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HKIMR Working Paper No.02/2017

February 2017



Hong Kong Institute for Monetary Research

香港金融研究中心

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Effects of Intermediate Input Tariff Reduction on Innovations in China

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Abstract

Innovation plays a key role in economic growth. In this paper, we investigate the effects of intermediate input tariff reduction on the innovation activities of domestic firms. Input tariff reduction has two opposite effects on the innovation decision of a firm: it may promote innovation because the cost of innovation activities decreases, but it may also result in a decrease in innovation because foreign technologies become cheaper. We use Chinese firm-level data from 1998 to 2007, which features a drastic input tariff cut in 2002 because of China's WTO accession, and find that input tariff cut results in less innovation undertaken by Chinese firms. The findings are obtained using the difference-in-differences technique and are robust to various specifications checks of the model. We also provide a theoretical framework to generate insights to the empirical findings.

Keywords: Trade liberalization, Intermediate Input, Innovation, Patent

JEL classification: F13, F15, O14, O31

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Acknowledgment: We benefitted from discussions with Elhanan Helpman, Hong Ma, Marc Melitz, Tommy Wu, Xi Weng, Li-an Zhou and the presentation at The UIBE International Trade Workshop (October 2014) and The Hong Kong Economic Association Conference (December 2014), seminar at Guanghua School of Management, Peking University (March 2015) and Bologna University (April 2015), Summer Workshop of HKIMR (August 2015), The HKU International Trade Workshop (December 2015), The Hitotsubashi-Peking University Workshop on Trade & Development (March 2016). We thank Chaoqun Zhan for his assistance in our research and the referees for their excellent comments and suggestions. Qiu appreciates financial support from HKIMR for visiting scholarship.

The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Hong Kong Monetary Authority, Hong Kong Institute for Monetary Research, its Council of Advisers, or the Board of Directors.

1. Introduction

Innovation and technological progress are key determinants of economic growth. In his 2014 State of the Union Address, U.S. President Barack Obama claimed that "the nation that goes all-in on innovation today will own the global economy tomorrow". The past few decades have witnessed the race for innovation and deepening globalization worldwide. How does trade liberalization influence the incentive of firms to engage in innovation activities? This important question has been addressed by a large body of literature. Most existing studies are based on final goods trade and confirm that trade is one of the most important factors that drive innovation (Kiryama, 2012). In contrast, this paper examines the effects of intermediate input tariff liberalization on firm innovation activities. Our study is based on Chinese firm-level data.

A growing share of international trade is in capital goods and intermediate inputs. At the global level, the share of capital goods in total trade increased from 21.0% in 1970 to 26.5% in 2006 while the share of intermediate goods in total trade increased from 7.5% to 13.0% (Onodera, 2009). From 2000 to 2006, the total value of China's capital and intermediate input imports increased by 151% and 256%, respectively. Another notable change is China's growing innovations. For example, China's share of global research and development (R&D) jumped from 2.2% in 2000 to 14.5% in 2011.¹ In 2011, China's patent office received the highest number of applications worldwide.² Thus, China is a good case for analyzing the effects of intermediate input imports on innovations. Drastic trade liberalization in China also makes the country a good case for valid empirical investigation of such an issue. On the one hand, the average input tariff rate in China dropped from 13.74% in 1998 to 8.13% in 2007, with the greatest cuts after 2001 when the country became a member of the WTO. On the other hand, the degrees of input tariff liberalization differ tremendously across industries. By utilizing these two features, namely, large and sudden tariff cuts due to the WTO accession and cross-industry variations of the cuts, we are able to use the difference-in-differences (DID)

¹ *Foreign Policy*, "It's official: China is becoming a new innovation powerhouse", Feb 6th, 2014.

² *The Economist*, "How innovative is China? Valuing patents", Jan 5th, 2013.

technique to assess empirically the effects of input tariff cuts on the innovation activities of domestic firms.

Against backdrop, our analysis shows that China's input tariff liberalization *reduces* innovation activities of firms as measured by patent filings. This negative effect is both statistically significant and economically important: a one-percentage point cut in input tariff rate results in about 0.15% to 0.28% drop in innovations. This finding is robust to different model specifications and concerns of the model. This finding is also interesting because it is neither obvious nor expected.

A cut in intermediate input tariffs could have positive and negative incentives to innovation activities. On the one hand, input tariff reduction enables a firm to purchase a larger quantity of input with more varieties and higher quality. This capability lowers a firm's incentive to undertake innovation because the firm can raise its production productivity or output quality through a cheaper channel (i.e., importing intermediate inputs). On the other hand, a firm may undertake R&D by using intermediate inputs, and its innovation activities may benefit from the technology embedded in imported inputs. As a result, the cost of undertaking R&D decreases or the effectiveness increases, and hence, a firm's incentive to do R&D increases. Our empirical finding implies that the innovation-reducing effect dominates the innovation-raising effect in China.³ We introduce a simple theoretical model to understand the mechanism at work, and find that under some very plausible conditions, a firm imports higher quality inputs in response to a tariff cut in intermediate input, which results in a reduction in innovation.

To the best of our knowledge, the present paper is the first to investigate the *direct* effects of intermediate input imports on innovation based on firm-level data. Two strands of related literature exist.⁴ In the first strand, some papers have examined the effects on innovations by

³ A good example which supports this general empirical finding is Changhong's response to imported technology. Changhong is a large TV maker in China. Through "imitation" the company was able to introduce many new product lines in early 1980s. Beginning in 1986, Japanese TV makers dumped the new generation of color TV production lines and key components to the Chinese market. In response, Chonghong stopped its own R&D but just purchased the Japanese technology because of the low cost. The full story can be found in <http://news.xinhuanet.com/fortune/2011-05/03/c121370462.htm>.

⁴ Grossman and Helpman (1991) provide a very comprehensive study on the relationship between trade and innovation. See Atkeson and Burstein (2010) and Burstein and Melitz (2013) for the recent approaches.

trade liberalization in general, but not by intermediate input imports in particular, and thus their conclusions and mechanisms differ considerably from the present paper. Generally speaking, trade affects innovation through various channels, such as transferring embedded technology, increasing market size, changing competition, realizing scale economies, and generating spillovers. Examples in this strand include Baldwin and Gu (2004), de Negri and Turchi (2007), Almeida and Fernandes (2008), Lileeva and Trefler (2010), Aw *et al.* (2011), Bustos (2011), and Bloom *et al.* (2015).⁵ In particular, Bloom *et al.* (2015) find that import competition from China leads to more innovations of European firms, but imports from other developed countries have no significant effect. Using firm-level data covering 43 developing countries, Almeida and Fernandes (2008) report that on average 53% of the technological innovations are embodied in new machinery or equipment and transferred from developed to developing countries through exports and multinational firms. In their analysis of 43595 firms in Brazil and Argentina, de Negri and Turchi (2007) find that national exporters are in general more innovative than non-exporters, with the percentage of innovating firms in these two categories being 48% and 36%, respectively.

The second strand of literature includes the recently emerging empirical studies on the effects of intermediate input imports on firm's performance.⁶ Several studies (Halpern *et al.*, 2011, on Hungarian firms; Kasahara and Rodrigue, 2008, on Chilean firms) find that imports of intermediates or declines in input tariffs are conducive to productivity gains. Productivity can increase through three channels via imported intermediate inputs: learning, improved input quality, and increase in input variety. Using Indonesian manufacturing plant-level data, Amiti and Konings (2007) find that a 10% fall in input tariffs leads to a 12% gain in the productivity of importing firms, which is much higher than the productivity gain from reducing output tariffs. Qualitatively similar results are also found by Topalova and Khandelwal (2011) based on Indian data. Goldberg *et al.* (2010) examine the effects of trade liberalization in India during the 1990s and find that domestic firms increase their product scope because they can access

⁵ Earlier empirical studies are based on country-level or industry-level data. For example, Coe and Helpman (1989) find strong international R&D spillovers through trade, based on evidence that the productivity growth of a country depends not only on its domestic R&D capital stock but also on the R&D capital stock of its foreign trading partners.

⁶ Theoretical studies have painted a clear picture (e.g., Ethier, 1982). Firms' performance can improve from intermediate input imports because of the increased variety of inputs and the utilization of technology embedded in imported inputs.

previously unavailable new input varieties. Approximately 31% of the new products are results of lower input tariffs. Using firm-level data from the French agrifood sector, Chevassus-Lozza *et al.* (2013) discover that lowering input tariffs increases the export sales of high-productivity firms at the expense of low-productivity firms. Bas (2012) shows that Argentine firms in industries experiencing larger input tariff reductions have higher probability of entering the export market. Using French data, Bas and Strauss-Kahn (2014) find that using more varieties of imported input results in higher TFP and export scope. However, not all results are positive. For example, van Biesebroeck (2003) finds that there is no productivity improvement for Columbia firms through the use of inputs import.⁷ Muendler (2004) also finds that the use of foreign inputs plays a minor role in the productivity change of Brazilian firms.

Similar to the present research, several studies have also examined the effects of Chinese input tariff reductions, but with different focuses. Using data on Chinese firms from 2000 to 2006, Yu (2015) finds that both input tariff and output tariff reductions improve firm productivity for both processing-trade and non-processing-trade firms. In particular, the effect of input tariff reduction on productivity is stronger than that of output tariff reduction. Ge *et al.* (2011) investigate the channels of firm productivity gains from input tariff cut and find supports for the learning, variety, and quality channels. Fan *et al.* (2015) and Bas and Strauss-Kahn (2015) examine the effect of Chinese input tariff reduction on the change in quality of export goods and find significant quality upgrade. Feng *et al.* (2016) study the connection between firm imports and exports, based on Chinese firm-level data from 2002 to 2006. They find that firms that expand their intermediate input imports raise the volume of their exports and increase their export scope. All these studies suggest that the channel through which intermediate input imports affect firm performance is the increased technology or quality embedded in imported inputs.⁸

⁷ Zhang (2014) decomposes productivity gains to static and dynamic gains. Dynamic gains come from the increase in knowledge and/or innovation of the importers because of imported intermediate inputs. He uses Columbia data to show that dynamic gains are more important than static gains.

⁸ Using new product sales as a measure of innovation, Liu and Buck (2007) show that Chinese firms increase their innovations when they import more technology. Using data from 1965 to 1995 for 86 countries, Connolly (2003) finds high technology imports from developed countries increase domestic innovations (perhaps through initial imitation), especially for developing countries. He argue that this is perhaps through reversed engineering.

Similar to this second strand of literature, our paper also focuses on intermediate input import. However, different from all those studies, we explore *directly* the effects on *innovation*, which distinguishes the present study from this strand of literature. Of course, the performance measures studied by the above-mentioned papers are not independent of innovation. For example, new products introduced by firms may be the result of firms' product R&D, and the improved quality of their products could be the outcome of their innovation specifically targeting quality improvement. However, those measures are not equivalent to innovation. The improvements of those performance could be the results of other efforts by firms, such as improved management practice or changes in organizational form along with trade liberalization, or as Ethier (1982) shows, improved performance could be the results of intermediate input imports because of the increased variety of inputs and the utilization of technology embedded in imported inputs.

Our finding is also different from all above-mentioned studies even if we consider the good performance being (partly) the result of innovations. For example, the increased product scope of Indian firms can be contributed to the larger amount of product R&D by firms, and the productivity gain by Indonesian importers is a result of more process R&D undertaken by these firms. While innovation has been "found" to *increase* in all studies discussed above (with the exception of two cases with insignificant results, i.e., van Biesebroeck, 2003, and Muendler, 2004) in response to intermediate input tariff reduction, in contrast, we directly show that patent applications of Chinese firms *decrease*, which indicates that innovation is different from other performance measures and separately investigating the trade effect on innovation of firms is important.

Innovation is an important topic in many disciplines including economics and management. Two of the many issues that the innovation literatures emphasize are incentive for innovation and spillovers/diffusion of innovation. Factors affecting incentives and spillovers include intellectual property rights (IPR) protection, market competition, education levels, and institutions. We can view the issue studied in the present paper as how embodied technology from upstream (intermediate inputs) affects, via diffusion, downstream innovation incentives.

In this regard, our paper is also loosely related to the MAKE-or-BUY issue discussed mostly in the industrial organization and management literatures. With the MAKE decision, firms conduct R&D in-house and develop their own technology, while with the BUY decision, they acquire technology externally. Veugelers and Cassiman (1999) provide a useful review of this literature. On one hand, there is substitution between the MAKE and BUY decisions. This view is developed based on transaction cost economics (Williamson, 1985) and property rights theory (Grossman and Hart, 1986). There are costs and benefits of using external technology as it helps lower innovation costs and gain time, but inevitably incurs transaction or agency costs. On the other hand, there is complementarity between MAKE and BUY. It has been argued that in-house R&D may serve to absorb, modify and improve external technology purchased by the firms (Cohen and Levinthal, 1989). Evidence for both substitution and complementarity can be found in the literature (Lyons, 1995; Cassiman and Veugelers, 2006). The mechanism which works in our paper is related but not exactly the same as those underlying the MAKE-or-BUY decision. Cheaper imported intermediate inputs can make the MAKE option less attractive because the importers can use the embodied technology directly, but can also make the BUY option less attractive because the cost of doing R&D is lower.

The remainder of this paper is organized as follows. In the next section, we describe our estimation strategy and data. We conduct empirical analysis and discuss the findings in Section 3. We explore the underlying mechanisms in Section 4. Concluding remarks are provided in Section 5.

2. Background, Empirical Strategy, and Data

2.1 China's Patent Applications

Similar to its impressive economic growth, China has also experienced drastic growth in patent applications received by the State Intellectual Property Office (SIPO). The total patent applications increased from 8558 in 1985 to 928177 in 2014, indicating an average annual

growth of 17.54% according to the World Intellectual Property Office (WIPO). Although patent applications started late and from a small base, China has become the largest country receiving patent applications since 2011, overtaking Japan in 2010 and the US in 2011. Many studies have attempted to provide explanations for the explosion of China's patent applications. Hu and Jefferson (2009) suggest and test five factors that account for the patent rise including intensification of R&D, growth of foreign direct investment (FDI), amendments to the patent law, ownership reform, and industry structural shift.

In fact, since China passed its first patent law in 1984, it has amended the law several times including 1992, 2000, and 2008 in addition to those made in accordance with the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). Interestingly enough, well before China's entry to the WTO, China's 1992 amendment had extended the duration of invention patent protection from 15 to 20 years, which is a major part of the TRIPS requirement. Hence, the TRIPS does not completely coincide with the 2002 tariff reduction from China's WTO accession.

According to the quantitative study of Future (2012), from 1986 to 2010, 2.106 million invention patent applications were published by SIPO, with about 53% of them are from entities within China. The growth during the period of 2000-2010 is even more spectacular, at an average annual rate of 28.4%. State-owned enterprises (SOE) were the main corporate inventors before the mid-1990s, but private companies have become the main corporate inventors in the later period. Geographically, the center of gravity of innovation focused on three cities (Beijing, Shanghai and Shenzhen) in the early years, but later spread all over the country. The Kairos Future's Report (2012) attributes the driving forces for the phenomenal growth of patent applications in China to factors such as policy incentives, increased R&D spending, rising levels of education, and liberalization of many sectors.

2.2 China's Accession to WTO

China began its economic reform and adopted an opening-door policy in 1979. The economy was still very closed at the beginning of the reform period. Hence, to open up its economy, the

Chinese government introduced a series of trade liberalization policies, including decentralizing foreign trade decisions, allowing manufacturing firms to engage directly in imports and exports, reducing import and export controls, removing import quotas, and lowering tariff rates. With the aim to integrate fully into the global market and make a strong commitment to trade liberalization, China began preparing its application for WTO entry in the late 1980s and was eventually accepted by the end of 2001. During the long negotiation period of WTO accession, China had unilaterally cut its tariffs many times, and its tariff cut in 2002, right after the accession, was very drastic. China's simple average tariff rates (including both intermediate inputs and final goods) dropped from 42.9% in 1992 to 26.6% in 1996, 17% in 2000, and 9.8% after the WTO accession.

Figure 1 plots the time trend of China's simple average *input* tariffs during the period 1996--2007. The figure shows that tariff rates dropped substantially in 1997, remained more or less unchanged during 1997--2001, and started to decrease in 2002 until it reached a steady state in 2005. While Figure 1 shows the general pattern of changes in input tariffs from all industries, a clear heterogeneity across industries can be observed behind the graph. Figure 2 shows the relation between input tariffs in 2001 and the decrease in average input tariffs between pre-WTO (1998-2001) and post-WTO accession (2002-2007) periods across industries, which is defined based on China's Input-Output Table 2002. Clearly, a strong positive correlation between the initial tariff level and the change of the tariff exists because of the WTO accession. That is, industries with higher initial tariff levels had larger reductions. As a result, input tariff levels in the post-WTO accession period are more uniform across industries than the levels in the pre-WTO accession period.

The input tariff liberalization of China offers us a great opportunity to examine the effects of input tariff reductions on firm behavior because of its large variations of changes over time and across industries.

2.3 Estimation Specification

Our analysis is based on the period of 1998-2007. Our objective is to estimate the effects of input tariff reduction on innovation activities of domestic firms. We overcome the identification problem by exploiting the presence of large variations in input tariff reduction across industries because of China's WTO accession, which is treated as an exogenous shock in most empirical studies using Chinese trade data (e.g., Fan *et al.*, 2015; Bloom *et al.*, 2015). We employ the DID technique to conduct the estimation. Industries with larger input tariff cuts are expected to make bigger adjustments. We thus examine the difference between the change in innovation activities by firms in industries with larger input tariff reductions because of the WTO accession (the treatment group) and the corresponding change by firms in industries with smaller input tariff reductions (the control group).

Specifically, we propose the following specification for our DID estimation:

$$y_{fit} = \beta \ln T01_i \cdot Post02_t + \mathbf{X}'_{fit} \boldsymbol{\gamma} + \lambda_f + \lambda_t + \varepsilon_{fit}, \quad (1)$$

where y_{fit} is the innovation activity of firm f in industry i in year t ; $\ln T01_i$ is the average tariff rate of inputs employed in the production of industry i in year 2001, which is used to measure the degree of input tariff reduction in industry i because of the WTO accession given that this initial tariff level is positively correlated with the degree of tariff cut (Figure 2); $Post02_t$ is an indicator of the post-WTO accession period, which is equal to one if $t \geq 2002$, and zero otherwise; λ_f is the firm fixed effect, used to control for all time-invariant characteristics of firms (as well as industries and regions); λ_t is the year fixed effect, used to control for all yearly shocks common to all industries, such as business cycles; \mathbf{X}_{fit} is a set of time-varying firm characteristics; and ε_{fit} is the error term. Following Bertrand *et al.* (2004) and Amiti and Konings (2007), we cluster the standard errors at the firm level to deal with the potential heteroskedasticity and serial autocorrelation. We control for time-varying firm characteristics (\mathbf{X}_{fit}) that may affect innovation activities. Characteristics include firm age, size, capital-labor ratio, exporting status, and equity share owned by foreign investors. The innovation of a firm may have a life cycle, and hence, we include in particular the square term of firm age, in addition to the linear term.

Our main interest focuses on parameter β . A positive sign of β indicates that input tariff cut increases the innovation activity of a firm, while a negative sign indicates the opposite effect. After obtaining our main empirical results from the above specifications, we will conduct a series of robustness checks to confirm the findings.

2.4 Key Variables

Our empirical model (1) has two key variables: firm-level innovation activity (dependent variable) and industry-level input tariff (the key explanatory variable).

Innovation activities can be measured by using either innovation input (e.g., R&D expenditure) or innovation output (e.g., patent filing). Different disadvantages and advantages are associated with each measure. Patent filing is generally considered as a better measure of innovation activities because it captures the effectiveness of innovation effort (including both observable and unobservable inputs), whereas R&D expenditure is only one particular (observable) input for innovation and fails to capture the quality of innovation. Following some studies in the literature (e.g., Aghion *et al.*, 2009; Hu and Jefferson, 2009; Hashmi, 2013), we use patent filing as the measure of innovation in this study.

Our dependent variable is the number of patents filed by a firm in a given year. We encounter a large number of observations of zero patent filing because many firms do not have any patent application in some of the years. We construct and use the following transformed measure as our dependent variable $y_{fit} = \ln \left[Y_{fit} + (Y_{fit}^2 + 1)^{1/2} \right]$, where Y_{fit} is the total number of patent filings by firm f in industry i in year t , to avoid the problem of too many zeros. This transformation allows us to keep all observations of zero patent filing and interpret our estimate β as the percentage change in patent filing. We prefer this transformation to other

log-like transformations, such as $\ln(Y_{fit} + 1)$, because of its flexibility. However, our results are robust to using $\ln(Y_{fit} + 1)$ as dependent variable.⁹

Our key explanatory variable is industry-level input tariffs. We construct this measure following the approach of Amiti and Konings (2007), Goldberg *et al.* (2010), and Topalova and Khandelwal (2011), who use Input-Output Tables. Specifically, input tariff for industry i (according to the classification in Input-Output Table) in year t is defined as the weighted average of the tariffs of goods that are used as inputs for industry i ; that is,

$$InT_{it} = \sum_j CostShare_{ij} \cdot OutT_{jt},$$

where InT_{it} is the input tariff of industry i in year t , $OutT_{jt}$ is the output tariff of industry j in year t (calculated as the simple average of tariffs of the Harmonized System (HS) six-digit products covered in industry j), and $CostShare_{ij}$ is the cost share of industry j in the production of a good in industry i . $CostShare_{ij}$ is calculated based on China's Input-Output Table of 2002. Accordingly, the industry classification in our study is also defined following the Input-Output Table of 2002. We use the year 2002 because China's Input-Output Table is only available every five years and 2002 is the middle year of our sample period. With this construction, we define input tariff of industry i in year 2001 as $InT01_i \equiv InT_{i2001}$, which is the main regressor we will employ in our empirical analyses.¹⁰

As pointed out by Amiti and Konings (2007), one drawback of using Input-Output Table in constructing input tariff is that the industrial classification of the Table is at a highly aggregate level, consequently the resulting input tariffs would also be at the same level. Hence, to obtain input tariffs at a more disaggregate level, we also construct InT_{it} from China's Customs Data by using the share of imports of industry j in the total imports by industry i to proxy $CostShare_{ij}$. In this latter measure, industries are defined at the four-digit level of the China

⁹ Our results are also robust to using alternative estimation methods particularly suitable for dealing with the problem of many zeros. It will be shown in the subsection of robustness check later (subsection 3.3).

¹⁰ Input subsidies prevailed in China in the period considered in this study. However, without knowing the details on the subsidies, one cannot construct precise or effective input tariffs. Probably because of this difficulty, all other papers on China (and many other developing countries) simply ignore the subsidies, and so does the present paper. However, as long as the subsidies are not closely correlated with tariff cuts, the results will not be systematically biased. The subsidy problem led us to exclude processing trade firms in our sample because they receive the largest subsidies in the form of tariff exemption.

Industrial Classification (CIC). Although this measure has other drawbacks (for example, input imports are affected by tariffs, and the share does not take domestic intermediate inputs into account), it has the advantage of being more disaggregate, and hence was used as a robustness check.

2.5 Data

Our empirical analysis relies on data that includes information on firm-level operation, firm-level innovations, and industry-level input tariffs. To this end, we construct our unique dataset by merging three data sources manually.

Our first data source is the Annual Survey of Manufacturing Enterprises, which is maintained by the National Bureau of Statistics (NBS) of China. This data includes all years from 1998 to 2007, and is the most comprehensive firm-level dataset in China, covering all SOEs and large non-SOEs with annual sales above five million yuan Renminbi (around US\$800,000). The number of firms in this dataset varies from over 140,000 in the late 1990s to over 336,000 in 2007. Firms are from all 31 provinces and direct-controlled municipalities in China and all manufacturing industries. The dataset provides detailed information on each firm, including official name, industry, and location as well as most items of each firm's operation and performance, based on the firms' accounting statements, such as age, employment, capital, intermediate inputs, new product sales, and ownership.

Following Cai and Liu (2013), we clean this dataset by dropping observations according to the basic rules of the Generally Accepted Accounting Principles. In particular, we drop firms from the data if any of the following is observed: (1) liquid assets are greater than total assets, (2) total fixed assets are greater than total assets, and (3) the net value of fixed assets is greater than total assets. We drop firms with fewer than eight workers because they fall under a different legal regime (Brandt *et al.*, 2012), firms with obviously wrong year of establishment (e.g., later than 2007 or earlier than 1900), and non-manufacturing firms (i.e., firms in mining, tobacco, and public utility industries according to China Industrial Classification System).

Processing trade is popular in China. However, we remove processing-trade firms from our data for two reasons. First, according to government policy, processing trade is exempted from import duties on imported inputs and materials, and the effective rate of input tariffs for processing-trade firms is zero, in both pre-WTO and post-WTO accession periods, hence, input tariff reduction does not have direct effects on them. Second, processing-trade firms may have very different production functions, import and export behaviors, and innovation motivations because they are provided with technologies, intermediate inputs, or product design by foreign parties.¹¹ However, firms engage in processing trade at different degrees. We drop manufacturing firms whose ratios of processing exports over their total exports are higher than 0.5.¹²

The second data source is SIPO. The SIPO dataset contains detailed information on each patent filing since 1985, including date of filing, official name and address of the applicant, name of the patent, and type of patent classified according to China's Patent Law, i.e., whether the application is for an invention patent, a utility model patent, or a design patent.

Some remarks on the use of SIPO data are in order. In general, measuring innovation activities is difficult. The report of OECD (2009) provides a good description of the advantages and drawbacks of using patent as a measure of innovation. In addition to patent filing data, other types of data to measure innovations exist, but some are almost impossible to obtain while some are even less satisfactory than patent filing. First, R&D expenditure measures innovation input, but R&D data is available only for years 2001-2003 and 2005-2007, and thus is not good for our DID estimation because data for only one year in the pre-

¹¹ Some recent papers, for example, Ge, *et al.* (2011) and Yu (2015), use processing-trade firms as control group in their DID estimation when investigating the productivity effect of input tariff cut in China. In our view, processing-trade firms are not a proper control group for other manufacturing firms as far as innovation is concerned because the two types of firms are incomparable qualitatively and should not share a common innovation trend. Thus, using processing-trade firms as the control group will result in biased estimates. For example, if processing-trade firms do not do any innovation and an upward trend exists for the innovation of other manufacturing firms, then using the processing-trade firms as the control group will significantly overestimate the impact of the tariff cut and may even change the sign of the estimate from negative to positive.

¹² The processing export ratio of a firm is calculated using China's Customs Data, which reports information on the type of export by each exporter. We pool together a firm's exports over the period 2000-2006 in the calculation to obtain the average processing trade ratio. Our results are robust to using the annual ratio (instead of the average ratio) to identify the processing firms. The results are also robust to dropping those manufacturing firms whose processing export ratios are higher than 0.9.

WTO period is available.¹³ Moreover, R&D data can also be severely distorted when various subsidy schemes are provided, which is the case in China. It is true that patent filing activities could be distorted by government policies, but the matter is the relative degrees. As for incentive for patent, Li (2012) provides a description of various policy initiatives at regional levels such as patent subsidy programs. The most important part of the subsidy programs is subsidizing patent filings, which varies across regions, but it is on average around just a few hundred RMB (Chinese currency unit, around RMB6.7 per USD at the present) per patent filing. In contrast, there is huge incentive for R&D. For example, companies classified as High and New Technology Enterprise can get a corporate income tax (CIT) rate cutting from the standard rate 25% down to only 15%. In addition, companies that meet the government's criteria can get 150% of eligible R&D expenses deducted before CIT. According to PWC (2015), slight change in R&D behavior might result in more eligible R&D tax benefits. Hence, we expect that distortion of R&D data is much severer than patent data.¹⁴

Second, China's patent filing and/or granting abroad is a good alternative because it may reflect more genius innovation, as argued by Holmes *et al.* (2015). Such data can be found in WIPO dataset. However, linking the WIPO data to the NBS data is almost impossible.¹⁵ In fact, at the aggregate level, we find that the ratio of total patents applied abroad by Chinese residents over all patents applied by Chinese residents is very stable over time and very small (only a few hundreds per year in the late-1990s), ranging from minimum 3.50% to 5.70% over the period 1999-2013, with an average 4.66%. Moreover, Wunsch-Vincent *et al.* (2015) show that China's foreign patents are concentrated in a few technology fields and in a few firms, mostly in the information technology sector. Hence, using these data in our study would not be of high value.

¹³ Despite this shortcoming of R&D data, we have also tried to replace patent filing with R&D expenditure in the same regression model used in this study and found that the estimate of the response of R&D to import tariff cut has the same sign (negative) as that of patent but is statistically insignificant. However, we do not want to make any conclusion based on this analysis unless we have longer-period R&D data, which is left for future research when data becomes available.

¹⁴ There is an ongoing debate on the correlation between R&D and patents in China. Hu and Jefferson (2009) find weak linkage between patent and R&D, but Dang and Motohashi (2015) argue that patent count is correlated with R&D input and financial output and so patent statistics are meaningful indicators of innovations. Following this debate, we also check the relationship between firms' R&D expenditure and patents based on our sample. We find that firms' R&D investment increases their patent filings.

¹⁵ The two datasets have no common identifier; WIPO contains English names only while NBS contains Chinese names only.

We match NBS and SIPO data using common information included in both datasets. Specifically, we merge the two datasets using the official names of firms, and then double-check the matched outcomes using location information of the firms. Our matching outcome is reasonably good, for two reasons. First, according to a report by NBS, about 8.8% of manufacturing firms in China applied for patents during 2004--2006. During the same period, the number of firms in our matched dataset constitutes about 4% of the total number of firms in the NBS dataset. This is a reasonably good match, given that the NBS dataset is very large (with more than 1.3 million observations after cleaning). Second, our matching technique is based on the names and location of firms, and we use the same technique for all industries and for the whole sample period (before and after WTO accession). Therefore, the degree of mismatch across industries does not appear to be correlated with the degree of input tariff reduction across industries. This alleviates considerably the potential estimation biases arising from the matching process.

Our third data source is the World Integrated Trade Solution (WITS) database, which is maintained by the World Bank, and contains tariff data at the HS six-digit level.¹⁶ The data are given at different HS versions over the years, and hence, we convert them to the HS02 version using the UN Statistics Division Concordance Table. We calculate industrial-level input tariffs by using this dataset together with the 2002 Input-Output Table of China.

We construct our unique dataset by merging the three databases. The matched dataset has an unbalanced panel of 337,257 firms and a total of around 1.3 million observations, with both detailed patent filing information and firm characteristics during the period of 1998--2007. Our analyses are based on this unique dataset.

In the robustness checks, we need to identify the processing trade status of firms (that is, whether or not the firm is a processing trade firm) and their importing status (that is, whether or not the firm imports inputs directly or not), which requires information from another data

¹⁶ WITS does not provide 2002 data and we obtain 2002 data from WTO.

source, that is, China's Customs Data (2000-2006). Hence, we also merge Customs data with NBS data by using the same method as Yu (2015). The Customs data contains most detailed information of each international trade transaction conducted by Chinese firms, including product code at HS six-digit level, value and quantity. This data also allows us to do our mechanism test.

Ge *et al.* (2011) and Yu (2015) use the merged Customs and NBS data in their studies, whereas we use it only for robustness check. Specifically, they confine their analyses to manufacturing firms that also make direct imports, which we call direct importers. Their studies omit a large number of manufacturing firms that do not make direct imports, which we call non-importers. However, non-importers may buy imported inputs from intermediaries and employ these inputs in their production. As pointed out by Goldberg *et al.* (2010), using the sample of direct importers may result in a bias. In the main analysis of our study, we use the entire NBS dataset. Therefore, our analysis will provide a more complete picture of how input tariff cut affects the innovation of firms.¹⁷

Table 1 presents the summary statistics and definitions of the main variables used in this study. Overall, a Chinese manufacturing firm applied for 0.15 patents per year on average, and the patent applications increased significantly from the pre-WTO to the post-WTO accession period. Input and output tariffs decreased significantly because of WTO accession. Almost all firm-level performances and industrial characteristics were improved. The degree of industrial competition also increased after 2001.

One potential concern is whether our key explanatory variable, the 2001 input tariff levels, is exogenous to individual firms. This concern is generally legitimate, but is alleviated here by the observation on the actual liberalization process in China. As shown in Figure 1, both mean tariff rate and standard deviation remained constant in the 1998-2001 period. This feature implies that the stability of tariffs holds not only for industry average, but also for

¹⁷ A related problem of using the whole sample is that some non-importers may not use any imported inputs. This possibility may bias the impact of intermediate input imports downwards. We do find stronger impact on importers than on non-importers, as shown in subsection 3.4.

individual industries. Thus, the input tariffs in 2001 were largely determined by the previous round of liberalization in 1997. That is, tariff rates in 2001 are *pre-determined* before our sample period and do not appear to be affected by innovation activities during the pre-WTO accession period. This finding can be confirmed by the data. Following Goldberg *et al.* (2010), we regress industrial innovation activities in the pre-WTO accession period on tariff rates in 2001 and find that tariff rates in 2001 are uncorrelated with innovation activities (see column 1 of Table 2). As shown in Table 2 (columns 2-5), other industrial performances are also not correlated with the 2001 input tariff rates. This independence result also holds for actual input tariff cuts from the WTO accession (instead of initial tariff rates in 2001), as shown by columns 6-10 of Table 2. This observation implies that either the users of imported inputs did not engage in serious lobbying activities during 1998-2001, or lobbying by users of imported inputs was not effective.

Timing of China's accession to WTO is regarded commonly as an exogenous shock at least to individual firms. Hence, a number of studies such as Fan *et al.* (2015) and Bloom *et al.* (2015) use it as an exogenous variable to proxy China's trade liberalization. We also take this approach.

3. Empirical Analysis and Findings

3.1 Main Results

Table 3 presents the regression results based on our DID specification (1), with control variables introduced step by step. All estimations show that input tariff reduction leads to a *decline* in innovation of firms. In column 1, with only firm fixed effect and year fixed effect being controlled for, we find a statistically significant and negative estimate for $InT01_i \cdot Post02_t$. The negative sign indicates that after China's WTO accession, firms in industries which face a larger cut in input tariffs (higher $InT01_i$) undertake less innovation. In column 2, we include several time-varying firm characteristics that may influence innovation

activities, such as age, size, capital-labor ratio, export status, and equity share owned by foreign investors. Evidently, the negative effect of input tariff reduction on innovation is very robust to these additional controls. As for the effects of the control variables, we find that firms having a shorter history, larger employment, or higher capital-labor ratio have more innovations. Exporters also have more innovations than non-exporters, which is consistent with the findings in the literature (e.g., Baldwin and Gu, 2004). However, the effect of foreign ownership is not statistically significant. As shown below (in columns 3-8), these findings are also robust after we introduce other control variables and use alternative measures of the key explanatory variable.

China's WTO accession brings changes in both input and output tariffs. Output tariff change may affect market competition in China, and consequently influence innovation incentives of firms. In column 3, we add a control for industrial output tariff $OutT_{it}$. We find that the estimate of $InT01_i \cdot Post02_t$ is still negative and statistically significant with a very similar magnitude as in columns 1-2. The effect of output tariff on innovation is statistically insignificant, which holds even when we introduce additional control variables and use alternative measures of the key explanatory variable (in columns 5-8).¹⁸ That is, input tariff liberalization has a stronger effect on firm innovation than output tariff liberalization. This comparison is similar to the findings in the literature that focus on firm productivity. For example, Amiti and Konings (2007) disentangle the effect of input tariff reduction from that of output tariff reduction and find that input tariff effect is at least twice as high as the output tariff effect in Indonesia.

If there exist any policy reforms introduced in China around the time of the WTO accession which may affect our treatment and control groups differently, then the effects of those policy reforms may also be captured in the DID estimates. In that case, the regression result from (1) will not be the pure effect of input tariff cuts. Indeed, two important reforms took place in the

¹⁸ How import competition in final goods affects innovation is a different topic. Bloom *et al.* (2015) provide a good review of this line of study and their own empirical study finds that trade liberalization that leads to more Chinese imports in Europe increases innovations of European firms. As the effect depends on the sources of competition, i.e., origin of the exporting countries, our finding (insignificant result) merely represents the average effect of output tariff reduction.

early 2000s: the SOE reform and the relaxation of FDI entry regulations. These reforms were on-going reforms that had started in the 1980s and 1990s, respectively, and accelerated after the WTO accession. The SOE reform resulted in a large-scale privatization, close-down of small SOEs, and an improvement in the efficiency of surviving (large) SOEs. The new FDI regulations relaxed the entry requirements for foreign investors and reduced the range of industries restricted to foreign investment. These reforms may not have differentiated effects on the treatment and control groups. However, to control for any possible confounding effects from these two policy reforms, we include two additional control variables in our DID estimation: $SoeShare_{it}$ (the ratio of the number of SOEs over the total number of domestic firms) and FDI_{it} (the logarithm of the number of foreign invested firms). The regression result (column 4) indicates that the negative effect of input tariff reduction on innovation is still present. Firms in industries with higher SOE shares tend to undertake less innovation, possibly because SOEs undertake less innovation on average, or the presence of SOEs in the market crowds out innovation activities of private firms. However, the presence of foreign firms has no significant effect on innovation activities of the domestic firms.

Thus far, we have used input tariff rates of 2001, $InT01_i$, to represent the degrees of tariff liberalization from China's WTO accession.¹⁹ We have strong reasons for using this measure as the key explanatory variable instead of yearly input tariff rates or actual input tariff reduction to interact with $Post02_i$. First, the schedule of tariff reductions upon WTO accession was released in 2002, and the schedule may be endogenous; hence, the phase-out process could be exploited by firms (Guadalupe and Wulf, 2010). Second, initial input tariffs are pre-determined in China. For this reason, in their analysis, Amiti and Konings (2007) also employ initial tariffs as the instrument for actual tariff changes. However, even though our choice of $InT01_i$ is well justified, we still want to check whether the results will be qualitatively different if these alternative measures are used. We first replace $InT01_i$ with actual input tariff changes, denoted as $DInT_i$. We define

¹⁹ Using the average tariffs over 1998--2001 or tariffs in 1998 generates similar results. The results are available upon request.

$DInT_i = InT_{i1998-2001} - InT_{i2002-2007}$, where $InT_{i1998-2001}$ is the average input tariff over the period 1998-2001, and $InT_{i2002-2007}$ is the average input tariff over the period 2002-2007. In column 5, we run the regression by replacing $InT01_i \cdot Post02_t$ in model (1) with $DInT_i \cdot Post02_t$. The effect of input tariff reduction is still statistically significant, negative, and even stronger than that using $InT01_i$. We then run simple OLS regression with yearly input tariff levels, denoted as InT_{it} , as key regressor, i.e., replacing $InT01_i \cdot Post02_t$ in model (1) with InT_{it} . Column 6 shows the regression results. The coefficient of InT_{it} is positive and statistically significant, indicating that lower input tariffs lead to significantly less innovation. Both results are qualitatively consistent with our main DID estimations.

We followed a common practice in literature (e.g., Goldberg *et al.*, 2010) to calculate industry-level input tariff using China's Input-Output Table. However, as pointed out earlier, such an approach is restrictive as the obtained input tariffs are available only at a highly aggregate level. We need to find a way that does not rely on Input-Output Table to obtain input tariffs at a finer level of industry disaggregation. The approach we take is to calculate the weighted average industry-level input tariffs at the CIC 4-digit level, denoted as $InTA01_i$, by using the import share constructed from Customs data as weights instead of using the cost share constructed from the Input-Output Table. We replace $InT01_i$ by $InTA01_i$ to run the regression with this new $InTA01_i$. The results are reported in column 7. The effect of input tariff reduction on innovation remains negative and statistically significant.

While industry-level input tariff is commonly used to proxy trade liberalization, a firm's production and corresponding decisions will not be affected by a change in tariffs of some intermediate inputs that the firm does not use in its production. For this reason, using firm specific (or firm-level) input tariff is desirable, i.e., only considering tariffs relevant to the firm. We follow Yu (2015) in calculating the weighted input tariff for each firm ($FIT01_i$), where the firm's import of each input in the initial year is used to construct the weight.²⁰ However, this

²⁰ See Yu (2015) for details of the construction.

approach applies to direct importers only. For non-importers, we use the average of firm-specific input tariffs (of direct importers) in each CIC four-digit industry for all of these firms in the same industry. In contrast, we drop all processing firms. We use the average pre-WTO firm-specific tariffs (i.e., firm-specific tariffs in 2000 and 2001) as the initial tariffs to keep as many observations with firm-specific tariffs as possible. With firm-specific tariffs, we run the regression using $FIT01_i \cdot Post02_t$ to replace $InT01_i \cdot Post02_t$ as regressor of interest. The results are reported in column 8 of Table 3. The main results are robust.²¹

In summary, we find that input tariff cut reduces innovation of the firms. This finding is statistically significant and robust to various model specifications and input tariff measures. The effect is also economically significant. For example, with the estimated coefficient (-0.2847) in the specification with actual tariff cut as key regressor (column 5), the average 4.64% input tariff cut because of China's WTO accession reduces the patent filings of firms by 0.0132. This decrease is quite significant because the average patent filings of the entire sample is 0.1507. That is, patent filings of firms drop by 8.76% as a result of input tariff liberalization.

3.2 Validity of the DID Specifications

The reliability of our estimates, which are reported in Table 3, depends on the validity of our DID specifications. In this subsection, we conduct a series of validity checks. The new regression results presented in Table 4 confirm the validity of our specifications.

Flexible estimation. In our main DID regression model, we use a time dummy variable, $Post02_t$, to separate the pre-WTO and post-WTO accession periods. The estimate from the interaction term, $InT01_i \times Post02_t$, yields the average treatment effect, which compares the difference between the treatment and the control groups in their *average* differences between

²¹ However, in this approach the direct importers account for only about 1% of the firms in our whole sample. This sample of direct importers is so small because these firms must exist and directly imports in year 2000 or 2001 (while there are many new entries after 2001), and many Chinese firms use imported intermediate inputs through intermediaries or trade companies. For example, our sample shows that during 2000-2006 22.73% of Chinese ordinary imports are conducted by intermediaries. Thus, we believe it is not representative to use the tariff of these 1% firms in the main analysis.

the pre-WTO and post-WTO accession periods. One drawback of such an approach is that it does not consider year to year changes. Hence, we now compare the difference between the treatment and control groups for every year in the entire period to remedy this weakness. Specifically, we use a flexible estimation specification to replace the interaction term $InT01_i \times Post02_t$ in model (1) with a series of interaction terms between $InT01_i$ and the year dummies, that is, $InT01_i \times t$ with t indicating 1999 through 2007. We run this regression and report the results in column 1 of Table 4. The estimated coefficients are statistically insignificant for all years before 2001, but become negative and statistically significant for every year from 2001 onwards. The magnitudes also become larger. These results clearly indicates the similarity between the two groups before the WTO accession, the innovation-reducing effect of input tariff cuts, and the increasing trend of the effect.

Industry-specific time trend. In the DID estimation, we assume that, conditional on $(\mathbf{X}'_{fit}, \lambda_f, \lambda_t)$, innovation activities of the treatment and control groups follow the same time trend. This assumption allows us to use innovation activities of the control group as the counterfactual of the treatment group in the post-WTO accession period. However, innovation trends in different industries (or different groups) could be different because they may be affected by industry-specific confounding factors. Normally, this issue can be dealt with by controlling for sector-year fixed effect, but cannot be done here because the key regressor (i.e., $InT01_i \cdot Post02_t$) of our empirical model is defined merely at industry-year level, which rules out the possibility of including industry-year fixed effect in the regressions. Alternatively, to check whether unobserved industry-specific factors would bias our estimates, we add an industry-specific linear time trend, $\lambda_i \cdot t$, to model (1). This addition enables us to control for all unobserved industry characteristics if they affect firm innovation in the form of a linear time trend. The regression result for the key explanatory variable is presented in column 2 of Table 4. The estimate is -0.1981 , which is negative and statistically significant. Thus, our estimate is not driven by any unobserved industry trends.

Placebo test I: Pre-WTO accession period. Following Topalova (2010), we conduct our first placebo test to examine the effect of input tariffs on firm innovation in the pre-WTO accession period (1998--2001). The premise is that because tariffs did not change much during that period, we should not expect any significant effect of input tariffs on innovation; if the result is the contrary, then it indicates the existence of some underlying confounding industrial factors (other than the WTO accession) that drive innovation. Accordingly, we replace $InTO1_i \cdot Post02_t$ by InT_{it} in (1) and run the regression for the sample in the pre-WTO accession period. The estimates are given in column 3 of Table 4. The effect of InT_{it} is not statistically significant. Hence, we can rule out the possibility that some underlying confounding factors drive innovation.

Placebo test II: Subsample of processing-trade firms. In our second placebo test, we run the regression model (1) using the subsample of processing-trade firms. As processing-trade firms enjoy zero input tariff rate during the entire period, their innovation decisions should not be affected much by the input tariff liberalization from China's WTO accession, and the estimation using the sample of processing-trade firms should produce an insignificant liberalization effect. We use two criteria to define processing-trade firms. One includes all firms with average ratios of processing exports over total exports larger than 90%, and the other consists of firms with average ratios larger than 50%. The processing export ratios are calculated based on the Chinese Customs Data.

The regression results are presented in columns 4 and 5 for the 90% and 50% criteria, respectively. Clearly, the coefficient of $InTO1_i \times Post02_t$ in both cases is highly insignificant, confirming the conjecture. This test suggests that manufacturing firms adjust their innovation activities in response to input tariff reduction after the WTO accession if, and only if, their imported inputs are actually affected by tariff reduction.

3.3 Robustness Checks

In this subsection, we further check the robustness of our results to address other concerns. Most of the results are presented in Table 5.

Industrial competition. The fact that market competition affects innovation activities is well known in innovation literature. In the main model, we have taken into account changes in import competition resulting from China's output tariff reduction. We further control for overall industrial competition by including the Herfindahl--Hirschman Index (HHI) in the model. The new variable, HHI_{it} , is the HHI for industry i in year t . Column 1 of Table 5 shows that our result is robust to including this competition variable.

Export opportunity. While China undertook considerable trade liberalization during the period of 1998-2007, trade liberalization also occurred in other countries. When foreign countries lower their tariffs on Chinese products, the market opportunity for Chinese exporters is increased, which may also induce them to adjust their innovation decisions. We handle this issue in two ways. First, we control for the export expansion opportunity by adding a term of industry-level total exports, $IndExp_{it}$. The regression results are reported in column 2 of Table 5. We find a positive and significant effect of industry export on a firm's innovation activity (estimated coefficient 0.0042). More importantly, the estimate of our key variable, $InT01_i \times Post02_t$, remains negative and statistically significant. Second, to isolate the export expansion effect, we run the regression using the subsample of non-exporting firms. The results are reported in column 3 of the table. The main result also holds for this sub-group of firms.

Intellectual property rights (IPR) protection. In the main analysis, we already controlled for SOE privatization and FDI entry deregulation, which occurred during China's WTO accession and could potentially affect the estimation. Another important policy change during the same period with even more obvious effect on innovation was the strengthening of IPR protection as required by TRIPS. One can argue that the average effect of TRIPS on innovation has already been controlled for by year dummies, but we can still explore the policy's differential effects across industries. As shown by Bilir (2014), the extent that an industry is affected by IPR changes is correlated with the length of the industry life cycle. Inspired by this observation, we control for the industry-differentiated effect of TRIPS by including the

interaction term between the length of product life cycle and post-WTO dummy, i.e., $T_i \cdot Post02_t$. The data of product life-cycle length can be obtained from Bilir (2014), but we need to match the SIC industry code in Bilir (2014) with the CIC. As Bilir's (2014) measure of product life-cycle length is only available for a limited number of industries, a significant loss of observations will take place when we include this control variable.

Following Bilir (2014), in our test, we also use different measures of product life-cycle length, i.e., the average life-cycle length, the life-cycle length based on the seventy-fifth and eighty-fifth percentiles of each citation lag distribution, in our test. We report the result of the use of the average life-cycle length in column 4 of Table 5. Our result is robust, and so are the results obtained from the use of other length measures which are omitted in the table.

Multi-product firms. Many firms produce multiple products that may span over different industries.²² Thus, our dependent variable (i.e., a firm's total number of patent filings) may cover many industries that experience different degrees of input tariff cut. Thus, the analysis will lead to an imprecise estimation of the impact of input tariff cut on firm innovation. Hence, to check whether our result is contaminated by this problem, we restrict our analysis to a subsample of firms that produce products all belonging to the same 3-digit industry.²³ We run regression (1) based on this subsample of "single-industry" firms and find that the effect of input tariff reductions on innovation remains negative and statistically significant, as shown in column 5 of Table 5.²⁴

Surviving firms. We notice from the summary statistics in Table 1 the presence of a decrease in average age of firms. This observation implies that a significant number of firms entered after 2001. From the data, we also observe a significant number of firms exiting. If the

²² Note that each firm reports one industry which it belongs to in the NBS survey even if it is a multi-product firm spanning many industries.

²³ We obtain product-level data from NBS of China for the period 2000-2006, which contains information of each product (defined at the five-digit product level) produced by every firm. As product-level data and NBS data use the same firm identity, we can easily match these two datasets and identify firms producing all goods within only one three-digit industry.

²⁴ Some firms may change location or industry affiliation over the sample period. Though these firms are very few and we have controlled for firm fixed effects, we conduct regressions with the sample of firms without such a change, and find similar results.

new entrants and/or exiting firms have different patenting behaviors, our earlier estimation results may also capture the selection effect, instead of the true effect of input tariff reductions. Hence, to check whether our estimates are driven by entry and exit, we focus on a subsample of surviving firms (i.e., firms in both the pre- and post-WTO accession periods). Results are reported in column 6 of Table 5. We still find negative effect of input tariff reductions and the magnitude becomes even larger, implying that the selection from entry and exit does not drive our findings and if it does, it causes a bias on our estimate downwards at the most.

Two-period estimation. The DID estimation and resulting statistical inference crucially depend on the accuracy of standard errors. In the main analysis, we followed Bertrand *et al.* (2004) to cluster standard errors at the firm level. As a robustness check, we use another approach, which is also suggested by Bertrand *et al.* (2004), to calculate the standard errors. In particular, we first collapse the panel structure into two periods (pre-WTO and post-WTO accession) and then use the White-robust standard errors. The regression results are presented in column 7 of Table 5. The results are qualitatively similar to the ones obtained before.

Firm-level productivity. Firms with different productivity levels may have different abilities or incentives to conduct innovation. Recall that in the main analysis, we included firm fixed effects in all regressions, which control for all firm-level time-invariant characteristics, including the *initial* productivity and other factors (e.g., corporate culture) that may affect innovation. However, productivity changes over time. Hence, to further control for the effects of productivity on innovation, we also introduce *contemporary* productivity levels of the firms to the model. In this robustness check, we use labor productivity (output/labor) to represent firm productivity. The new results are reported in column 8 of Table 5. Our key finding remains robust. The results also show that more productive firms are more innovative, which is consistent with the findings in literature.

Firm size. Firms of different sizes may have different incentives to undertake innovation because of different investment returns. Firms of different sizes may also have different

innovation trends. Thus, to check whether introducing a control for the differential trends across sizes will affect our estimation, we add a series of interaction terms between the initial labor size (to capture firm size) and year dummies in our regression. The new results are reported in column 9 of Table 5. We find that our key estimation is robust to this size consideration.²⁵

Alternative estimation methods. In the main model, we use the OLS method to estimate the effect of input tariff cut on firm innovation. Now, we check our results using alternative estimation methods. First, we use the Fixed-effect Poisson model. Column 1 of Table 6 reports the result (the coefficients are incidence-rate ratios). We still obtain significantly negative effect of input tariff cut on firm patent filings. However, only 98868 observations (about 7.8% of the whole sample) remain in the regression because all firms with just one observation or firms with all zero outcomes are dropped automatically in such nonlinear regressions for panel data. Second, to remedy the severe data loss problem associated with the Fixed-effect Poisson model, we also use the Random-effect Poisson model, which keeps all observations. We obtain very similar results, as shown in column 2 of Table 6.

Third, firms may make innovation decisions in a sequential manner, that is, they first decide whether to innovate and then how much to innovate. In this case, a two-step selection model is more appropriate. We check whether our results are robust to this two-step selection model estimation, and to do so requires an excluded variable that affects firms' decision on whether to innovate but not affect firms' decision on how much to innovate. Following Sanyal and Ghosh (2013), we use each firm's patent stock since 1995 (denoted by *Inpatentr95*) as exclusion restriction in the first step Fixed-effect Logit regression, with patenting indicator as dependent variable. Then, in the second step, we include the inverse Mill's ratio from the first step to correct the potential selection bias in the regression. The results of the two-step selection model are reported in columns 3 and 4 of Table 6. The results show that past innovation behavior affects current innovation decision and the existence of a selection effect

²⁵ Note that in column 9 of the table, we do not report the estimates of the newly introduced interaction terms; for otherwise, the table will be too long. Our regression result shows that all these interaction terms are positive and statistically significant, implying that larger firms are always more innovative.

in innovation. Most importantly, input tariff cut clearly decreases both the likelihood and the intensity of innovation. However, a similar problem as in the Fixed-effect Poisson model occurs, that is, we experience a significant loss of observations in the first-step regression.

In sum, our findings are robust to alternative nonlinear regression models despite the significant cost of using such regressions (i.e., a substantial loss in observations).

Importing behavior. After focusing on the effect of input trade liberalization on innovation, we now turn to the direct relation between intermediate input imports and innovation. Specifically, we check whether the reduction in patenting occurs after firms begin to import, or in other words, whether input tariff cut affects firm innovation through the change in importing behavior of firms. We therefore use a two-stage IV regression method to investigate (i) whether input tariff cut affects firms' importing behavior (first-stage regression), and (ii) whether the changed importing behavior in turn affects firms' innovation behavior (second-stage regression), using input tariff cut to instrument the importing behavior. Because we need firms' importing behavior information to perform this method, we combine NBS data with Customs data for the period 2000-2006. We identify each firm's importing status in each year from Customs data, and define a dummy variable $ImpStart_{ft}$ that indicates whether firm f starts to import intermediate inputs in year t . The dummy variable equals zero for the years before the firm starts to import and unity afterwards. We restrict our sample to initial non-importers, that is, firms that did not export in the first year they entered the sample. The IV regression results are reported in columns 5 and 6 of Table 6. The first-stage result shows that input tariff cut increases the likelihood of importing intermediate inputs, which in turn reduces innovation as shown by the second-stage result.

3.4 Heterogeneous Effects

Firms are heterogeneous in many dimensions, and so are innovations. We explore the possible heterogeneous effects of input tariff reductions on innovations. Results are reported in Table 7.

Types of innovation. Our data have detailed information with regard to the types of innovation. Chinese Patent Law classifies patents into three categories, namely, invention, utility model, and design. Invention patents refer to technical innovations on products, methods, or both; utility model patents refer to technical proposals on the shape and/or structure of a product; and design patents refer to changes in the shape and/or color of a product. The requirements for obtaining each of the three patents are very different, with the invention application having the most difficult requirements and the design application having the easiest requirements. Thus, asking whether the effects of input tariff cuts on these innovations differ significantly is also reasonable. Columns 1-3 present the empirical results obtained from regressions based on each of the three types of innovation. We find that input tariff cuts reduce all types of innovation significantly.

Capital intensity. Industries differ in many dimensions, which could potentially affect firms' responses to input tariff reductions. Capital-labor ratio, or simply capital intensity, is a determinant of innovation, and differs significantly across industries. We ascertain if the main result of our analysis is sensitive to capital intensity of the industries by rerunning the regression using a subsample of industries with high capital intensity and a subsample of industries with low capital intensity, respectively. We calculate the capital-labor ratio of each four-digit CIC industry in the pre-WTO accession period (the simple average of the ratios in those years) to construct the two subsamples. The low capital-intensity industry group includes all industries with a capital intensity lower than the 25th percentile of the entire sample, whereas the high capital-intensity industry group includes all industries with a capital intensity higher than the 75th percentile of the entire sample. Column 4 of Table 7 reports the regression results from the low capital-intensity group while column 5 reports those from the high capital-intensity group. We find negative effects of input tariff reduction on innovation in both groups. The effect is stronger for firms from high capital-intensity industries than from low capital-intensity industries. This comparison is consistent with the fact that firms with high capital-intensity undertake more innovations and thus are more affected by the reduction.

Distance from technology frontier. Aghion *et al.* (2009) argue that the distance from the world's technology frontier is an important factor in determining firm responses in innovation to market competition. We explore whether the input tariff reductions also lead to different responses by firms with different distance from the world's technology frontier.

We divide the sample into five quantiles based on the average total factor productivity (TFP) of firms in the pre-WTO accession period.²⁶ Quantiles are constructed within each CIC four-digit industry. We run regressions for the subsample of the first quantile firms (i.e., firms far from the frontier) and the subsample of the fifth quantile firms (i.e., firms close to the frontier), respectively. Columns 6 and 7 report the results. We find that for low-productivity firms, the effect of input tariff reductions on innovation is insignificant, whereas for high-productivity firms, the effect is significantly negative. One possible reason for such a difference is that low-productivity firms do not use much imported intermediate input in their production nor do they engage actively in innovation, and thus, their innovation activities are not sensitive to changes in input tariffs.

Ownership. In terms of ownership structure, three types of firms primarily exist in China: SOEs, domestic private firms, and foreign invested enterprises (FIEs). FIEs are all business entities established in China with part or all of foreign capital. They include both Sino-foreign joint ventures and wholly foreign-owned enterprises. Determining whether firms with different ownership structures have different responses to input tariff reduction would be an interesting exercise. Columns 8-10 show the results for SOEs, domestic private firms, and FIEs, respectively. All types of firms reduce their innovations significantly in response to input tariff liberalization. The negative effect on SOEs is the weakest. Perhaps, the innovation incentives of SOEs are less responsive to market and cost conditions. The effect on FIEs is the strongest, which may suggest that they depend more on imported intermediate inputs for production and innovations.

²⁶ TFP is estimated using the Levinshon and Petrin (2003) method at the level of two-digit CIC industry and with information of value added, employment, fixed assets, and intermediate inputs. All nominal variables are deflated using the deflators from Brandt *et al.* (2012).

Direct importers and non-importers. We classified firms into direct importers, which are firms that import intermediate inputs directly by themselves, and non-importers. While direct importers are affected directly by input tariff cuts, non-importers may also be affected indirectly because they may purchase imported inputs from intermediaries. Amiti and Konings (2007) show that direct importers in Indonesia are affected more by tariff reductions than non-importers. We examine whether the difference obtained for Indonesian firms also exist for Chinese firms by running regressions using the sample of direct importers and non-importers, respectively. Columns 11 and 12 show the effect on direct importers and non-importers, respectively. We find that both types of firms reduce their innovations, with direct importers reducing more than non-importers.

4. Mechanism: A Simple Model and Evidence

Why does a tariff cut in intermediate input imports reduce firm innovations? To understand this interesting observation, we provide one explanation derived from a highly simplified and stylized model in Subsection 4.1. We put the equilibrium analysis (the proof of the results) in the appendix. In Subsection 4.2, we conduct further empirical analysis which generates results consistent with the main predictions from the model, thereby providing support for the model.²⁷

4.1 Model and Results

Consider a firm facing demand for its product as $P(y)$, where y is the quantity and P is the price with $P'(y) < 0$. Production requires both domestic intermediate input, denoted as d , and imported intermediate input, denoted as x . Assume that production function takes the following form: $y = f(x, d)\theta(\beta, r)$, where $f(\cdot)$ is a usual production function and $\theta(\bullet)$, which represents the level of productivity, is an increasing function of the quality of the imported

²⁷ The model of endogenous input and output quality choices proposed by Kugler and Verhoogen (2012) can also be modified to provide insights on how firms respond to intermediate input tariff cut by adjusting their decisions.

intermediate input β and the firm's innovation r . Let p^d be the price of domestic intermediate input, $p^x(\beta)$ the price of imported intermediate input, which is an increasing function of quality (i.e., $p^{x'} > 0$), p^r the price of imported input for innovation activity, and d the import tariff.

Given p^x , p^r , p^d and τ , the firm's optimization problem is

$$\max_{\{\beta, r, x, d\}} [P(y)y - \varphi^x(\beta)x - \varphi^r r - p^d d].$$

Suppose that the second order conditions for optimization hold. Let us use subscript to denote partial derivative. In the appendix, we prove the following proposition.

Proposition 1. *Suppose that θ_r or $\frac{p^{x'}}{p^x}$ is sufficiently small and $\theta_{\beta\beta} > 0$. Then, a decrease in the tariff (τ) on intermediate input will result in a rise in intermediate input quality (β), but a reduction in innovation activity (r). The firm's productivity (θ) will increase.*

When τ decreases, many possible combinations of optimal responses from the three decision variables, namely, x , β and r , exist and the possibility of all three increasing is very possible because of the price effect (cheaper now). However, our analysis identifies an interesting (and somewhat surprising) outcome: r decreases. This decrease is accompanied with an increase in β . The intuition is in fact very clear. Note from the analysis leading to the corollary that the condition on θ_r and that on $\frac{p^{x'}}{p^x}$ are in relative terms. Thus, understanding the result based on the condition that both θ_r and $\frac{p^{x'}}{p^x}$ are small is a better option. In this case, although everything (x and r) is cheaper, spending the money most efficiently to improve output and profit remains a concern. Because the marginal improvement in productivity by increasing innovation is small (θ_r), and the percentage increase in the price of intermediate

input with higher quality ($\frac{p^{x'}}{p^x}$) is also small but the effect of further raising productivity from using higher quality intermediate input increases ($\theta_{\beta\beta} > 0$), increasing the quality of the intermediate input by reducing innovation raises profits, because these inputs serve as substitutes in raising productivity.

The implications of increasing intermediate input quality and reducing innovation on the quantity of import (x) are less clear. With the increase in productivity ($\theta_\tau < 0$), the marginal revenue of increasing input rises, and so x should go up. However, if the cost of import, τp^x , has also increased because of higher quality input, then x will have a tendency to decrease. Our analysis shows that under the condition stated in Proposition 1, in response to a tariff cut, x may increase or decrease.

4.2 Empirical Evidence: Input Quality or Quantity?

We now turn to further empirical analysis to determine the relevance of the above proposed mechanism on how the intermediate input imports of firms respond to tariff cuts. Specifically, we investigate how input tariff cuts affect the value (exclusive of tariffs), quantity, and quality (or price, exclusive of tariffs) of intermediate input imports.

From Customs data, we can obtain detailed information on imports at the HS six-digit level; thus, our regressions are conducted at a more disaggregate level. We first drop all processing imports to process the data before running the regressions. We then identify imports of intermediate inputs using the Classification by Broad Economic Categories (BEC) published by the United Nations Statistics Division. This classification requires us to convert product affiliations in all the years before 2002 to the HS2002 version with the concordance table from the United Nations Statistics Division.

Following Goldberg *et al.* (2010), we conduct the regression analyses (for import price, quantity and value) based on the following model:

$$y_{ijt} = \alpha Tariff01_i \cdot Post02_t + \lambda_i + \lambda_t + \lambda_j \cdot t + \varepsilon_{ijt},$$

where y_{ijt} is the logarithm of quantity, value, and unit value of imported intermediate input i (at HS six-digit level) of industry j (at HS two-digit level) in year t ; $Tariff01_i$ is the tariff of input i in year 2001; $Post02_t$ is the WTO accession dummy as defined previously; and ε_{ijt} is the robust error term. We control for product fixed effect (λ_i) and year fixed effect (λ_t) in all regressions. Because industries may have different time trends, we further control for HS two-digit industry-specific linear time trend ($\lambda_j \cdot t$).

The regression results are reported in Table 8. For each dependent variable, we run the regressions for China's total intermediate input imports from all countries, from OECD countries, and from non-OECD countries, respectively.

As predicted by Proposition 1, if θ_r or $\frac{p^{x'}}{p^x}$ is sufficiently small, which we think is quite plausible for China. Then, in response to input tariff cuts, firms may switch from importing low-quality to high-quality inputs. In this case, import price will be higher because higher quality means higher price. This view is confirmed by columns (1)-(3).²⁸ However, the prediction on the import quantity is less clear, depending on other conditions. Our results show that import quantity drops, as reported in columns (4)-(6). Because price increases while quantity decreases, the change in value is generally ambiguous. Nevertheless, we find that imported value also decreases, as shown by columns (8)-(10).

An alternative way to proxy input quality is to look at the origin of the exporting country, with OECD countries' exports representing higher quality. Although both total quantity and value decrease, the share of input imports from OECD increases in both quantity [column (7)] and value [column (11)], lending further support to the quality upgrade.

²⁸ This finding complements Bas and Strauss-Kahn (2015). There is an important difference though. Bas and Strauss-Kahn (2015) find that, relative to processing-trade firms, ordinary-trade firms increase their import quality after the trade liberalization. Here we show that among ordinary-trade firms, those facing higher trade liberalization intensity increase their import quality more.

As intermediate inputs are classified into intermediate and capital goods in the BEC classification, we also check the two types of intermediate inputs separately and the results are similar.

5. Conclusion

The effects of trade on innovation have long been a hot topic in both academic and policy circles. Trade in intermediate inputs has become increasingly important in the world economy. This paper investigates the effects of intermediate input trade liberalization on firm innovation, which complements the emerging literature that investigates the effects of intermediate input trade liberalization on firm performance from different perspectives such as productivity, product scope, and product quality.

We exploit the quasi-natural experiment of China's WTO accession in 2001 and the rich data on Chinese firms and find that input tariff reductions in China reduce innovations of the Chinese firms. This result is robust to a series of model specifications, and significant both statistically and economically.

The driving force underlying the negative effect of intermediate input imports on firm innovation is that high-quality input imports substitute for internal innovation of firms. Theoretically, intermediate input imports can be complements to internal innovation in the sense that high-quality inputs help lower innovation cost. On the contrary, cheaper intermediate inputs from abroad can be substitutes for firm innovation because firms can buy instead of making them. Our empirical evidence show that the input tariff cut leads firms to opt for lesser imports but choose higher-quality intermediate inputs, whereby reducing innovations.

Although the results are somewhat surprising, they are not incompatible with results obtained by other studies on the effects of intermediate input tariff reductions on the other aspects of the performances of the Chinese firms, such as productivity (Yu, 2015) and export quality (Fan *et al.*, 2015; Bas and Strauss-Kahn, 2015). Introducing a general theoretical framework that can produce all these results and provide a clear mechanism is an attractive prospect. Such a model will also be helpful in predicting whether our negative effect can also be found in other countries. Further empirical studies on the experiences of other countries on the effects of intermediate input trade liberalization on innovation are also encouraged, such as Goldberg *et al.* (2011) on India.

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Appendix

Proof of Proposition 1.

In this proof, we reduce the number of decision variables to make our points as simple as possible. To this end, we make two simplifying assumptions. First, we assume that all inputs for R&D are imported. Second, to focus on import decisions, assume that $f(\cdot)$ takes the Leontief form and the price of domestic input is sufficiently low that the firm always chooses the level of domestic input equal to that of the imported input. This step allows us to omit the domestic input from the production function, and ignoring the cost of domestic input from the profit will not affect the qualitative results. With further simplification, we can write the production function as $y = x\theta(\beta, r)$. We will return to discussing the implications of relaxing these two assumptions later. Relaxing these assumptions will not alter the qualitative aspect of the result and may even reinforce it. Consequently, the firm's optimization problem becomes

$$\max_{\{\beta, r, x\}} [P(y)y - \varpi^x(\beta)x - \varpi^r r].$$

Using subscript to denote partial differentiation, we obtain first-order conditions:

$$P'x^2\theta\theta_\beta + Px\theta_\beta - \varpi^{x'}x = 0,$$

$$P'x^2\theta\theta_r + Px\theta_r - \varpi^r = 0,$$

$$P'x\theta^2 + P\theta - \varpi^x = 0,$$

which can be rewritten as

$$P'x\theta + P = \varpi^{x'} \frac{1}{\theta_\beta}, \quad (2)$$

$$P'x\theta + P = \varpi^r \frac{1}{\theta_r} \frac{1}{x}, \quad (3)$$

$$P'x\theta + P = \varpi^x \frac{1}{\theta}. \quad (4)$$

Combining (2) with (3) and (4), respectively, we obtain

$$x = \frac{p^r}{p^{x'}} \frac{\theta_\beta}{\theta_r}, \quad (5)$$

$$\theta = \frac{1}{p^{x'}} p^x \theta_\beta. \quad (6)$$

Let us focus on a simple case in which $P'' = 0$ and $p^{x''} = 0$. Differentiating (6) with respect to τ and using $\theta_\tau = \theta_\beta \beta_\tau + \theta_r r_\tau$ yields

$$\beta_\tau = A r_\tau, \text{ where } A \equiv \frac{\theta_r}{\theta_{\beta\beta}} \left(\frac{p^{x'}}{p^x} - \frac{\theta_{\beta r}}{\theta_r} \right). \quad (7)$$

Similarly, differentiating (5) with respect to τ and using (7) gives

$$x_\tau = B r_\tau, \text{ where } B \equiv \left[\frac{p^r}{p^x} - \frac{x}{\theta_r} (A \theta_{\beta r} + \theta_{rr}) \right]. \quad (8)$$

Differentiating (1) with respect to τ , we have

$$2P' [x(\theta_\beta \beta_\tau + \theta_r r_\tau) + \theta x_\tau] = p^{x'} \left[\frac{1}{\theta_\beta} - \frac{\tau}{\theta_\beta^2} (\theta_{\beta\beta} \beta_\tau + \theta_{\beta r} r_\tau) \right].$$

Substituting (7) and (8) into the above equation and rearranging the terms yields

$$\left[\underbrace{2P'(Ax\theta_\beta + x\theta_r + B\theta)}_C + \tau \underbrace{\left(\frac{p^{x'}}{\theta_\beta} \right)^2 \frac{\theta_r}{p^x}}_D \right] r_\tau = \frac{p^{x'}}{\theta_\beta}.$$

Hence, if $C < 0$, we will have $r_\tau > 0$ because $D > 0$. Using (5) - (8), we can rearrange the terms to get

$$C = \frac{p^x p^r}{\theta_{\beta\beta}} \left(\frac{\theta_\beta}{p^{x'}} \right)^2 \left[\left(\frac{\theta_{\beta r}}{\theta_r} - \frac{p^{x'}}{p^x} \right)^2 - \frac{\theta_{\beta\beta} \theta_{rr}}{\theta_r^2} \right] + x \theta_r + \frac{p^r}{p^{x'}} \theta_\beta. \quad (9)$$

Then, with some manipulation, we have $C < 0$ if and only if

$$(\theta_{\beta\beta} \theta_{rr} - \theta_{\beta r}^2) \frac{1}{\theta_r^2} > \frac{p^{x'}}{p^x} \left[\frac{p^{x'}}{p^x} - 2 \left(\frac{\theta_{\beta r}}{\theta_r} - \frac{\theta_{\beta\beta}}{\theta_\beta} \right) \right]. \quad (10)$$

Note from (7) that if $A < 0$, then β_τ and r_τ will have the opposite signs, and if $\theta_{\beta\beta} > 0$, then $A < 0$ if and only if

$$\frac{p^{x'}}{p^x} < \frac{\theta_{\beta r}}{\theta_r}. \quad (11)$$

The above analysis leads to the following lemma:

Lemma 1: Suppose $\theta_{\beta\beta} > 0$. Conditions (10)-(11) are sufficient conditions for $\beta_\tau < 0$ and $r_\tau > 0$.

Let us further suppose that $\theta_{\beta\beta}\theta_{rr} - \theta_{\beta r}^2 > 0$ to obtain more meaningful conditions. Then, LHS of (10) is decreasing in θ_r while RHS is increasing in θ_r . Moreover, LHS can be very large when θ_r is very small. Thus, (10) holds when θ_r is sufficiently small. Even if θ_r is not very small (so that LHS is not very large), (10) still holds if $\frac{p^{x'}}{p^x}$ is sufficiently small. An interesting

observation is that (11) also requires θ_r to be sufficiently small or $\frac{p^{x'}}{p^x}$ be sufficiently small.

Hence, the effects of tariff on intermediate input quality and innovation activity are established.

Let us turn to the effect on productivity. Note that $\theta_\tau = \theta_\beta\beta_\tau + \theta_r r_\tau$. Thus, when θ_r is sufficiently small, we also have $\theta_\tau < 0$ because according to Corollary 1, $\beta_\tau < 0$ although $r_\tau > 0$. Alternatively, using the fact that $\beta_\tau = Ar_\tau$ and $\theta_r > 0$ and with the result $r_\tau > 0$, we can easily show that the necessary and sufficient condition for $\theta_\tau < 0$ is

$$\frac{p^{x'}}{p^x} < \frac{\theta_{\beta r}}{\theta_r} - \frac{\theta_{\beta\beta}}{\theta_\beta}. \quad (12)$$

Thus, we have a result on productivity similar to Corollary 1; that is, when θ_r or $\frac{p^{x'}}{p^x}$ is sufficiently small, a decrease in tariff (τ) on intermediate input will result in higher productivity (θ).

Note that condition (12) is stronger than (11). Thus, the condition stated in Proposition 1 should be the condition that satisfies (12).

Recall that we imposed two simplifying assumptions to carry out the above analysis. If the firm uses both domestic input and imported input for R&D, as the imported input becomes

cheaper, the firm will substitute domestic input with imported input. However, compared to the case without domestic input, the decrease in R&D cost as a result of a decrease in τ is smaller. Hence, given the condition in Corollary 1, the firm will have a stronger incentive to reduce R&D. That is, the result stated in Corollary 1 is reinforced.

If substitution between domestic input and imported intermediate input for production is performed, then the level of domestic input (d) will be chosen optimally. As a direct effect, tariff drop will clearly reduce the use of domestic input. The firm will face a similar situation in choosing the other three variables, x , β and r . We do not expect to see the qualitative aspect of Corollary 1 to change. The increase in productivity as a result of higher β may push the use of domestic input, which is the indirect effect. Whether the use of domestic input will go up or down remains ambiguous.

Table 1. Summary Statistics

Variables	All (1)	pre-WTO (2)	post-WTO (3)	Difference (3)-(2)	Definition
Patent	0.1507 (0.0089)	0.0698 (0.0037)	0.1787 (0.0120)	0.1089 (0.0205)	Total no. of patents
Invention	0.0465 (0.0080)	0.0073 (0.0015)	0.0601 (0.0107)	0.0528 (0.0183)	no. of invention patents
Utility	0.0467 (0.0012)	0.0225 (0.0013)	0.0551 (0.0015)	0.0326 (0.0027)	no. of utility patents
Design	0.0574 (0.0016)	0.0400 (0.0021)	0.0634 (0.0020)	0.0234 (0.0037)	no. of design patents
Input Tariff	0.0996 (0.0009)	0.1285 (0.0016)	0.0821 (0.0009)	-0.0464 (0.0017)	Industrial input tariff
Age	10.1022 (0.0102)	13.7903 (0.0249)	8.8264 (0.0103)	-4.9639 (0.0228)	Firm age
Age squared	234.0097 (0.5156)	393.7576 (1.3160)	178.7502 (0.5117)	-215.0074 (1.1645)	Firm age squared
Exporting	0.2784 (0.0004)	0.2651 (0.0008)	0.2830 (0.0005)	0.0179 (0.0009)	Firm exporting status indicator
Labor	4.7841 (0.0010)	5.0096 (0.0020)	4.7062 (0.0011)	-0.3035 (0.0022)	Log of firm employment
Capital/Labor	3.2936 (0.0012)	3.0529 (0.0024)	3.3764 (0.0014)	0.3235 (0.0028)	Log of capital-labor ratio
Foreign Share	0.0641 (0.0002)	0.0518 (0.0003)	0.0683 (0.0002)	0.0164 (0.0005)	Foreign share holding
TFP	2.4688 (0.0011)	2.2031 (0.0021)	2.5610 (0.0012)	0.3579 (0.0024)	Firm productivity
Output Tariff	0.1328 (0.0016)	0.1700 (0.0030)	0.1102 (0.0016)	-0.0598 (0.0031)	Industrial output tariff
SOE share	0.1672 (0.0032)	0.2863 (0.0055)	0.0949 (0.0028)	-0.1914 (0.0056)	Share of SOEs
FIE no.	3.7195 (0.0270)	3.3805 (0.0439)	3.9209 (0.0334)	0.5405 (0.0550)	Logarithm of no. of FIEs
HHI	0.0520 (0.0015)	0.0547 (0.0025)	0.0504 (0.0019)	-0.0043 (0.0031)	Herfindahl-Hirschman Index

Note: Standard errors in parentheses.

Table 2. Correlation between Input Tariff and Pre-WTO Industrial Performance

	(1)	(2)	(3)	(4)	(5)
Variables	Ln(patent)	Output	Output Share of Domestic Firms	Value-add per Capita	Capital-labor Ratio
Input Tariff in 2001	-1.6748 (1.2713)	-0.0636 (0.1118)	-0.0072 (0.0353)	0.0357 (0.0776)	-0.1041 (0.0897)
Observations	280	280	280	280	280
R-squared	0.0058	0.0010	0.0002	0.0007	0.0031

	(6)	(7)	(8)	(9)	(10)
VARIABLES	Ln(patent)	Output	Output Share of Domestic Firms	Value-add per capita	Capital-labor Ratio
Decrease in Input Tariff	0.2204 (3.3125)	0.3833 (0.3449)	-0.0130 (0.0841)	0.0211 (0.1807)	-0.1451 (0.2786)
Observations	280	280	280	280	280
R-squared	0.0000	0.0047	0.0001	0.0000	0.0008

Notes: The dependent variable in each column is the growth rate of the corresponding industrial performance during 1998-2001. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Basic Results

Variables	(1) Ln(patent)	(2) Ln(patent)	(3) Ln(patent)	(4) Ln(patent)	(5) Ln(patent)	(6) Ln(patent)	(7) Ln(patent)	(8) Ln(patent)
InT01*Post02	-0.1555*** (0.0189)	-0.1561*** (0.0190)	-0.1516*** (0.0194)	-0.1886*** (0.0203)				
DlnT*Post02					-0.2847*** (0.0549)			
Input Tariff						0.1853*** (0.0405)		
InTA01*Post02							-0.0286** (0.0116)	
FIT01*Post02								-0.0231** (0.0109)
Firm controls								
Age		-0.0014*** (0.0003)	-0.0014*** (0.0003)	-0.0011*** (0.0002)	-0.0011*** (0.0002)	-0.0011*** (0.0002)	-0.0011*** (0.0003)	-0.0008*** (0.0002)
Age squared		0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Exporting		0.0110*** (0.0016)	0.0110*** (0.0016)	0.0109*** (0.0016)	0.0109*** (0.0016)	0.0109*** (0.0016)	0.0109*** (0.0017)	0.0107*** (0.0018)
ln(Labor)		0.0225*** (0.0011)	0.0225*** (0.0011)	0.0228*** (0.0011)	0.0228*** (0.0011)	0.0228*** (0.0011)	0.0214*** (0.0011)	0.0196*** (0.0011)
ln(Capital/Labor)		0.0047*** (0.0005)	0.0047*** (0.0005)	0.0047*** (0.0005)	0.0047*** (0.0005)	0.0047*** (0.0005)	0.0044*** (0.0005)	0.0039*** (0.0005)
Foreign Share		-0.0010 (0.0035)	-0.0010 (0.0035)	-0.0012 (0.0035)	-0.0012 (0.0035)	-0.0013 (0.0035)	-0.0022 (0.0037)	0.0002 (0.0046)
Industrial controls								
Output Tariff			0.0151 (0.0132)	-0.0024 (0.0133)	0.0039 (0.0133)	-0.0090 (0.0147)	0.0172 (0.0135)	0.0148 (0.0132)
SOE no.				-0.0889*** (0.0114)	-0.0785*** (0.0111)	-0.0781*** (0.0111)	-0.0712*** (0.0117)	-0.0653*** (0.0114)
FIE no.				0.0006 (0.0010)	0.0010 (0.0010)	0.0004 (0.0010)	0.0007 (0.0011)	0.0007 (0.0011)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,280,731	1,270,473	1,270,473	1,268,326	1,268,326	1,268,326	1,162,812	1,084,519
R-squared	0.5117	0.5132	0.5132	0.5141	0.5140	0.5140	0.5149	0.5078

Note: Robust standard errors clustered at firm in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Validity of the Specifications

Variables	(1) Ln(patent)	(2) Ln(patent)	(3) Ln(patent)	(4) Ln(patent)	(5) Ln(patent)
	Flexible	Linear trend	Pre-WTO	Processing firms	Processing firms
InT01*Post02		-0.1981*** (0.0215)		-0.3630 (0.6725)	-0.2775 (0.2099)
Input Tariff			-0.0485 (0.0535)		
InT01*Year1999	0.0263 (0.0224)				
InT01*Year2000	0.0101 (0.0230)				
InT01*Year2001	-0.0739*** (0.0255)				
InT01*Year2002	-0.1275*** (0.0272)				
InT01*Year2003	-0.1645*** (0.0280)				
InT01*Year2004	-0.2133*** (0.0313)				
InT01*Year2005	-0.2704*** (0.0326)				
InT01*Year2006	-0.3414*** (0.0335)				
InT01*Year2007	-0.3938*** (0.0349)				
Firm controls	Y	Y	Y	Y	Y
Industrial controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	1,268,326	1,268,326	323,879	89,316	131,293
R-squared	0.5142	0.5141	0.6127	0.8145	0.6500

Note: Robust standard errors clustered at firm in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Robustness Checks

Variables	(1) Ln(patent)	(2) Ln(patent)	(3) Ln(patent)	(4) Ln(patent)	(5) Ln(patent)	(6) Ln(patent)	(7) Ln(patent)	(8) Ln(patent)	(9) Ln(patent)
Sample	All	All	non-Exporters	Life-cycle	Single-product	Surviving firms	Two-period	TFP	Initial size
lnT01*Post02	-0.1887*** (0.0203)	-0.1851*** (0.0205)	-0.1151*** (0.0185)	-0.1971*** (0.0227)	-0.1737*** (0.0210)	-0.2000*** (0.0203)	-0.1627*** (0.0273)	-0.1919*** (0.0212)	-0.1776*** (0.0202)
HHI	-0.0037 (0.0402)								
Total Exports		0.0042*** (0.0013)							
Length*Post02				-0.0087*** (0.0031)					
Post02							0.0210*** (0.0039)		
Ln(Output/Labor)								0.0131*** (0.0007)	
Firm controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industrial controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y		Y	Y
Observations	1,268,326	1,267,582	913,640	973,993	1,174,680	572,405	475,172	1,195,919	1,268,326
R-squared	0.5141	0.5141	0.5110	0.5195	0.5100	0.4497	0.7913	0.5136	0.5156

Notes: Robust standard errors clustered at firm in parentheses; *** p<0.01, ** p<0.05, * p<0.1. In column 9 we include a series of interaction terms between the initial labor size and year dummies.

Table 6. Alternative Estimation Methods

ARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	Patent	Patent indicator	Ln(patent)	ImpStart	Ln(patent)
	FE Poisson	RE Poisson	1st step	2nd step	1st stage	2nd stage
lnT01*Post02	-3.3218*** (1.1609)	-3.5040*** (0.7862)	-2.0515*** (0.5660)	-0.8275** (0.3282)	0.0384*** (0.0146)	
ImpStart						-2.9826*** (0.7515)
Age	-0.016 (0.0119)	-0.0116 (0.0097)	-0.0311*** (0.0057)	-0.0131*** (0.0032)	0.0017*** (0.0002)	0.0046*** (0.0014)
Age squared	0.0002 (0.0002)	0.0002 (0.0002)	0.0004*** (0.0001)	0.0002*** (0.0001)	-0.0000*** 0.0000	-0.0001*** 0.0000
Exporting	-0.0217 (0.0614)	0.0402 (0.0563)	-0.0056 (0.0432)	0.001 (0.0231)	0.0231*** (0.0015)	0.0759*** (0.0176)
ln(Labor)	0.6446*** (0.0837)	0.7795*** (0.0532)	0.1758*** (0.0337)	0.1544*** (0.0194)	0.0220*** (0.0010)	0.0808*** (0.0166)
ln(Capital/Labor)	0.1050*** (0.0406)	0.2361*** (0.0306)	-0.0137 (0.0198)	0.0403*** (0.0118)	0.0035*** (0.0004)	0.0136*** (0.0028)
Foreign Share	-0.3359* (0.1974)	-0.2004 (0.1627)	-0.1489 (0.0952)	0.0346 (0.0493)	0.0176*** (0.0050)	0.0523*** (0.0149)
Output Tariff	0.0821 (1.1219)	0.0071 (0.7686)	0.8485** (0.4135)	-0.2534 (0.2413)	-0.0117 (0.0106)	-0.0238 (0.0242)
SOE no.	-1.1608* (0.6122)	-1.0104** (0.5011)	-0.1161 (0.2538)	-0.4275*** (0.1460)	0.1452*** (0.0100)	0.3759*** (0.1076)
FIE no.	-0.0908 (0.0720)	-0.1291*** (0.0458)	0.0424 (0.0277)	0.0284* (0.0158)	0.0038*** (0.0009)	0.0107*** (0.0032)
Inpatentr95			4.5846*** (0.0432)			
lambda				-0.6782*** (0.0339)		
Observations	98,868	1,268,326	96,201	31,127	870,661	870,661
R-squared				0.7638	0.6630	
Number of firm	17,241	335,998	16,446			309,713

Note: Robust standard errors clustered at firm in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Heterogeneous Effects

Variables	(1) Invention	(2) Utility	(3) Design	(4) Ln(patent)	(5) Ln(patent)	(6) Ln(patent)
Sample	All	All	All	Low K/L	High K/L	Low TFP
lnT01*Post02	-0.0821*** (0.0082)	-0.1027*** (0.0109)	-0.0464*** (0.0160)	-0.0961 (0.0643)	-0.3564*** (0.0533)	-0.0267 (0.0228)
Firm controls	Y	Y	Y	Y	Y	Y
Industrial controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	1,268,326	1,268,326	1,268,326	357,154	334,867	112,972
R-squared	0.4871	0.4928	0.4690	0.4837	0.5630	0.3670

Variables	(7) Ln(patent)	(8) Ln(patent)	(9) Ln(patent)	(10) Ln(patent)	(11) Ln(patent)	(12) Ln(patent)
Sample	High TFP	SOEs	Private	Foreign	Importer	non-Importer
lnT01*Post02	-0.2963*** (0.0516)	-0.1272*** (0.0466)	-0.1476*** (0.0230)	-0.2678*** (0.0605)	-0.3246*** (0.1192)	-0.0928*** (0.0180)
Firm controls	Y	Y	Y	Y	Y	Y
Industrial controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	771,325	116,023	902,130	250,173	112,983	843,283
R-squared	0.5535	0.4996	0.5259	0.5472	0.6872	0.5642

Note: Robust standard errors clustered at firm in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Effects on Import Value, Quantity and Price

Sample	Import price			Import quantity				Import value			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All sources	From OECD	From nonOECD	All sources	From OECD	From nonOECD	Share from OECD	All sources	From OECD	From nonOECD	Share from OECD
Tariff01*Post02	0.0046*** (0.0014)	0.0063*** (0.0015)	0.0063*** (0.0014)	-0.0123*** (0.0030)	-0.0129*** (0.0034)	-0.0218*** (0.0038)	0.0004 (0.0004)	-0.0072*** (0.0028)	-0.0063** (0.0031)	-0.0135*** (0.0037)	0.0007** (0.0003)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HS6 FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
HS2 Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	25,212	24,845	23,533	25,212	24,845	23,533	24,855	25,233	24,876	23,576	24,876
R-squared	0.9676	0.9642	0.9459	0.9240	0.9176	0.8914	0.6666	0.9058	0.9058	0.8499	0.6870

Notes: In all regressions we control for year and HS 6-digit industry fixed effects, and HS 2-digit industry linear time trend. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: China's Input Tariff Trend: 1996-2007

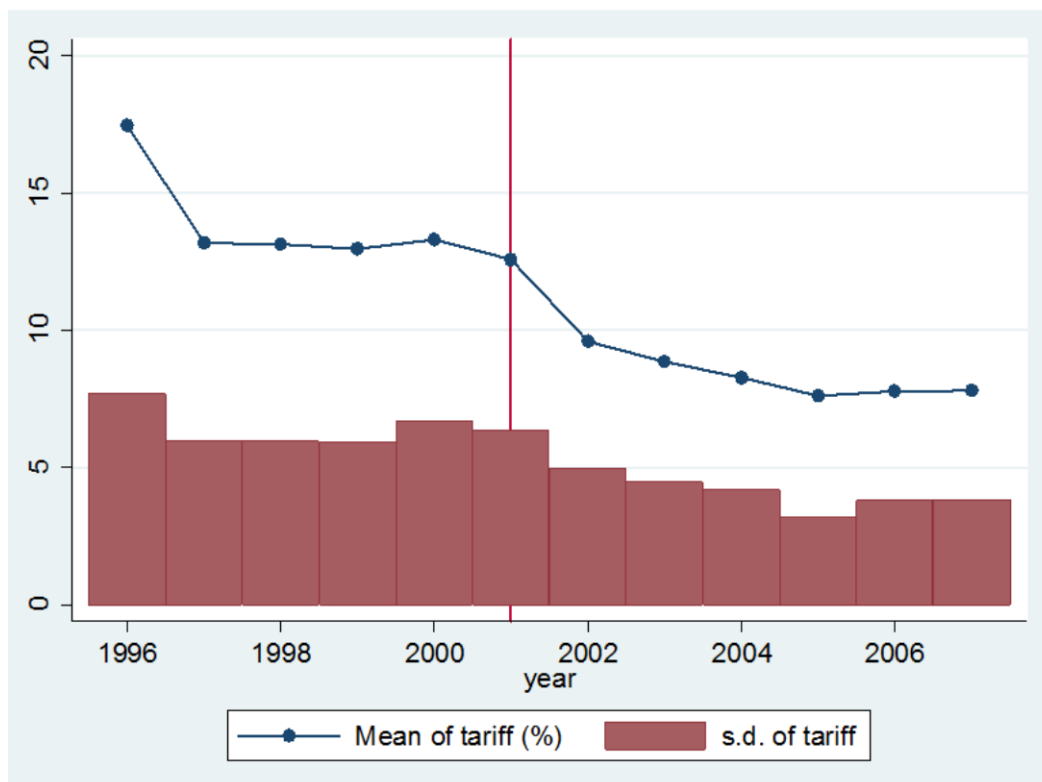


Figure 2: Initial Tariffs and Their Reductions Cross Industries Defined Based on Input-Output Table

