange rate between the currency of country c and the *Renminbi*, $EX_{c,t}^{IMP}$ be the exchange rate for importing countries, and $EX_{c,t}^{EXP}$ be the exchange rate for exporting countries. Different currencies have distinct units; for the sake of comparison, we employ the average of $EX_{c,t}$ from 2000 to 2006 to normalize currency c . The calculated average normalized exchange rate¹⁶ drops significantly from 1.03 to 0.71 and from 1.05 to 0.74 for the merged sample and the estimation sample, respectively. The evolution of the calculated exchange rate displays a similar pattern.

4.2.2 Weight selection and aggregation

For the variables mentioned above, *tariff*, *WES* and *WID* are at the country-product-year level, exchange rates are at the country-year level, so we need to aggregate them into the firm-year level. For illustrative purposes, we define

$$I_{i,t}^{IMP} \in \{tariff_{i,t}, WES_{i,t}, EX_{i,t}^{IMP}\}$$

as the desired firm-year level instrument for firm i in year t , and we let

$$I_{c,p,t}^{IMP} \in \{tariff_{c,p,t}, WES_{c,p,t}, EX_{c,p,t}^{IMP}\}$$

be the corresponding sub-level variables constructed in the previous subsection for a transaction record of firm i importing from country c and selling product p (in HS 6-digit) in year t . In

¹⁶ The exchange rate (EX_{ct}) is the annual average exchange rate, denoted in foreign currency c per *Renminbi*. Hence an increase in EX_{ct} is an appreciation of the *Renminbi* against currency c . To aggregate all source countries, we normalize EX_{ct} by its over-time mean value, thereby removing unit differences.

particular, we define $s_{i,c,p}^{IMP}$ as the share of the c - p pair in total imported intermediates for firm i in the pre-sample year. Following Hummels et al. (2014), we set the year 2000 as the pre-sample year. First, we choose 2000 because we have no earlier information on detailed international trade transactions for firms. In addition, the pre-sample weight, which is fixed across the entire sample, can eliminate the potential endogeneity problem caused by firms' self-selection into the importing market. Specifically, let C_i and P_i be the set of source countries for firm i and the set of all varieties in the pre-sample year, respectively. We define the instrument for importing activities for firm i at year t as follows:

$$I_{i,t}^{IMP} = \begin{cases} \sum_{c \in C_i} \sum_{p \in P_i} s_{i,c,p}^{IMP} I_{c,p,t}^{IMP} & \text{if } I_{c,p,t}^{IMP} \in \{tariff_{c,p,t}, WES_{c,p,t}\} \\ \sum_{c \in C_i} s_{i,p}^{IMP} I_{c,p,t}^{IMP} & \text{if } I_{c,p,t}^{IMP} = EX_{c,t}^{IMP} \end{cases} \quad (15)$$

where $s_{i,p}^{IMP} = \sum_{p \in P_i} s_{i,c,p}^{IMP}$. Similarly, we can define the instruments for exporting activities as follows:

$$I_{i,t}^{EXP} = \begin{cases} \sum_{c \in C_i} \sum_{p \in P_i} s_{i,c,p}^{EXP} I_{c,p,t}^{EXP} & \text{if } I_{c,p,t}^{EXP} = WID_{c,p,t} \\ \sum_{c \in C_i} s_{i,p}^{EXP} I_{c,p,t}^{EXP} & \text{if } I_{c,p,t}^{EXP} = EX_{c,t}^{EXP} \end{cases} \quad (16)$$

where $s_{i,p}^{EXP} = \sum_{p \in P_i} s_{i,c,p}^{EXP}$. Finally, we use the weighted tariff rate, weighted exchange rate, and the weighted averages of world export supply as instruments for imports. We employ the weighted exchange rate and weighted averages of world export demand for exports.

5. Estimation results

5.1 Preliminary analyses: the effect of import on innovation

Our empirical strategy is to find firm-year level instruments for imports and exports so that we can relate changes in firms' innovation investment to exogenous parts of changes in importing and exporting activities after we control for time-invariant fixed effects and time-varying firm-level characteristics. This identification strategy allows us to estimate the response of firm-level innovation to exogenous changes in importing and exporting activities.

In model (14), imports and exports are endogenous variables. As suggested by Wooldridge (2010), we include the full set of instruments in all of the first-stage regressions. To ensure the robustness of our estimation, first we run the first-stage regressions both with and without firm controls for all the regressions; second, we use two measures of import intensity and export intensity, that is, the ratio of the import (export) value to the sales value and/or total assets. We report the first-stage estimation results in Table 1A, with all standard errors clustered at the city level. In the columns of Group A, we present the regression results for imports and exports scaled by sales; Group B contains the results for imports and exports scaled by total assets. The sign and significance of the coefficients for the two groups are quite similar. Focusing on Group 1, changes in tariffs, import exchange rates, and world export supply have the predicted signs for import intensity; as expected, changes in world import demand are positively related to export intensity.

Interestingly, in both groups, we find that the export exchange rate is positively related to export intensity. Note that the change in the export value includes fluctuations in both price and quantity. An exogenous appreciation in the exchange rate increases the export price and decreases the export quantity. Our regression results show that the price effect dominates the quantity effect in the case of China.

Table 1A here

Table 1B here

In the second stage, we use the predicted imports and exports as independent variables and relate them to the innovation intensity. We first run the second-stage regressions using the least-square estimator. Given the censoring feature of our data set, the least-square estimator is neither unbiased nor consistent. We therefore also estimate the equation using the Tobit model, which takes the censoring feature of innovation intensity into consideration and consistently estimates the slope. For all regressions, we cluster the standard errors at the city level. The results are reported in Table 1B. We find that the exogenous increase in imports increases the firm's R&D intensity, which is consistent with our prediction in proposition 1. In Group 1, columns (1) and (2) show that the coefficient of predicted imports is significant at the 1% significance level whether we control for additional firm-level variables or not. However, the results are not robust once we scale the variables using fixed asset and add additional firm-level control variables (see column (6)).

The results displayed in columns (3)-(4) and (7)-(8) show a positive relationship between import and innovation intensity, suggesting that imports stimulate innovation investment. Since the dependent variable of our empirical model is left-censored, the estimation results of two-stage least squares (2SLS) may have downward bias. Compared with the results of 2SLS, the estimation results of the Tobit model have larger coefficients for the predicted import intensity and export intensity, indicating a higher economic significance level. As we note, a large share of Chinese firms does not participate in innovation activities: the averages of RD^a and RD^b for all non-processing importers are .00094 and .0046, respectively. For the entire sample, the averages of RD^a and RD^b are .00062 and .0031, respectively. By contrast, the estimated coefficient of predicted intermediate imports in column (4) is .0027, which is almost 3 times the mean R&D intensity for all the non-processing importers and over 4 times the mean R&D intensity of the entire sample, thereby revealing strong economic significance. When we scale R&D using the total fixed assets, the interested coefficients still indicate sizable effects of intermediate imports on R&D intensity. In addition, columns (4) and (8) show that exports also increase innovation investment, even when we include productivity and additional firm-level controls in our regressions.

To fully understand the impacts of imports on innovation, we also use the R&D dummy (RDD) as the measure of a firm's innovation activities. The estimation strategy is similar to that of the previous section, except that now the second-stage regression is implemented using the Probit model. Table 2 reports the estimation results. We find that for both groups, the coefficients are not significantly positive at the 10% significance level whether or not we include the firm-level controls. In conclusion, no robust evidence supports a significant positive relationship between

participation in importing activities and the probability of participating in innovation activities. In other words, at the extensive margin, no supporting evidence shows that importing activities stimulate innovation in our dataset. As such, in what follows, we focus on discussing the results on R&D intensity.

Table 2 here

5.2 Discussion on the mechanism

In the previous subsection, we reported the estimation results for two-stage instrumental regressions, showing that the exogenous positive shocks of imports lead to an increase in a firm's innovation intensity. In this subsection, we take our work a step further, investigating the possible channels through which imports might affect innovation. In a nutshell, our discussion is based on the parameter β . As we have mentioned in the theoretical model section, β can represent either the knowledge stock or the absorbing ability. Larger knowledge stock and/or higher absorbing ability can cause β to increase.

5.2.1 Knowledge stock of import sources

Firms have different import sources; each import source has its own technological development level and knowledge stock (a). We expect that firms that have larger shares of imports from high-income countries benefit more from knowledge spillovers, which leads to higher innovation intensity. To test this hypothesis, we estimate the following model:

$$RD_{i,j,k,o,t} = \alpha_0 IMP_{i,j,k,o,t} + \alpha_1 IMP_{i,j,k,o,t} \times High + \beta_0 EXP_{i,j,k,o,t} + \beta_1 EXP_{i,j,k,o,t} \times High + \gamma TFP_{i,j,k,o,-1} + X'_{i,j,k,o,t} \theta + \lambda_j + \lambda_k + \lambda_o + \lambda_t + \varepsilon_{i,j,k,o,t} \quad (17)$$

where *High* is a dummy variable that equals 1 if the import source country is categorized as high-income and 0 otherwise. We employ two approaches to classify the import source countries: (1) we treat all OECD countries as high-income sources and define *High*=1 if the share of imported intermediates from OECD countries is equal to 1, and (2) we add non-OECD high-income countries according to the standards of World Bank and define *High*=1 if the share of imported intermediates from high-income countries is equal to 1.

Table 3 here

In equation (17), we have four endogenous variables: *IMP*, *IMP* × *High*, *EXP*, and *EXP* × *High*. Similar to our identification strategy in the previous section, here we include a full set of instruments for these variables in the first-stage regression. In the second-stage regression, we use the predicted values for them to estimate the equation using the Tobit model. We include pre-sample productivity and additional firm-level controls, and we control for fixed effects and time effects for all the regressions, clustering standard errors at the city level. To save space, we only report the results of the second-stage regressions in Table 3. We note that the interaction term, *IMP* × *High*, is significantly (both economically and statistically) positive for different classifications of high-income sources and different scaling methods. Examining solely the regressions using sales as the scaling variable and classifying only OECD countries as the high-income sources (column (1)), ceteris paribus, a one-unit increase in the import intensity from

high-income source countries increases the innovation intensity .0082 units more than that from non-high-income source countries, which is over 8 times the size of the coefficient for solely importing from non-high-income importing sources. The results show that knowledge spillovers from high-income sources play a more important role in encouraging innovation activities.

5.2.2 Ability to absorb knowledge

A. High-tech firms against low-tech firms How knowledge spillovers affect the impact of imports on innovation is determined not only by the importing sources but also by the firm's absorbing ability. By importing, firms have access to new materials and new designs. However, learning from these imports requires such firms to be innovative or at least potentially innovative. Recall that in our model, when $\beta = 0$, the firm ultimately receives no actual knowledge spillovers; when β is larger, the firm can benefit more from knowledge spillovers.

To test the effect of absorbing ability, we divide our sample into high-tech and low-tech groups based on the two-digit classification of industries¹⁷. We follow the identification strategy used in the previous sections and report the results in Table 4. We find that the coefficient of predicted import intensity is greater in the group of high-tech firms than it is for the low-tech firms, with .0065 rather than .0008, and .0069 rather than -.0010. However, no such pattern is found for the coefficients of predicted export intensity. Interestingly, we find that the positive effect of exports on innovation is more significant for low-tech firms, which may imply that exporting to low-income countries generates higher profit mark-ups for firms.

Table 4 here

B. Ownership structure China has an industry structure in which private firms are more productive and more innovative. Song et al. (2011) document the surge in private firms as the major driving force behind China's economic growth. Based on these results, we expect that private firms, which are more innovative, will experience a greater innovation-enhancing effect from importing. To test this prediction, we divide our sample into private firms and non-private firms (including SOEs and foreign firms) and estimate equation (14) for each.

Table 5 here

Table 5 reports the results for the second-stage regressions. It shows that the importing activities of private firms have a positive effect on R&D intensity, but the coefficients for non-private firms are negative and insignificant. The coefficients of predicted export intensity remain positive and significant in all private firms, which may indicate that exports also play an important role in stimulating the innovation investment by private firms.

6. Robustness Checks

In this section, we consider possible alternative strategies for performing a series of robustness checks for our analyses. For the sake of brevity, we only report the second-stage regression results

¹⁷ The details of classification are explained in the appendix.

of instrumental variables estimations¹⁸. All the second-stage estimations are implemented using the Tobit model.

6.1 Sample Selection

6.1.1 Deletion of processing trade

In previous analyses, we excluded all the processing firms from our sample because most of processing firms do not innovate at all. According to China customs regulations, processing firms enjoy duty-free imports and exports. Processing firms are usually credit-constrained and occupy low value-added positions in the global value chain (Manova and Yu, 2012). Given this, including processing firms in our analysis would bias our estimators toward zero. The particularity of processing firms motivates us to exclude them from our analysis. Nonetheless, we deem investigating the robustness of our results to the exclusion of processing firms an important task.

We consider various alternative ways of excluding processing firms. In particular, we consider excluding firms whose shares of processing imports are 40%, 60%, 80%, and 100%. We then estimate our benchmark equation (14) for each subsample. Table 6 displays the estimation results. We find that as the chosen sample increases in its percentage of processing imports, the estimated coefficients for imports and exports decrease and become insignificant. This finding convinces us that processing firms receive few actual knowledge spillover effects from importing intermediates. Including processing firms in our analyses would cause the estimators to be biased downward and would produce misleading results.

Table 6 here

6.1.2 Duration of intermediates importing

When selecting our sample, we include firms that do not continuously import intermediates. This approach makes the sample large enough to efficiently perform our analysis. However, firms do display intermittent patterns when importing intermediates. According to our dataset, some firms occasionally enter and exit the importing market. One might suppose that our estimated innovation-enhancing effects are due to firms' behaviors of entry and exit rather than variations in import intensity. To assuage this concern, we repeat our analyses using the sub-sample with almost consecutive intermediates importing activities. In particular, we select the firms that have continuous intermediates importing for over four years during our sample period (2000-2006). Table 7 reports the estimation results from equations (14) and (17) for the sub-sample. The coefficients of predicted imports and the interaction term $IMP \times High$ remain positive and significant, confirming our previous results. In addition, the sizes of the coefficients are very close to the results reported in Table 1B and Table 2.

Table 7 here

¹⁸ All supplementary results are available upon request.

6.2 Alternative instruments set

In previous regressions, we included the exchange rate as an instrument for importing and exporting activities. However, since China's exchange rate is highly regulated, its fluctuation may not properly reflect exogenous changes in importing and exporting activities. Given this concern, we exclude both the import exchange rate and the export exchange rate in our instrument set. We then rerun the regressions in our preliminary analysis and find that our basic results remain robust using the alternative instrument set. Details of the results are displayed in Table AP1 in the appendix.

6.3 Clustering Standard Errors at Different Levels

In our previous analyses, we calculated the standard errors by clustering at the city level. This is because (1) China's cities have substantial heterogeneity due to the large geographical scale of the provinces and (2) local city governments have a certain degree of freedom to make policies in their domains (Liu and Lu, 2015). However, one may still worry about whether our results would remain robust if we clustered our standard errors at other levels. As robustness checks, we calculate the standard errors clustered at the province level and industry-year level, respectively. Our results remain robust to these checks. We present these results in Tables AP2 and AP3 in the appendix.

7. Conclusion

The important effect of international trade on innovation activities has long been a central issue in the literature. The literature has recently focused on the import side of international trade and its impact on innovation. Using a simple theoretical model to illustrate the impact of imports on innovation, we find that imports stimulate firms' innovation through knowledge spillovers, which reduce the cost and/or increase the expected revenue of innovation. We employ a unique combined dataset of Chinese manufacturing firms and use tariff reduction, exchange rate variation, and changes in world supply and demand to construct instruments for potential endogenous variables. This paper documents a positive causal relationship between imports and innovation activities for Chinese firms. The (statistically and economically) positive and significant effect of imports on innovation remains stable after a series of robustness checks.

Our analysis of the underlying mechanism finds that: (1) importing from high-income sources has a greater effect on innovation intensity; (2) high-tech firms enjoy a greater marginal effect from importing on innovation; and, (3) compared with non-private firms, private firms gain more in terms of innovation from importing. Our study suggests that future analyses of the impact of international trade on firm-level activities should pay more attention on the importing side. Apart from exporting, importing also plays a significant role in firms' development.

References

- Amiti, M. and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: evidence from Indonesia. *American Economic Review* 97 (5), 1611–1638.
- Atkeson, A. and A. Burstein (2010). Innovation, firm dynamics, and international trade. *Journal of Political Economy* 118 (3), 433–484.
- Berg, K. A. and N. C. Mark (2015). Third-country effects on the exchange rate. *Journal of International Economics* 96 (2), 227–243.
- Bloom, N., P. M. Romer, S. J. Terry, and J. V. Reenen (2013). A trapped-factors model of innovation. *American Economic Review* 103 (3), 208–213.
- Bøler, E. A., A. Moxnes, and K. H. Ulltveit-Moe (2015). R&D, international sourcing, and the joint impact on firm performance. *American Economic Review* 105 (12), 3704–3739.
- Brandt, L., J. Van Biesebroeck, and Y. Zhang (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics* 97 (2), 339–351.
- Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: evidence on the impact of MERCOSUR on Argentinian firms. *American Economic Review* 101 (1), 304–340.
- De Loecker, J. (2007). Do exports generate higher productivity? Evidence from Slovenia. *Journal of International Economics* 73 (1), 69–98.
- Dixit, A. K. and J. E. Stiglitz (1977). Monopolistic competition and optimum product diversity. *American Economic Review* 67 (3), 297–308.
- Eaton, J., F. Kramarz, and S. Kortum (2004). Dissecting trade: firms, industries, and export destinations. *American Economic Review* 94 (2), 150–154.
- Eaton, J., S. Kortum, and F. Kramarz (2011). An anatomy of international trade: evidence from French firms. *Econometrica* 79 (5), 1453–1498.
- Ethier, W. J. (1982). National and international returns to scale in the modern theory of international trade. *American Economic Review* 72 (3), 389–405.
- Fu, X. (2008). Foreign direct investment, absorptive capacity and regional innovation capabilities: evidence from China. *Oxford Development Studies* 36 (1), 89–110.
- Goldberg, P. K., A. Khandelwal, N. Pavcnik, and P. Topalova (2008). Imported intermediate inputs and domestic product growth: evidence from India. Working Paper 14416, National Bureau of Economic Research.
- Gorodnichenko, Y., J. Svejnar, and K. Terrell (2010). Globalization and innovation in emerging markets. *American Economic Journal: Macroeconomics* 2 (2), 194–226.
- Halpern, L., M. Koren, and A. Szeidl (2015). Imported inputs and productivity. *American Economic Review* 105 (12), 3660–3703.
- Hu, A. G. and G. H. Jefferson (2009). A great wall of patents: what is behind China's recent patent explosion? *Journal of Development Economics* 90 (1), 57–68.
- Hummels, D., R. Jørgensen, J. Munch, and C. Xiang (2014). The wage effects of offshoring: evidence from Danish matched worker-firm data. *American Economic Review* 104 (6), 1597–1629.
- López, R. A. and N. Yadav (2010). Imports of intermediate inputs and spillover effects: evidence from Chilean plants. *The Journal of Development Studies* 46 (8), 1385–1403.
- Liu, Q. and Y. Lu (2015). Firm investment and exporting: evidence from China's value-added tax reform. *Journal of International Economics* 97 (2), 392–403.

- Lu, Y. and L. Yu (2015). Trade liberalization and markup dispersion: evidence from China's WTO accession. *American Economic Journal: Applied Economics* 7 (4), 221–253.
- Lu, Y. and T. Ng (2012). Do imports spur incremental innovation in the South? *China Economic Review* 23 (4), 819–832.
- Manova, K. and Z. Yu (2012). Firms and credit constraints along the global value chain: processing trade in China. Working Paper 18561, National Bureau of Economic Research.
- Manova, K. and Z. Zhang (2012). Export prices across firms and destinations. *Quarterly Journal of Economics* 127 (1), 379–436.
- Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71 (6), 1695–1725.
- Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64 (6), 1263–1297.
- Pavcnik, N. (2002). Trade liberalization, exit, and productivity improvements: evidence from Chilean plants. *Review of Economic Studies* 69 (1), 245–276.
- Romer, P. M. (1987). Growth based on increasing returns due to specialization. *American Economic Review* 77 (2), 56–62.
- Song, Z., K. Storesletten, and F. Zilibotti (2011). Growing like China. *American Economic Review* 101 (1), 196–233.
- Teshima, K. (2008). Import competition and innovation at the plant level: evidence from Mexico. *Unpublished paper, Columbia University*.
- Topalova, P. and A. Khandelwal (2011). Trade liberalization and firm productivity: the case of India. *Review of Economics and Statistics* 93 (3), 995–1009.
- Upward, R. and Z. Wang (2016). Quota restrictions and intra-firm reallocations: evidence from Chinese exports to the US. *Economics Letters* 144, 71–74.
- Wang, Z. and Z. Yu (2012). Trading partners, traded products and firm performances of China's exporter-importers: does processing trade make a difference? *World Economy* 35 (12), 1795–1824.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Figures and Tables

4 Model Specification and Identification

4.1 Model specification

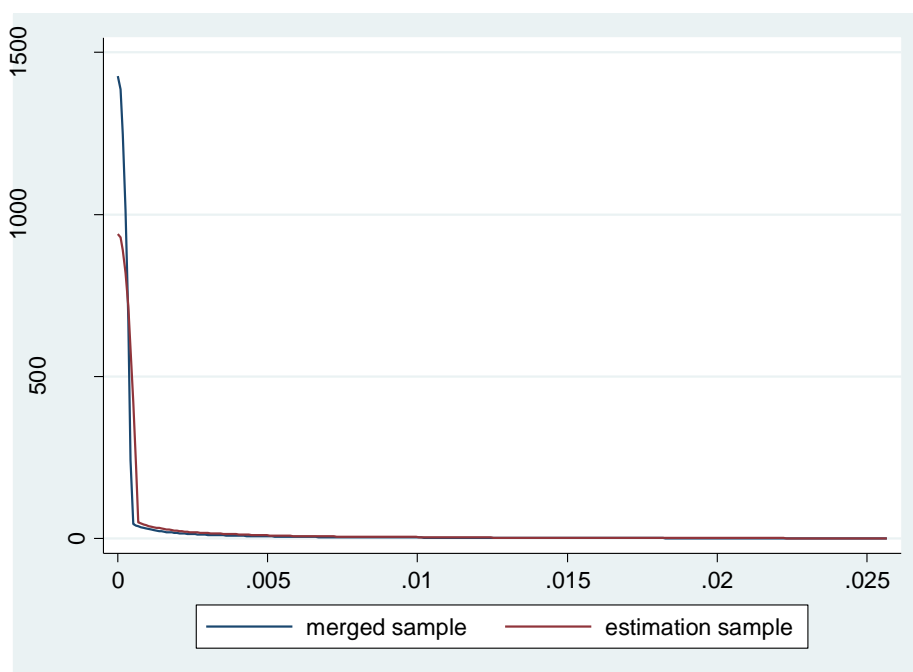


Figure 1 Distribution of R&D density

4.2 Instruments construction

4.2.1 Variables construction

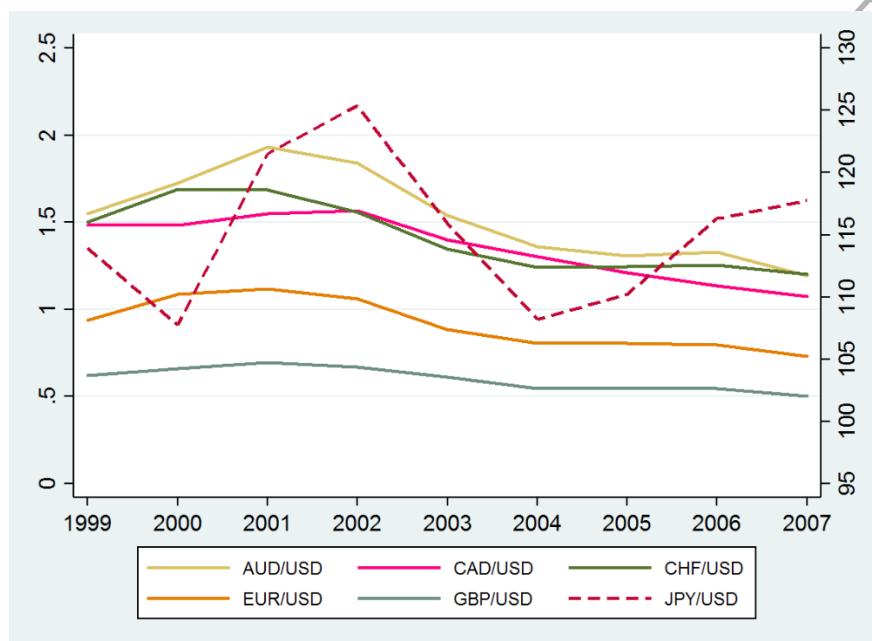


Figure 2 Trends in nominal bilateral exchange rates between US dollars and other currencies

Note: AUD: Australian Dollar ,CAD: Canadian Dollar ,CHF: Swiss Franc ,EUR: European Currency ,GBP :

Great Britain Pound ,JPY: Japanese Yen. The USD-JPY exchange rate is measured along the right vertical axis. Data source: OECD Statistics.

5 Estimation Results

5.1 Preliminary analyses: the effect of importing on innovation

Table 1A First stage of IV regressions

	A. SCALED BY SALE				B. SCALED BY TOTAL ASSET			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IMP^a	EXP^a	IMP^a	EXP^a	IMP^b	EXP^b	IMP^b	EXP^b
$\log(tariff)$	-0.3464*** (-5.83)	0.2188** (2.14)	-0.3572*** (-6.67)	0.0495 (0.43)	-0.2970*** (-4.72)	0.5827*** (3.18)	-0.3310*** (-5.16)	0.1299 (0.78)
$\log(EX^{IMP})$	0.1487*** (27.16)	-0.0537*** (-3.51)	0.1296*** (16.07)	-0.0228 (-1.31)	0.1619*** (20.53)	-0.1058*** (-3.91)	0.1461*** (15.51)	-0.0446 (-1.24)
$\log(WES)$	0.0042*** (3.69)	-0.0110*** (-5.75)	0.0055*** (3.81)	-0.0024 (-0.89)	0.0050*** (5.78)	-0.0079** (-2.00)	0.0060*** (3.68)	0.0054 (1.10)
$\log(EX^{EXP})$	-0.0209** (-2.27)	0.1586*** (9.60)	-0.0171 (-1.50)	0.1711*** (8.47)	-0.0190** (-2.51)	0.1694*** (7.22)	-0.0193* (-1.84)	0.1812*** (6.89)
$\log(WID)$	0.0000 (0.03)	0.0163*** (7.62)	0.0018 (1.51)	0.0160*** (4.58)	0.0013 (1.15)	0.0245*** (6.65)	0.0033** (2.26)	0.0223*** (5.01)
firm-level controls	no	no	yes	yes	no	no	yes	yes
fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
time effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	9,745	9,919	6,300	6,392	9,769	9,957	6,299	6,419
R-squared	0.2936	0.2348	0.3549	0.3121	0.2783	0.1875	0.3500	0.3138
F statistic for Instruments	237.1	134.7	98.85	77.02	170.4	87.32	98.59	45

Notes: IMP^a (EXP^a) represents import (export) intensity as measured by the ratio of imports (exports) value to sales value; IMP^b (EXP^b) represents import (export) intensity as measured by the ratio of imports (exports) value to total assets. Firm-level controls include a firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. The F-test is the test of the validity of the instruments. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively.

Table 1B Second stage of IV regression: import and R&D intensity

VARIABLES	A. SCALED BY SALE				B. SCALED BY TOTAL ASSET			
	2SLS		IV-TOBIT		2SLS		IV-TOBIT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RD^a				RD^b			
IMP^{hat}	0.0018*** (2.64)	0.0027*** (2.66)	0.0053*** (14.88)	0.0027*** (5.66)	0.0014** (2.14)	0.0015 (1.61)	0.0045*** (14.25)	0.0007* (1.72)
EXP^{hat}	0.0001 (0.29)	0.0007 (1.26)	0.0000 (0.02)	0.0027*** (9.48)	0.0003 (0.89)	0.0006* (1.74)	0.0006*** (3.38)	0.0024*** (12.39)
firm-level controls	no	yes	no	yes	no	yes	no	yes
fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
time effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	9,042	5,930	9,042	5,930	9,077	5,959	9,077	5,959
R-squared	0.0803	0.1062	-	-	0.0669	0.0970	-	-
Chi-square statistic	-	-	1155.60	1000.62	-	-	1079.22	943.00

Notes: IMP^a (EXP^a) represents import (export) intensity as measured by the ratio of imports (exports) value to sales value; IMP^b (EXP^b) represents import (export) intensity as measured by the ratio of imports (exports) value to total assets. Firm-level controls include a firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. The F-test is the test of the validity of the instruments. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the test result for the significance of the entire model.

Table 2 Second-stage regressions: import and R&D dummies

Variables	Dependent variable: RDD			
	(1)	(2)	(3)	(4)
	IV^a	IV^b	IV^a	IV^b
IMP^{hat}	0.3973 (1.00)	0.4433 (1.23)	-0.4159 (-0.75)	-0.4445 (-0.90)
EXP^{hat}	-0.0784 (-0.27)	0.0497 (0.22)	0.2078 (0.56)	0.3187 (1.06)
firm-level controls	no	no	yes	yes
fixed effect	yes	yes	yes	yes
time effect	yes	yes	yes	yes
Observations	8,983	8,983	5,834	5,834
LR test	1060.46	1060.52	967.33	968.55

Note: IV^a (IV^b) represents that sales (fixed) assets is used as scaling variable in the first-stage regression, RDD is discrete choice variable for innovation. Firm-level controls include the firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the test result for the significance of the entire model.

5.2 Discussion on the mechanism

5.2.1 Knowledge stock of import sources

Table 3 Import and innovation: channel of import sources

Variables	OECD		HIGH-INCOME	
	(1) RD^a	(2) RD^b	(3) RD^a	(4) RD^b
IMP^{hat}	0.0011** (2.30)	-0.0003 (-0.76)	-0.0018*** (-3.51)	-0.0022*** (-5.12)
$IMP^{hat} \times High$	0.0082*** (14.13)	0.0064*** (11.65)	0.0089*** (17.92)	0.0061*** (13.24)
EXP^{hat}	0.0023*** (8.07)	0.0023*** (11.73)	0.0025*** (8.39)	0.0023*** (10.75)
$EXP^{hat} \times High$	0.0006** (2.19)	0.0002 (0.97)	-0.0010*** (-3.64)	-0.0005** (-2.26)
firm-level controls	yes	yes	yes	yes
fixed effect	yes	yes	yes	yes
time effect	yes	yes	yes	yes
Observations	5,928	5,957	5,928	5,957
Chi-square statistic	1008.28	947.39	1009.34	947.61

Notes: IMP^{hat} (EXP^{hat}) represents predicted import (export) intensity from the first-stage. RD^a (RD^b) represents R&D intensity as measured by the ratio of R&D investment to the sales value (total assets). IMP^a (IMP^b), EXP^a (EXP^b) are used in the first-stage regression for RD^a (RD^b). Firm-level controls include the firm's age, size, capital intensity, leverage, collateral, and pre-sample TF. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the test result for the significance of the entire model.

5.2.2 Ability to absorb knowledge

A. High-tech firms against low-tech firms

Table 4 Absorbing ability: different industries

Variables	RD^a		RD^b	
	HIGH-TECH	LOW-TECH	HIGH-TECH	LOW-TECH
IMP^{hat}	0.0065*** (10.09)	0.0008* (1.66)	0.0069*** (14.25)	-0.0010** (-2.18)
EXP^{hat}	-0.0020*** (-4.47)	0.0029*** (11.07)	0.0004 (1.24)	0.0023*** (12.21)
firm-level control	yes	yes	yes	yes
fixed effect	yes	yes	yes	yes
time effect	yes	yes	yes	yes
Observations	810	5,120	827	5,132
Chi-square statistic	275.62	1461.31	259.84	1380.42
Test on difference	49.37		154.93	

Notes: IMP^{hat} (EXP^{hat}) represents predicted import (export) intensity from the first-stage. RD^a (RD^b) represents R&D intensity as measured by the ratio of R&D investment to the sales value (total assets). IMP^a (IMP^b), EXP^a (EXP^b) are used in the first-stage regression for RD^a (RD^b). Firm-level controls include the firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the test result for the significance of the entire model. Test on difference is the chi-square test on the difference of coefficients of IMP^{hat} between two subgroups.

B. Ownership structure

Table 5 Absorbing ability: different ownership structures

Variables	RD^a		RD^b	
	PRIVATE	NON-PRIVATE	PRIVATE	NON-PRIVATE
IMP^{hat}	0.0230*** (19.84)	-0.0018 (-0.55)	0.0256*** (25.51)	-0.0027 (-0.91)
EXP^{hat}	0.0064*** (11.60)	-0.0008 (-0.34)	0.0034*** (10.22)	0.0001 (0.04)
firm-level control	yes	yes	yes	yes
fixed effect	yes	yes	yes	yes
time effect	yes	yes	yes	yes
Observations	936	5,102	940	5,128
chi-square statistic	416.36	847.34	386.46	821.66
Test on difference	51.20		87.82	

Notes: IMP^{hat} (EXP^{hat}) represents predicted import (export) intensity from the first-stage. RD^a (RD^b) represents R&D intensity as measured by the ratio of R&D investment to the sales value (total assets). IMP^a (IMP^b), EXP^a (EXP^b) are used in the first-stage regression for RD^a (RD^b). Firm-level controls include the firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the test result for the significance of the entire model. Test on difference is the chi-square test on the difference of coefficients of IMP^{hat} between two groups.

6 Robustness Checks

6.1 Sample selection

6.1.1 Deletion of processing trade

Table 6 Robust checks: different standards of classifying processing trade

Variables	RD^a				RD^b			
	40%	60%	80%	100%	40%	60%	80%	100%
IMP^{hat}	0.0033*** (7.08)	0.0022*** (5.18)	-0.0003 (-0.58)	-0.0058 (-0.97)	0.0014*** (3.36)	0.0003 (0.86)	-0.0013*** (-2.93)	-0.0040 (-0.83)
EXP^{hat}	0.0029***	0.0019***	-0.0001	-0.0003	0.0024***	0.0016***	0.0000	0.0001
firm-level controls	yes	yes	yes	yes	yes	yes	yes	yes
fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
time effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5,472	6,487	8,078	34,821	5,502	6,520	8,112	34,835
chi-square statistic	952.27	1060.50	1236.12	2491.33	889.09	997.72	1159.63	2377.91

Notes: IMP^{hat} (EXP^{hat}) represents predicted import (export) intensity from the first-stage. RD^a (RD^b) represents R&D intensity as measured by the ratio of R&D investment to the sales value (total assets). IMP^a (IMP^b), EXP^a (EXP^b) are used in the first-stage regression for RD^a (RD^b). Firm-level controls include the firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the testing result for the significance of the entire model.

6.1.2 Duration of intermediates importing

Table 7 Robustness checks: duration of intermediate importers

VARIABLES	A. LESS THAN 4 YEARS		B. NO LESS THAN 4 YEARS			
	RD^a	RD^b	RD^a	RD^b	RD^a	RD^b
IMP^{hat}	0.0052 (1.00)	-0.0013 (-0.19)	0.0024*** (5.04)	0.0010*** (2.61)	0.0011*** (2.16)	0.0001 (0.17)
$IMP^{hat} \times High$					0.0070*** (11.15)	0.0054*** (9.69)
EXP^{hat}	-0.0030*** (-3.04)	-0.0031*** (-3.22)	0.0010*** (3.36)	0.0011*** (5.80)	0.0008*** (2.69)	0.0012*** (6.20)
$EXP^{hat} \times High$					0.0004 (1.29)	0.0001 (0.33)
firm-level controls	yes	yes	yes	yes	yes	yes
fixed effect	yes	yes	yes	yes	yes	yes
time effect	yes	yes	yes	yes	yes	yes
Observations	255	258	5,416	5,439	5,414	5,437
chi-square statistic	132.16	105.37	946.75	921.31	952.28	924.28

Notes: IMP^{hat} (EXP^{hat}) represents predicted import (export) intensity from the first-stage. RD^a (RD^b) represents R&D intensity as measured by the ratio of R&D investment to the sales value (total assets). IMP^a (IMP^b), EXP^a (EXP^b) are used in the first-stage regression for RD^a (RD^b). Firm-level controls include the firm's age, size, capital intensity, leverage, collateral, and pre-sample TFP. Controls for fixed effects include a full set of 3-digit industry dummies, ownership dummies, and province dummies. The time effect is controlled for by using the year dummies. All standard errors are clustered at the city level; t-statistics are in parentheses. *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively. The Chi-square statistic is the testing result for the significance of the entire model.