

# Import Competition and Firm Innovation: Evidence from China

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## Abstract

This paper investigates whether and how import competition affects firm innovation. Using China's WTO accession as a quasi-natural experiment, we find that import competition reduces firm innovation, which is consistent with the Schumpeterian Competition Effect. We then test a number of related theories proposed in the literature using rich variations across regions, firms, and patent types. We find support for the preference and knowledge spillover effects, but not for the escape-competition and trapped factor effects. These results shed light on the mixed findings of import competition effects on firm innovation across countries in the literature.

**Keywords:** Import competition; Firm innovation; Schumpeterian Effect; Spillover Effect; Preference Effect; Escape-Competition Effect; Trapped Factor Effect

**JEL Codes:** F12, F13, F14, F15, L11, L13, O31.

# 1 Introduction

Does import competition increase a nation’s innovative activities? The literature has found mixed results across countries. A recent review by [Shu and Steinwender \(2019\)](#) found “overwhelmingly positive evidence for such in developing economies, largely positive evidence for such in Europe, and mixed evidence for such in Northern America.” What accounts for these cross-regional variations in the import competition effect on innovation?

In this paper, we contribute to the literature in two ways by re-examining the effect of import competition on firm innovation in the context of China. First, findings from within China (the largest developing economy and the second-largest economy in the world) offer new evidence to the literature. China provides a good research laboratory: on the one hand, China saw significant reductions in its import tariffs in the early 2000s to fulfil its WTO accession commitment; on the other hand, China has experienced rapid growth in innovative activities over the past few decades. For example, as shown in [Figure 1](#), total patent filings rose from less than 75,000 in 1998 to more than 280,000 in 2005. This dynamic change in innovation offers us an excellent setting with which to identify the trade liberalization effect.

[Insert Figure 1 Here]

Second, China is a large country with significant regional variations in such as stage of development, institutional quality, etc. Furthermore, China has a large pool of firms with substantial heterogeneity in productivity, innovative capacity and so on. Meanwhile, China adopts a patent system with three categories, namely invention, utility, and design, where each has different technological requirements and advancement in innovative degrees. To shed light on the mixed findings in the literature, we use rich variations across regions, firms, and patent types to examine a number of the theories proposed in the literature.

Our research setting exploits China’s accession to the World Trade Organization (WTO) at the end of 2001. After 15 years of applying, China successfully joined the WTO in November 2001 and started to fulfil its tariff reduction obligations in 2002 (e.g., the unweighted average tariff dropped from 15.3% in 2001 to 12.3% in 2004, whilst weighted average tariffs fell from 9.1% to 6.4% during the same period). However, China’s tariff reduction upon WTO accession exhibited great heterogeneity across industries. Those industries with higher initial tariffs in 2001 experienced greater tariff reductions after the WTO accession (for more details, see [Section 2.2](#)). Such a disparity in the degree of trade liberalization (and hence, degree of import competition) across industries provides us with an opportunity to conduct a difference-in-differences (DD) identification - that is, to compare the degree of innovation in industries facing large increases in import competition before and after the WTO accession compared to that in industries with small increases in import competition during the same period.

Manually matching three datasets for China (i.e., tariff data, patent filing data, and firm-level data), we find that import competition reduces firm innovation: overall patent filings fell in industries experiencing greater liberalization upon WTO accession relative to those experiencing less. The findings were robust to a battery of validity checks relating to our DD estimation, including checking the expectation effect and controlling for

other ongoing policy reforms. They also remained robust to checks for other econometric concerns, such as the aggregation issue, the multi-industry issue, and the cross-product within-industry tariff variations issue.

Meanwhile, we conduct a series of heterogeneous effect analyses to examine a number of theoretical models. First, [Aghion et al. \(2005\)](#) showed that when firms are locked in neck-and-neck competition, higher levels of competition will drive high-productivity firms to innovate more to escape the competition of their rivals (the escape competition argument). Alternatively, the preference argument suggests that less productive firms may provide incentives to managers to survive in an environment of competition with their rivals ([Raith 2003](#)). By looking at the effects across firms, we find that the effect of import competition on firm innovation is statistically and economically insignificant for initially low productivity firms, in contrast to the significantly negative effect for initially high productivity firms. This is consistent with the preference argument, but not with the escape competition argument. Second, import competition reduces the opportunity costs of various trapped factors, and therefore lowers the costs of innovation ([Bloom et al. 2013](#)). By examining the effects across regions, we do not find significant differences in estimated effects across provinces with different degrees of factor markets frictions. These findings suggest that the trapped factor argument does not work in our research setting. Third, we find that the import competition effect is positive though statistically insignificant with regard to design innovation, but negative and statistically significant with regard to invention and utility model innovations, with the effect on invention being a little stronger than that on the utility model. Given that learning from observing foreign products and discovering tricks to pass the patent application examination decreases from design innovation, to utility model innovation and to invention innovation, these results lend support to the spillover effect argument. <sup>1</sup>

Our work is related to a growing and important strand of the literature that investigates how globalization affects the incentives for innovation. In particular, [Shu and Steinwender \(2019\)](#) review the recent literature on the impact of trade liberalization on firm innovation, and conclude that “In summary, the studies in our review find overwhelmingly positive evidence in developing economies, largely positive evidence in Europe, and mixed evidence in Northern America.” Our findings of a negative effect in China (that is, outside Northern America) provides new evidence to the literature. Meanwhile, we use rich variations across regions, firms, and patent types to further our understanding of when and where the positive effect of import competition on firm innovation is derived.

Recently, a few papers have examined the effects of international trade and investment on firm innovation in China. For example, [Liu and Qiu \(2016\)](#) studied the effect of input tariffs on firm innovation; [Bombardini, Li and Wang \(2018\)](#) looked at the distributional effect of import competition on firm innovation (i.e., firms with different productivity levels); [Liu and Ma \(2017\)](#) studied the export uncertainty effect on firm innovation; [Chen, Shao and Zhu \(2018\)](#) investigated the effects of FDI deregulation on firm innovation. In contrast to these studies, we focus on the mean effect of output tariff cuts and their differential effects across different types of innovation. We also control for the effects of inputs, exports and FDI. The most closely related paper to ours is [Bombardini, Li and](#)

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<sup>1</sup>In the literature, knowledge spillovers essentially occur in the expanding varieties model ([Romer 1990](#)) or quality ladder model ([Grossman and Helpman 1993](#)). In the former, the scale effect is at work as greater variety reduces the entry costs to firms. In the latter, the firm learns from frontier technology to upgrade its quality.

Wang (2018), who also studied the effect of import competition on firm innovation in the context of China. The key difference between our work and Bombardini, Li and Wang (2018) is that we estimate the overall effect of import competition on innovation and the differential effects to shed light on the various and disparate findings in the literature, while they considered the differential impacts across firms with different productivity levels. Further, we study the contemporary effect, while they consider the lagged two years effect.

## 2 Background

### 2.1 China's Accession to the WTO

In July 1986, China notified the General Agreement on Tariffs and Trade (GATT, the predecessor of the WTO) that the country would like to resume its status as a GATT-contracting party, a process that eventually lasted 15 years. Between 1987 and 1992, as China was debating the direction of its economic reforms, its return to GATT was suspended. The momentum resumed after Deng Xiaoping's southern tour speech in 1992, and in July 1995 China officially filed the application to join the WTO.

The pivotal part of China's WTO accession process involved bilateral negotiations between China and WTO members. The first country that signed a bilateral agreement (in August 1997) with China with regard to China's accession to the WTO was New Zealand. However, the negotiations between China and the United States took 25 rounds and four years to reach an agreement, which ultimately occurred in November 1999. Thereafter, China reached agreements with a further 19 countries within half a year, including Canada in November 1999 and the European Union in May 2000. In September 2001, China reached an agreement with Mexico, which indicated that negotiations with all WTO member countries had been completed. Finally, the WTO's Ministerial Conference approved by consensus the text of the agreement for China's entry into the WTO on November 10, 2001.

As a requirement for membership of the WTO, China carried out large-scale tariff reductions between 1992 and 1997. Specifically, in 1992, China's (unweighted) average tariff was as high as 42.9%. Shortly after the GATT Uruguay Round negotiations, China substantially reduced its tariffs: the average tariff dropped from 35% in 1994 to around 17% in 1997. Tariffs remained stable after 1997 until China joined the WTO at the end of 2001. At the beginning of 2002, China started to fulfil its tariff reduction responsibilities as a WTO member country. According to the WTO accession agreement, China would complete the tariff reduction by 2004 (with a few exceptions to be completed by 2010), whereby the average tariffs on agricultural and manufacturing goods would be reduced to 15% and 8.9%, respectively.

Figure 2 plots China's (unweighted) average tariffs during the period 1996-2007. It can be seen that tariff rates dropped substantially in 1996, remained relatively stable during the period 1997-2001, and gradually began to reduce in 2002 until reaching a steady state in 2005. The unweighted average tariff dropped from 15.3% in 2001 to 12.3% in 2004, whereas the weighted average tariffs decreased from 9.1% to 6.4%.

[Insert Figure 2 Here]

Interestingly, tariff reduction on accession to the WTO was somewhat heterogeneous across products. As shown in Figure 2, the ratio of tariffs at the 25th percentile over those at the 75th percentile also showed a sharp drop in 2002 and then stabilized after 2005. In Figure 3, we further plot the relation between tariffs in 2001 (the year just before accession to the WTO) and the changes in tariffs between 2001 and 2005 across four-digit industries (the level used in the main regression analysis).<sup>2</sup> Clearly, there is a strong, positive correlation, implying that industries with higher tariffs before accession to the WTO experienced more tariff reductions afterwards. Presumably, China had to reduce its tariffs to the appropriate WTO-determined levels, which themselves are quite uniform across products, whereas by contrast China's pre-WTO tariffs themselves differed considerably across products.

[Insert Figure 3 Here]

## 2.2 The Patent System in China

The Chinese patent system has some similarities and some differences to that employed in the United States. The United States recognizes three different patent types: utility patents (new and useful process, machine, article of manufacture, or composition of matter), design patents (new, original, and ornamental designs for articles of manufacture), and plant patents (distinct and new plant varieties). China does not recognize plant patents and divides the utility patent into two categories, namely invention patents and utility model patents. In addition to these two types of patents, China also grants design patents.

The invention patent in China is very similar to the utility patent in the United States. It protects "any new technical solution relating to a product, a process or improvement" (Article 2 in Chinese Patent Law). The application for an invention patent in China requires the submission of information by the applicant in a highly similar manner to that required in the United States for a utility patent; and, similar to the Patent and Trademark Office (PTO) in the United States, the State Intellectual Property Office of China (SIPO) conducts a thorough investigation as to the novelty, inventiveness, and usefulness of the innovation before issuing the patent. On average, it can take from three to five years to grant an invention patent. If approved, the patent is granted for a maximum of 20 years.

A utility model patent in China lies somewhere between a U.S. utility patent and a design patent in that it protects "any new technical solution relating to the shape, structure, or combination thereof, of a product which is fit for practical use" (Article 2 of Chinese Patent Law). It is not subject to a substantive examination, however, as in the case of an invention patent. Although a utility model patent does not have to meet the same level of inventiveness as an invention patent, the utility patent still has to pass the novelty test and must meet criteria for practical use and functionality. It is often seen as an improvement in functionality rather than an entirely new solution, as in the case of an invention patent. Therefore, a utility patent can be granted as soon as one year after the filing date. A utility model patent provides protection for 10 years.

A design patent in China is much like a design patent in the United States in that

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<sup>2</sup>A similar pattern was uncovered at the HS-6 product level (results available upon request).

it protects “any new design of the shape, pattern, colour, or combination thereof, of a product, which creates an aesthetic feeling and is fit for industrial application ” (Article 2 of Chinese Patent Law). The requirements for design patents are lower than those for utility patents. That is, there is no substantive examination and no technical nor functional thresholds; however, the patents must be different from prior designs. A design patent in China can be granted for up to 10 years.

Table 1 shows, for each of the 29 two-digit industries, the total number of patent filings, the average number of patent filings per firm, and the proportion of firms that have ever filed a patent. Electrical Equipment (30,793 filings), Electrical Machinery (26,267 filings), and Transport Equipment (10,707 filings) are the top three industries in terms of total numbers. Other Manufacturing (26 filings), Chemical Fibre (315 filings), and Petroleum Processing (494 filings) are the bottom three industries. However, these numbers may be inflated by the total number of firms in each industry. By looking at the average patent filings per firm, we find intuitively that high-tech and capital-intensive industries are larger in number, for example, Electric Equipment (0.6887 filings per firm), Electric Machinery (0.3245 filings per firm), and Special Equipment (0.1786 filings per firm). Low-tech and labour-intensive industries tend to have smaller numbers, for example, Food Processing (0.0168 filings per firm), Garments (0.0196 filings per firm), and Print and Record Medium Reproduction (0.0199 filings per firm).

[Insert Table 1 Here]

Industries have different propensities to file patents. Generally, low-tech and labour-intensive industries have a higher propensity to file design patents, while high-tech and capital-intensive industries are more prone to file invention and utility model patents. For example, Stationery, Educational and Sporting Goods, and Food Production and Beverages are the top three industries in the average design patent filings per firm. Electric Equipment, Medical, and Electric Machinery have the largest average number of invention patent filings per firm.

### 3 Data

Our analysis draws on three datasets that use different identity codes. Therefore, we matched the data manually to create a unique firm-level dataset containing industry-level tariff information, firm-level innovation information, and other firm-level characteristics.

We first used the WTO’s *Tariff Download Facility* to obtain information about Chinese tariffs. The tariff data provide, for each product defined at the HS-6 digit level, detailed information on the number of tariff lines, the average, minimum, and maximum ad valorem tariff duties, etc. The tariff data are available for 1996, 1997, and the period between 2001 to the most recent year. As the tariff information on the WTO website is missing for the period 1998-2000, for those years we used data from the World Integrated Trade Solution website, which is maintained by the World Bank. Meanwhile, as different HS codes were used before and after 2002, we matched the 1996 HS codes (also used for the 1997–2001 tariffs) to the 2002 HS codes (used for the 2001–2006 tariffs) using the standard HS concordance table. There are 5,036 HS-6 products from manufacturing industries in our tariff data.

We then aggregate tariffs from the HS product level to the industry level. We first matched the HS classification to the Chinese Industrial Classification using the concordance table from the National Bureau of Statistics of China. Then, for each industry and each year, we calculated the simple average tariff. However, one may be concerned that such aggregation may conceal substantial variations in tariff reduction across products within a given industry; that is, products are assigned equally for the degree of the tariff reduction. To address this concern, we, in a robustness check, construct a weighted average tariff, and hence, give products different degrees of influence according to their initial import share.

To capture the degree of firm innovation, one can use either innovation inputs (e.g., R&D spending) or innovation outputs (e.g., patents application). We follow the literature by using patent filing information (see, for example, [Aghion et al. 2005](#); [Hashmi 2013](#)). By definition, a patent provides the holder a temporary monopoly rent for the corresponding innovation. Relative to R&D spending, using patents has the advantage that they are available for developing countries such as China. In particular, our firm-level data only have R&D information for two post-WTO years. Patenting is also highly correlated with R&D expenditures ([Griliches 1990](#)). [Autor et al. \(2017\)](#) further discuss three attractive features of using patent filing data to capture the degree of innovative activities.<sup>3</sup> However, it is important to be aware of the issues relating to the use of such a measure. For instance, patents could underestimate technology because the innovation must be important enough to be registered as a patent and technologies cannot be codified in patents.

The patent filing data were obtained from the State Intellectual Property Office of China (SIPO). The data contains detailed information on each patent filing since 1985, such as the date of filing, the name and address of the applicant, the name of the patent, and also the type of the patent (i.e., whether the patent is an invention patent, a utility model patent, or a design patent).

A drawback of the patent filing data set is that it does not have much information about firm characteristics (except for the name and address). We obtained all the necessary firm characteristics from our third data source, the *Annual Survey of Industrial Firms* (ASIF), as maintained by the National Bureau of Statistics of China, for the period between 1998-2005. This is the most comprehensive firm-level dataset available in China, as it covers all state-owned enterprises (SOEs) and non-state-owned enterprises with annual sales above five million renminbi (around US\$600,000). The number of firms varies from more than 140,000 in the late 1990s to more than 243,000 in 2005, spanning all 31 provinces or province-equivalent municipalities and all manufacturing industries, which ensures invaluable national representativeness. The dataset provides detailed firm information, including name, industry affiliation, location, and all operation and performance items from the accounting statements such as age, employment, capital, intermediate inputs, and ownership.

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<sup>3</sup>Specifically, they point out that: 1) "One attractive feature of patent data relative to other measures of innovative activity is that the year in which a patent application is filed provides a reasonable proxy for the year in which an invention occurs"; 2) "A second attractive feature is that the patent record contains a wealth of information on the nature of the invention, including the technology class of the patent"; and 3) "A third attractive feature of patents is that patent citations provide an ex post indication of the quality and impact of the innovation". We will exploit the second attractive feature to disentangle the heterogeneous impact of trade liberalization across types of innovation.

As the patent filing data and the ASIF data have different firm identity codes, we manually merged the two data by firm name reported in both data and double-checked our matching with the firms' location information.<sup>4</sup> This may raise certain concerns regarding the matching quality, which may then bias our estimation. Specifically, if the mismatching degree changes discontinuously across industries with different degrees of trade liberalization at the time of the WTO accession, our estimator would then reflect the mismatching errors rather than the trade liberalization effect. While we cannot directly examine the quality of matching, several threads of evidence largely dispel this concern. First, we find that our matched data account for 36.1% of total patent filings by all firms (including both manufacturing and non-manufacturing firms) in the patent filing data for the period between 1998-2005. While the patent filing data do not further distinguish firms into manufacturing and non-manufacturing firms, according to the two economic censuses conducted in 2004 and 2008, manufacturing firms accounted for about one-fifth of the total number of firms in China. Concerning the fact that the ASIF data contain mostly large manufacturing firms, the matching between the patent filing data and the ASIF data is reasonably good. Meanwhile, according to a report by the National Bureau of Statistics of China, about 8.8% of the manufacturing firms with annual sales above five million renminbi applied for patents during 2004-2006. In our matched data, for the period between 2004-2005, about 4% of firms applied for patents. Given that the patent filings increased quickly in the 2000s, we should have obtained a reasonably good match. Furthermore, we applied consistent rules to the data matching throughout the entire sample period (from 1998 to 2005) and there is no reason to expect that there are discontinuities in the degree of mismatch across industries with different degrees of trade liberalization at the time of the accession to the WTO, thereby alleviating concerns about estimation biases arising from matching process.

The matched data have an unbalanced panel of 440,877 firms and a total of around 1.3 million observations, with detailed patent filing information and firm characteristics for the period 1998-2005.

## 4 Evidence

### 4.1 Estimation Specification

To identify the impact of import competition on innovation, we explore the fact that after China joined the WTO, some previously more protected industries (i.e., industries with higher tariffs in 2001) experienced larger tariff reductions, due to the WTO agreement, and hence more import competition, whereas other previously more open industries (i.e., industries with lower tariffs in 2001) saw smaller changes in tariffs and hence less liberalization. The timing of the tariff reductions (2002) and variations in degrees of industrial liberalization provide the opportunity to conduct a difference-in-differences (DD) estimation; that is, to compare the change of innovative activities in previously more protected industries (the treatment group) before and after 2001 with the corresponding change in previously more open industries (the control group) during the same period (see, for example, [Guadalupe and Wulf 2010](#), for a similar practice).

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<sup>4</sup>Due to the different firm identity codes used by different ministries in China, the use of the official name of firms to match different data sources is widely adopted.



The specification of our DD estimation is:

$$y_{fit} = \alpha_f + \beta \text{Tariff}_{i2001} \cdot \text{Post02}_t + \mathbf{X}'_{fit} \gamma + \lambda_t + \varepsilon_{fit}, \quad (1)$$

where  $f$ ,  $i$ , and  $t$  represent a firm, four-digit industry which is the finest classification in our data, and year, respectively;  $y_{fit}$  measures the innovation made by firm  $f$  in industry  $i$  in year  $t$ ;  $\text{Tariff}_{i2001}$  is the tariff rate of industry  $i$  in 2001;  $\text{Post02}_t$  is a (step function) indicator of the post-WTO period, taking a value of 1 if it is 2002 and onward, and 0 otherwise; and  $\varepsilon_{fit}$  is the error term. To deal with the potential heteroskedasticity and serial autocorrelation, we cluster the standard errors at the industry-year level (see [Bombardini, Li and Wang \(2018\)](#)).

$\alpha_f$  is the firm fixed effect, controlling for all time-invariant heterogeneity across firms, industries and regions, such as regional geographic features, industry inherent distributions of different innovation types, etc.  $\lambda_t$  is the year fixed effect, controlling for all yearly shocks common to industries such as business cycles, technological progress, changes in the patenting system, etc.

Given that there are many zero patent filings at the firm level, we use the following transformed measure as our outcome variable:

$$y_{fit} = \ln [Y_{fit} + 1],$$

where  $Y_{fit}$  is the total number of patent filings by firm  $f$  in industry  $i$  in year  $t$ .<sup>5</sup>

To isolate the effect of import competition, we control for several time-varying firm characteristics ( $\mathbf{X}_{fit}$ ) that may affect firms' innovation, such as firm age, firm size, capital-labour ratio, exporting status, share owned by foreign investors, and share owned by the state.<sup>6</sup>

Meanwhile, as in the ASIF data, each firm only reports one industrial affiliation, presumably its main industry. However, it is possible that firms may produce goods in multiple industries (but we only observe one due to the limitations of the data). This might cause an estimation issue: our estimation may ignore the effect of import competition from other industries in which firms have production but which are not reported in the data. To check whether our estimates are biased because of this multiple-industry issue, we first conduct a robustness check at the three-digit industry level, in which the multiple-industry issue is less severe. Moreover, we have obtained product-level data from the National Bureau of Statistics of China for the period between 2000-2005, which contains information about each product (defined at the five-digit product level) produced by the firm, firm identity, etc. As the product-level data and the ASIF data use the same firm identity, we can easily match these two datasets, and conduct a robustness

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<sup>5</sup>Another way to deal with the zero patent filings is to use the Poisson or zero-inflated negative binomial model. However, we cannot get convergence in estimating these models, presumably because we include a large set of firm and year dummies, which may also cause the incidental parameter problem in non-linear models; see, for example, [Lancaster \(2000\)](#)

<sup>6</sup>The intellectual property rights (IPR) protection in China is still not particularly strong, which may then reduce firms' incentive to innovate. While the overall IPR environments are captured by year fixed effects  $\lambda_t$ , what concerns us is the potential heterogeneous impacts across firms. For example, the IPR protection may affect the patenting behaviour of foreign and domestic firms differently. Indeed, in our data, we did find that the effects of import competition on firm innovation were different for foreign firms, state-owned firms, and private firms in China. To contain this potential bias, we include firm ownership as additional controls in the regressions.

check by focussing on a subsample of firms producing all goods within only one four-digit industry.

Note that we use the interaction of tariffs in 2001 ( $Tariff_{i2001}$ )<sup>7</sup> and the post-WTO indicator ( $Post02_t$ ) as our regressor of interest, instead of yearly tariffs ( $Tariff_{it}$ ). One motivation for such was that the schedule of tariff reduction upon China’s accession to the WTO was released in 2002, and hence the phase-out process was expected and could be exploited by firms. Meanwhile, as elaborated in Liu and Trefler (2011), the use of the interaction between  $Tariff_{i2001}$  and  $Post02_t$  can capture both the real and expected effects of trade liberalization.

## 4.2 Graphical Results

Figures 4 and 5 contain plots of the trends over time for the total and average number of patent filings per firm for high-tariff industries (industries with tariffs above the sample median in 2001, i.e., our treatment group) and low-tariff industries (industries with tariffs below the sample median in 2001, i.e., our control group) for 1998–2005.

[Insert Figures 4 and 5 Here]

It is clear that in the pre-WTO period (1998–2001, i.e., the pre-treatment period), the two groups had quite similar trends. Such parallel pre-treatment trends in firm innovation between the treatment and control groups alleviates the concern that our treatment and control groups are *ex ante* incomparable, lending support to our DD identifying assumption.

Meanwhile, there is a visible divergence in firm innovation trends after 2002, that is, the time when China started to reduce its tariffs upon its accession to the WTO. The consistency in timing between the divergence in firm innovation and accession to the WTO suggests that trade liberalization affects firm innovation. Specifically, import competition has a clear negative effect on overall innovation.

In the remaining parts of this section, we use a regression analysis to establish formally the innovation effect of import competition (induced by the tariff reduction upon the WTO accession).

## 4.3 Main Results

The regression results for the DD specification (1) are presented in Table 2. We start with a simple DD specification that includes only firm and year fixed effects in column 1. Our regressor of interest,  $Tariff_{i2001} \cdot Post02_t$ , is negative and statistically significant, suggesting that firms innovated less after 2002 in industries with higher tariffs in 2001 than those in industries with lower tariffs in 2001. Given that industries with higher tariffs in 2001 experienced more tariff reduction and import competition after 2002, this result implies that import competition reduces firm innovation.

In column 2, we add some time-varying firm characteristics that may correlate with the outcome variable (i.e., firm innovation) and the regressor of interest (i.e., the degree

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<sup>7</sup>Using average tariffs for 1997-2001 or tariffs in 1997 generates similar results (available upon request), presumably because tariffs did not change much between 1997 and 2001.

of trade liberalization). Specifically, we include firm age (single and squared terms), firm size, capital–labour ratio, exporting status, and equity share owned by foreign investors. Evidently, our results are robust to these additional controls.

If there were other policy reforms differentially targeting our treatment and control groups around the time of accession to the WTO (i.e., the end of 2001), our DD estimates may also capture the effects of these other policy reforms, making it difficult to pinpoint the effect of trade liberalization. There were two important ongoing reform efforts in the early 2000s, the SOE reform and the relaxation of foreign direct investment (FDI) regulations. To control for any confounding effects from these two policy reforms, we include in our DD estimation *SOE Share* (measured by the ratio of the number of SOEs over the total number of firms) and *FDI share* (measured by the ratio of the number of foreign invested firms over the total number of firms)<sup>8</sup> in 2001, interacted with our Post-2002 dummy. Specifically, we add two control variables (the fraction of SOEs and of foreign-invested firms of all firms, respectively) in a stepwise manner in columns 3 and 4, then include both of them in column 5. Our main findings still remain robust.

We experiment with weighted average industrial tariffs in column 6 to address the concern that products are affected differently within a given industry. The actual magnitude might change somewhat but the negative pattern remains consistent and significant.

In columns 7 and 8, we further disentangle the import competition effect on innovation at the extensive and intensive margins. Specifically, we investigate whether the effect comes from the fact that firms become less likely to apply for patents (the extensive margin) and/or that firms applied for fewer patents (the intensive margin). To this end, we regress the patent-filing indicator (which equals unity if the firm files any patent in that year, zero otherwise) on our regressor of interest in column 7, and find a statistically significant negative effect. Meanwhile, in Column 8 we repeat the exercise as described for Column 5, but this time we focus on the sample of firms that have ever applied for patent. The estimates shown in columns 7 and 8 show a consistently negative and statistically significant effect. These results suggest that import competition reduces innovation at both the intensive margin and the extensive margin.

In summary, the results in Table 2 show that import competition results in firms innovating less. Our findings of negative innovation response to import competition echo similar findings in the U.S. (e.g., Autor et al. 2017), but are in sharp contrast to results using data from Latin American and Asian countries (e.g., Teshima, 2009; Iacovone et al., 2011; Ahn et al., 2018). In the remainder of this paper, we examine the validity of our identifying assumption and other econometric estimation concerns, and then investigate several possible theories that are proposed in the literature to explain the different findings for different countries.

[Insert Table 2 Here]

#### 4.4 Checks on the Identifying Assumption

The identifying assumption associated with our DD estimation specification (Equation 1) is that conditional on a whole list of controls  $(\alpha_f, \mathbf{X}_{fit}, \lambda_t)$ , our regressor of interest,

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<sup>8</sup>As discussed in the introduction, the alternative channel for spillovers in addition to imports is investment from foreign firms.

$Tariff_{i2001} \cdot Post02_t$ , is uncorrelated with the error term,  $\varepsilon_{fit}$ , i.e.,<sup>9</sup>

$$E[\varepsilon_{fit} | Tariff_{i2001} \cdot Post02_t, \alpha_f, \mathbf{X}_{fit}, \lambda_t] = E[\varepsilon_{fit} | \alpha_f, \mathbf{X}_{fit}, \lambda_t]. \quad (2)$$

In other words, innovation in the treatment group would have followed the same trend as that in the control group if there had been no trade liberalization in 2002. To address this issue, we will apply a linear trend regression as we will explain below.

In addition, there may be other challenges to our identifying strategy, specifically the non-random selection of tariffs in 2001, the timing of the accession to the WTO, and certain other simultaneous policy reforms. In this subsection, we present the results of a battery of robustness checks on the identifying assumption of our aforementioned DD estimation. The regression results are presented in Table 3.

*Industrial Trend.*—The analyses above controlled for a series of firm characteristics and fixed effects. However, there may still be a concern that industries may have different trends that might compromise the comparability of the treatment and control groups. To check this concern, we include an industry-specific linear time trend, e.g.,  $\alpha_i \cdot t$ . This enables us to control for unobserved industry characteristics in a limited format, that is, provided they affect firm innovation in a specification of a linear time trend. The regression results are presented in column 1. Evidently, our regressor of interest remains negative and statistically significant, implying that our estimates are not driven by these unobserved underlying industry characteristics.

*Expectation Effect.*—There may be a concern that China’s WTO accession by the end of 2001 was expected and firms could then have adjusted their behaviour even before the tariff reduction happened after 2002. However, the process of China’s accession to the WTO was very lengthy, taking about 15 years to complete, and the approval required a consensus by all WTO member countries. Despite China having achieved important breakthroughs by signing agreements with the United States in 1999 and the European Union in 2000, there were still many residual issues that were unresolved until mid-2001. Hence, the timing of China’s accession to the WTO was largely uncertain before 2001.

Nonetheless, as a first robustness check we include an additional control in the DD regression,  $Tariff_{i2001} \times Y2001$  (where  $Y2001$  indicates the year 2001), to examine whether firms changed their innovative behaviour in anticipation of the accession to the WTO in the following year. Estimation results are reported in column 2. The coefficient of  $Tariff_{i2001} \times Y2001_t$  was found to be statistically insignificant and very small in magnitude, suggesting that there is no such expectation effect. Moreover, the coefficient of our regressor of interest remains negative and statistically significant.

Furthermore, we flexibly estimate the effect of trade liberalization on firm innovation. Specifically, our regressor of interest becomes  $Tariff_{i2001} \times \lambda_t$ , which calculates a series of coefficients corresponding to each year in our data. This test allows us to check whether the treatment and control groups are comparable up to the time of accession, and hence further exclude any expectation effects. As shown in column 3, in the pre-WTO period,

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<sup>9</sup>Note that the identification does not require our control variables to be exogeneous, e.g.,

$$E[\varepsilon_{it} | \alpha_i, \mathbf{X}_{it}, \lambda_t] = 0.$$

In other words, for these control variables, the estimated coefficients may not have a causal interpretation. See Stock and Watson (2012, page 274) for further discussion and proof of this point.

all the estimated coefficients are positive, insignificant, and small in magnitude. However, immediately after accession, the estimated coefficients become negative. These results further corroborate our previous findings in Figure 4, that is, trade liberalization (through the WTO accession at the end of 2001) triggered a fall in firm innovation.

*Placebo Test I: Pre-WTO Period.*—To check our identifying assumption further, we conduct three placebo tests. The first placebo test follows Topalova (2010) in looking at the effects of tariffs on firm innovation in the pre-WTO period (1998-2001). The premise is that as tariffs did not change much during this period, and thus we would not nominally expect any significant effects; the contrary might indicate the existence of some underlying confounding factors. As shown in column 4, we indeed find that, as expected, tariffs had no significant effect on firm innovation in the pre-WTO period.

*Placebo Test II: Processing trade firms.*—There is a special category of firms in China that completely conduct processing trade for foreign buyers, that is, these firms take offshoring orders from foreign firms and export all their products abroad. In this sense these firms are immune to domestic import competition, and thus their innovative activities should theoretically not be affected by import competition. We identify these firms in our sample and run a regression for this subsample of firms. We find in column 5 that Chinese tariff cut did not affect these processing trade firms’ innovation.

*Placebo Test III: Randomization of Trade Liberalization.*—As a further robustness check, we randomly assign tariffs in 2001 to industries and randomly select a year for the WTO accession. We then construct a false regressor of interest  $Tariff_i^{false} \cdot Post_t^{false}$ , and conduct a regression analysis using the specification (1). Given the random generating process of the data,  $Tariff_i^{false} \cdot Post_t^{false}$  is expected to have no effects; otherwise, it may indicate the misspecification of equation (1). We repeat the exercise 500 times to increase the veracity of the placebo test. The mean and standard deviation of the 500 coefficients are reported in column 6. Evidently, the mean value is small in magnitude and highly insignificant, leading further support to the validity of our research design.

[Insert Table 3 Here]

## 4.5 Other Robustness Checks

In this subsection, we present another series of robustness checks on other econometric concerns. The result of the regression are presented in Table 4. We find that our main finding is robust to these considerations.

*Negative Binomial Regression.*—Our outcome variable is patents, which is a typical count variable. As it is over-dispersed, with the sample standard deviation (5.1948) being much larger than the sample mean (.1168), we conduct a fixed-effect Negative Binomial Regression to check whether our finding is robust to the estimation method. The result in column 1 of Table 4 confirms that import competition significantly decreases innovation.

*Checks on the Multi-Industry Issue.*—A potential concern is that firms could produce multiple products spanning different industries, and hence our aforementioned DD estimation may miss the liberalization effect from industries outside the affiliated four-digit

industry reported by the firms in the data. To check this concern, we try two robustness checks. First, we use a more aggregated industry level tariff (i.e., the three-digit industry level tariff) to rerun our regression. As it is less likely that firms span more aggregated level industries, this helps to mitigate the multi-industry concern. Second, we obtain a dataset from the National Bureau of Statistics of China for 2000-2005 that contains information about whether firms produce five-digit level products across different four-digit industries. With this information we are able to focus on a subsample of firms producing only in one four-digit industry and check the robustness of our results. As shown in columns 2 and 3, we find that the innovation effect of trade liberalization remains negative and statistically significant.

*Two-Period Estimation.*—One concern with the DD estimation is how one can accurately calculate the standard errors and hence the statistical inference. Thus far, we have followed the suggestion by [Bertrand, Duflo and Mullainathan \(2004\)](#) to cluster the standard errors at the industry-year level. As a robustness check, we use another approach suggested by [Bertrand, Duflo and Mullainathan \(2004\)](#), that is, collapsing the panel structure into two periods, one before and the other after the WTO accession, and then use the White-robust standard errors. Meanwhile, this exercise also allows us to compare the long-term average effect of trade liberalization on firm innovation. The regression results are presented in column 4. Clearly, we obtain similar (but larger) results.

*Industry Level Regressions.*—Our regressor of interest is at the four-digit industry level, therefore our estimate of the impact of import competition is the industrial average effect, even though our regressions are at firm level. Here we directly conduct an industry level regression by aggregating our firm level variables to the industry level to check the robustness of our main finding. Column 5 shows that the industrial total patents are still decreased by import competition. In column 6, we further check the industrial extensive margin effect of import competition, that is, how the import competition affects the number of firms that apply for patents. We find that this number also falls.

[Insert Table 4 Here]

## 5 Explanations

Our aforementioned analysis documents a negative impact of import competition on firm innovation. This is consistent with the Schumpeterian effect, in which import competition reduces post-innovation returns and hence dampens ex ante innovation incentives. However, studies in the literature also find some positive effects of import competition on firm innovation in the context of other countries, e.g., [Teshima \(2009\)](#), [Iacovone, Keller and Rauch \(2011\)](#), [Bloom, Draca and Van-Reenen \(2016\)](#), [Aghion et al. \(2007\)](#), etc. This suggests that there are some positive forces in place associated with import competition. [Shu and Steinwender \(2019\)](#) summarize three positive forces proposed in the literature: (1) the escape competition effect ([Arrow \(1962\)](#); [Aghion et al. \(2005\)](#)); (2) the preference effect (e.g., [Hart, 1983](#); [Leibenstein, 1978](#)); and (3) the trapped factor effect ([Bloom et al., 2018](#)). Meanwhile, the availability of new imports may generate knowledge spillovers to domestic producers, which in turn enhance the possibility of innovation.

To gain a further understanding of our findings and shed light on the mixed findings in the literature, we, in this section, first examine whether our results mainly operate through the import competition channel and then use rich variations across regions, firms, and patent types to examine the relevance of these forces of the positive effects of import competition.

## 5.1 Import Competition Channel

To further establish that our findings are mainly due to the intensified competition by foreign imports, we first investigate whether imports increase after the tariff reduction and then exclude other channels, such as foreign market access, brought about by the accession to the WTO.

*Tariff Reduction and Imports.*—With import and tariff information both available at the HS-6 product level, we accordingly conduct the analysis of import response to trade liberalization at this level. However, there are many HS-6 product categories with zero import value, which creates a potential estimation bias (i.e., the sample selection issue). To correct for the zero trade value issue, we use the Poisson pseudo-maximum likelihood estimation described by [Silva and Tenreyro \(2006\)](#). Specifically, we regress the level of imports on our regressor of interest ( $Tariff_{p2001} \times Post02_t$ , where  $Tariff_{p2001}$  is the tariff of product  $p$  in 2001) along with a set of product and year dummies. The regression results are presented in column 1 of Table 5. We find that imports increase in those product categories experiencing more tariff reduction, corroborating our import competition argument.

[Insert Table 5 Here]

*Market Access Effect.*—The WTO accession is multilateral; that is, China’s trading partners may also reduce their barriers on imports from China, thus enlarging the market access to Chinese firms. There is ample evidence that increased export markets have a positive effect on innovation ([Lileeva and Trefler \(2010\)](#), [Aw, Roberts and Xu \(2011\)](#)). To fix the idea that the change in firm innovation comes from the increase in the degree of domestic competition generated by tariff reduction, we include an interaction term between the weighted average foreign tariffs imposed on China’s exports in 2001 and the  $Post02_t$  to control for access to foreign markets. The regression results are presented in column 2. We find that export tariff cut has an insignificant effect while the impact of import tariff cuts remains significant, lending support to the import competition argument.

*Input Tariff.* — In addition to the final good tariffs that we have investigated thus far, the WTO accession also reduces intermediate input tariffs faced by Chinese firms, which may also affect firm innovation ([Liu and Qiu, 2016](#)). We include industrial input tariffs in column 3 of Table 5 to check whether our main finding holds. We find that input tariffs are positively correlated with firm innovation, as consistent with [Liu and Qiu \(2016\)](#). More importantly, our main result stays unchanged: the coefficient of output tariff in 2001 interacted with the post-WTO indicator in a manner that is still significantly negative.

## 5.2 Escape Competition and Preference Effects

The escape competition and preference effects both predict that import competition increases firms' incentive to innovate, but have different implications for firms with different initial productivity levels. The former concerns the pre-innovation market returns; that is, the intensified competition by imports reduces status quo profits and hence pushes firms to innovate. As foreign exporters are generally more productive than domestic firms in China, the neck-and-neck competition implies that initially more productive firms have the greater incentive to innovate so as to escape the competition from foreign imports. The preference effect focusses on the within-firm inefficiency (such as managerial slack), and import competition can help discipline these inefficient activities and increase firm innovation. As initially unproductive firms have considerable room to improve efficiency, the preference effect implies larger positive import competition effects in initially less productive firms.

To examine the relevance of these two effects in our setting, we group firms into four quantiles based on their average productivity in the pre-WTO period within each four-digit industry. We then run separate regressions for each quantile. The results are reported in columns 1-4 in Table 6. All quantiles show negative coefficients; however, the effect for the lowest productivity quantile is statistically and economically insignificant. These findings suggest a larger positive or a smaller negative effect for initially less productive firms, which is ultimately more consistent with the preference effect argument than that of the escape competition effect.

[Insert Table 6 Here]

Our results also echo those by [Shu and Steinwender \(2019\)](#), who find a positive effect of import competition on firm innovation in Spanish family firms (initially unproductive) but not in professionally managed firms. However, our findings are different from those reported in [Bombardini, Li and Wang \(2018\)](#), who also use Chinese setting but find the import competition increases innovation for the most productive firms. One major difference between our work and that of [Bombardini, Li and Wang \(2018\)](#) is that we study the contemporary effect while they look at the lagged two years effect. It could be that import competition disciplines firm inefficiency in the shorter term, but the escape competition motives take time to realize.

## 5.3 Trapped Factor Effect

[Bloom et al. \(2018\)](#) propose another explanation for the positive import competition effect on firm innovation, namely that there are some factors trapped within a firm (due to specific switching costs). The negative shocks from import competition may then reduce the opportunity costs of these trapped factors and hence increase the returns from innovation. [Shu and Steinwender \(2019\)](#) hypothesise that "frictions in the markets might be the largest in developing countries and the lowest in Northern America", which may then explain the different findings of import competition on firm innovation across countries.

China is a large country with substantial regional variations in institutional quality, such as market frictions, which provides us with the opportunity to examine the relevance



of the trapped factor argument. Specifically, we use the Chinese Regional Marketization Indices developed by Fan et al. (2003). To capture factor market frictions, we use the index of factor markets development, which contains three sub-indices: the marketization degree of financial industry, the mobility of labour, and the commercialization of technological achievements. All the indices are measured at the provincial level, with a larger value indicating better market development. We conduct separate regressions for each province, and then correlate the estimated coefficients obtained with the factor market development indices. If the trapped factor effect works, provinces with larger frictions are expected to show stronger positive effects of import competition on firm innovation. We do this analysis for the overall index of factor markets development, as well as for the three sub-indices.

Results are plotted in Figures 6a-6d, with 6a for the overall factor markets development index and 6b-6d for the three sub-indices, respectively. We consistently find weak correlations between the estimated effects of import competition and provincial factor market development. These findings suggest that the trapped factor argument does not work in our research setting.

[Insert Figure 6 Here]

## 5.4 Spillover Effect

Foreign imported products may contain advanced technologies or new product features which can generate knowledge spillovers to domestic firms, especially in developing countries. This creates a positive effect of import competition on firm innovation. To formally establish this argument, we extend the standard trade model to allow an endogenous selection of product quality (see also [Dhingra 2013](#)) in the Appendix. Our model entails two effects of trade on firm innovation. The first is that the increase in competition reduces firms' future profits from innovation and hence dampens their incentive to innovate, i.e., the standard Schumpeterian competition effect. The second is the spillover effect; that is, firms can share the knowledge stock possessed by foreign firms through learning from observing and competing with foreign products. Hence, the overall effect of trade liberalization on firm innovation depends on the relative importance of these two effects.

To examine the relevance of the spillover argument, we use variations across innovation types. According to Chinese Patent Law, applications for invention patents are subject to strict examination of the utility, novelty, and non-obviousness, and, compared with the existing technologies, the innovation must have "prominently substantive characteristics and significant improvement." However, utility model and design patents are more or less incremental innovations and are not subject to examination for novelty and non-obviousness. Generally, both are granted on a registration basis. Compared with the requirement for the design patent, which focusses only on the appearance or the shape, the requirement for the utility model patent application is stricter in the sense that utility model innovation must also be functionally useful and have "substantive characteristics and improvement" compared with existing technologies. Hence, we expect that the spillover effect arising from observing foreign products and discovering tricks to pass the patent application examination decreases from design innovation, to utility model innovation, and to invention innovation. Our theoretical analysis in the Appendix formally establishes these predictions.

For the empirical examination, our patent data contains information about patent types. Specifically, patents are classified into three categories at the filing stage; that is, invention, utility model, and design patents. We then conduct separate regressions for the three types of innovations. The results are reported in columns 1-3 in Table 7. Interestingly, we find differential effects of import competition on different types of innovations. Specifically, the effect is positive though statistically insignificant for design innovation, but negative and statistically significant for invention and utility model innovations, with the effect for invention being a little stronger than that for utility model. These results lend support to the spillover effect. They are also consistent with the literature: for example, Gorodnichenko, Svejnar and Terrell (2010) find that firms in developing European countries engage more in small-step innovations in response to imports.

[Insert Table 7 Here]

## 6 Conclusion

The impact of trade liberalization on growth has long been a hot issue in the discussion of globalization. In this paper, we investigated whether trade liberalization positively or negatively affects firm innovation, which is regarded as one of the key determinants of long-term economic growth. To establish the causality from trade liberalization to innovation, we employed the Difference-in-Differences technique to exploit the quasi-natural experiment brought about by China's accession to the WTO. Specifically, this accession generated industrial heterogeneity in tariff reduction, based on which we compared firms in industries experiencing greater liberalization with those in industries experiencing less liberalization.

We have found that trade liberalization reduced a firm's overall innovation, and this finding is robust to a series of checks. Furthermore, following the review in [Shu and Steinwender \(2019\)](#) we have checked a number of potential explanatory mechanisms proposed in the literature. In particular, by taking advantage of the rich variation of our dataset, we examine the alternative effects such as the escape competition effect, the preference effect, the trapped factor effect and the spillover effect. Our data seems to agree with the preference effect and the spillover effect but not the other two effects.

Our findings complement the current literature on the growth effect of trade liberalization. In particular, the findings remind us of the potential heterogeneity of the effect on innovation. For example, trade liberalization may be detrimental for fundamental innovation activities due to the negative Schumpeterian effect unless firms can obtain substantial positive spillovers from foreign firms.

## References

- Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and Innovation: An Inverted U Relationships." *Quarterly Journal of Economics*, 120(2): 701–28.

- Aghion, Philippe, Richard Blundell, Rachel Griffith, Peter Howitt, and Susanne Prantl.** 2007. “Entry, Innovation, and Growth: Theory and Evidence.” *Review of Economics and Statistics*.
- Arrow, K.** 1962. “Economic Welfare and the Allocation of Resources to Invention.” In *The Rate and Direction of Economic Activity*. Princeton University Press.
- Autor, David, David Dorn, Gordon Hanson, Gary Pisano, and Pian Shu.** 2017. “Foreign Competition and Domestic Innovation: Evidence from U.S. Patents.” MIT mimeo.
- Aw, Bee, Mark Roberts, and Daniel Xu.** 2011. “R & D Investment, Exporting and Productivity Dynamics.” *American Economics Review*, 101(4): 1312–44.
- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan.** 2004. “How Much Should We Trust Differences-in-Differences Estimates?” *Quarterly Journal of Economics*, 119: 249–75.
- Bloom, Nicholas, Mirko Draca, and John Van-Reenen.** 2016. “Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity.” *Review of Economic Studies*, 83(1): 87–117.
- Bloom, Nicholas, Paul Romer, Stephen J. Terry, and John Van-Reenen.** 2013. “A Trapped-Factors Model of Innovation.” *American Economic Review*, 103(3): 208–13.
- Bloom, Nicholas, Paul Romer, Stephen Terry, and John Van-Reenen.** 2018. “Trapped Factors and China’s Impact on Global Growth.” Working Paper.
- Bombardini, Matilde, Bingjing Li, and Ruoying Wang.** 2018. “Import Competition and Innovation: Theory and Evidence from China.” working paper.
- Bustos, Paula.** 2011. “Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms.” *American Economic Review*, 101(1): 304–40.
- Chen, Xiaoping, Yichun Shao, and Lianming Zhu.** 2018. “Identifying the Knowledge Diffusion of Multinational Firms.” Working Paper.
- Dhingra, Swati.** 2013. “Trading Away Wide Brands for Cheap Brands.” *American Economic Review*, 103(6): 2554–84.
- Griliches, Z.** 1990. “Patent statistics as economic indicators: A survey.” *Journal of Economic Literature*, 28(4): 1661–1707.
- Grossman, Gene, and Elhanan Helpman.** 1993. *Innovation and Growth in the Global Economy*. MIT Press.
- Guadalupe, Maria, and Julie Wulf.** 2010. “The Flattening Firm and Product Market Competition: The Effect of Trade Liberalization on Corporate Hierarchies.” *American Economic Journal: Applied Economics*, 2(4): 105–27.

- Hart, O.D.** 1983. “The Market Mechanism as an Incentive Scheme.” *Bell Journal of Economics*, 14(2): 366–382.
- Hashmi, Aamir Rafique.** 2013. “Competition and Innovation: The Inverted-U Relationship Revisited.” *Review of Economics and Statistics*, 95(5): 1653–68.
- Iacovone, L., W. Keller, and F. Rauch.** 2011. “Innovation Responses to Import Competition.” Working paper.
- Jovanovic, Boyan, and Glenn M. MacDonald.** 1994. “Competitive Diffusion.” *Journal of Political Economy*, 102(1): 24–52.
- Lancaster, Tony.** 2000. “The incidental parameter problem since 1948.” *Journal of Econometrics*, 95: 391–413.
- Leibenstein, H.** 1978. “On the Basic Proposition of XEfficiency Theory.” *American Economic Review*, 68(2): 328–332.
- Lileeva, Alla, and Daniel Trefler.** 2010. “Improved Access to Foreign Markets Raises Plant-level Productivity... For Some Plants.” *Quarterly Journal of Economics*, 125(3): 1051–99.
- Liu, Qing, and Hong Ma.** 2017. “Export Uncertainty and Innovation: Firm Level Evidence from China’s WTO Accession.” Working Paper.
- Liu, Qing, and Larry Qiu.** 2016. “Intermediate Input Imports and Innovations: Evidence from Chinese Firms Patent Filings.” *Journal of International Economics*, 166–83.
- Liu, Runjuan, and Daniel Trefler.** 2011. “A Sorted Tale of Globalization: White Collar Jobs and the Rise of Service Offshoring.” NBER Working Paper No. 17559.
- Melitz, Marc.** 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica*, 71(6): 1695–1725.
- Raith, M.** 2003. “Competition, Risk and Managerial Incentives.” *American Economic Review*, 93(4): 1425–36.
- Romer, Paul.** 1990. “Endogenous Technological Change.” *Journal of Political Economy*, 98(5): 71–102.
- Shu, Pian, and Claudia Steinwender.** 2019. “The Impact of Trade Liberalization on Firm Productivity and Innovation.” In *Innovation Policy and the Economy*. Vol. 19. NBER.
- Silva, J. M. C. Santos, and Silvana Tenreyro.** 2006. “The Log of Gravity.” *The Review of Economics and Statistics*, 88(4): 641–58.
- Teshima, K.** 2009. “Import Competition and Innovation at the Plant Level: Evidence from Mexico.” Working Paper.
- Topalova, Petia.** 2010. “Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India.” *American Economic Journal: Applied Economics*, 2(4): 1–41.

## Appendix

In this section, we use a simple model to illustrate how trade liberalization affects firms' innovation behaviour and how it has different effects on different types of innovation. Specifically, we extend the Melitz (2003) model to allow an endogenous selection of product quality (see also Dhingra 2013).

### 6.1 Model Setup

*Demand.*—There is a continuum of horizontally differentiated varieties. Let us denote  $\Theta$  the set of all available varieties in the market. The utility of a representative consumer is drawn from domestic and imported goods. If we call  $D$  and  $M$  the composite domestic and imported goods, respectively, and assume that they are imperfectly substitutable, we have the following utility function:

$$U = \left( D^{\frac{\mu-1}{\mu}} + M^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}} \quad (3)$$

where  $\mu > 1$  indicates the elasticity of substitution between domestic and imported goods. From this utility function, we can derive the total demand for the domestic good and the total demand for the imported good as:

$$D = \left( \frac{P_D}{P} \right)^{-\mu} \frac{E}{P}, M = \left( \frac{\tau P_M}{P} \right)^{-\mu} \frac{E}{P} \quad (4)$$

where  $P = [(P_D)^{1-\mu} + (\tau P_M)^{1-\mu}]^{\frac{1}{1-\mu}}$  is the Home price index,  $P_D$  and  $P_M$  are the domestic and imported price indices,  $E$  indicates the Home aggregate expenditure, and  $\tau$  is the import tariff.

Our focus is the domestic market, in particular how domestic firms respond to trade liberalization. To this end, we assume the utility from the composite domestic good is given by:

$$D = \left[ \int_{i \in \Theta} \theta_i^{\frac{1}{\sigma}} (q_i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}, \sigma > 1$$

where  $\theta_i$  represents product quality with  $i$  denotes the variety. Hence, the demand for each product is given by:

$$q_i = \theta_i \left( \frac{p_i}{P_D} \right)^{-\sigma} D, \quad (5)$$

where  $P_D$  is the domestic price index,  $P_D = \left[ \int_{i \in \Theta} \theta_i p_i^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$ .

*Production.*—Labour is the only factor in our model and the wage is normalized to be 1. Every firm entering the market has to incur a fixed entry cost  $f_e$ . Upon paying

this entry cost, the firm draws its productivity level  $\varphi$  from a distribution  $G(\varphi)$ , which is assumed to be a Pareto distribution for ease of illustration.<sup>10</sup> Specifically, we assume:

$$G(\varphi) = \frac{\varphi_m^k}{\varphi^k}$$

where  $\varphi_m$  is the lower bound of productivity.

As in other trade models (e.g., Melitz 2003), there is a fixed cost of production  $f$  if the firm is active. Note that this fixed cost is different from the entry cost  $f_e$ . We model the variable production cost as the inverse of firm productivity, i.e.,  $c = \frac{1}{\varphi}$ . This variable cost is independent of the quality of the product.<sup>11</sup>

*Innovation, Learning, and Patenting.*—In our model, we allow the firm to invest in innovation to improve its product quality  $\theta$ . Specifically, we follow Grossman and Helpman (1993) to model the costs of innovation: resources (in terms of labour) have to be committed to boost the quality of the product. Although higher quality products require more investment in innovation, we allow innovation costs to be reduced via learning activities. For example, a firm can learn from other firms' products to speed up the procedure of making its product better.

Meanwhile, afraid of being copied by its competitors, a firm can apply for a patent to ensure that no other firms are able to sell an identical product, which then preserves the firm's market power in a monopolistic competitive fashion. To receive its patent, the product has to pass a quality control test. If the quality improvement is significant according to the test, the application will be approved.

The innovation cost function takes the following form:

$$I(\theta) = v(\theta) * f(\alpha, X), \quad (6)$$

where  $v(\theta)$  is the cost of the committed labour for quality  $\theta$ . To illustrate our point, we set  $v(\theta) = \theta^n$  and  $n > 1$ . The function  $f(\alpha, X)$  captures the firm's learning effect, to be discussed later, where  $X$  captures the set of firms/products that the firm can learn from, and  $\alpha$  is the learning parameter.<sup>12</sup>

We assume that the learning effect is formulated as  $f(\alpha, X) = \alpha^X$ , where  $0 < \alpha < 1$  and  $X$  is the number of foreign firms, i.e.,  $X = \int_{\varphi_x}^{+\infty} dG(\varphi) = \frac{\varphi_m^k}{\varphi_x^k}$  where  $\varphi_m$  and  $\varphi_x$  are the productivity thresholds for foreign and Home firms to operate in the Home market, respectively.<sup>13</sup> According to this learning effect, more foreign firms  $X$  bring down the

<sup>10</sup>All our results will go through with any general form of  $G(\cdot)$ .

<sup>11</sup>It is natural to assume that the marginal costs of producing quality goods are higher. However, this assumption does not change our model, as we can always factor the production costs in the demand function (Equation 5)

<sup>12</sup>Note that because the investment in quality has two components, one interpretation of our setup is that the firm can improve the quality of its product either by producing new knowledge (the first component) or by learning from others (the second component). A similar idea can be found in Jovanovic and MacDonald (1994).

<sup>13</sup>Our setup is isomorphic in the empirical sense to the ones used in Grossman and Helpman (1993). Indeed, if we take logs, both approaches yield a product of the stock of knowledge ( $X$ ) and the learning parameter  $\alpha$ . Both approaches lead to the same result. Our approach is chosen purely because it allows us to have a micro-foundation for the parameter  $\alpha$ . More discussion of our approach can be found in Appendix A.

innovation costs.

Finally, to bridge our theory to the empirical tests in the next section, we need to link the quality investment to the number of patents. To this end, we assume that the number of patents is a strictly increasing function of the level of quality. This is because a breakthrough innovation has many more corresponding patents than a small change in quality. For simplicity, we assume that all patents of the same type have the same quality improvement embedded. In other words, the number of patents by a firm is a linear function of its investment in quality.

## 6.2 Equilibrium Analysis

The firm in our model has two decisions to make: how to price its products and how much to invest in improving quality. We consider each decision below.

*Pricing Strategy.*—As upgrading quality does not affect the firm’s variable cost, the firm chooses its pricing strategy to maximize its profit given a level of quality  $\theta$ :

$$\max_p pq - cq - I(\theta)$$

where the demand  $q$  is given from Equation (5). This yields the optimal price, which equals the variable cost multiplied by the constant markup:

$$p = \frac{\sigma}{\sigma - 1}c. \quad (7)$$

*Quality Selection.*—With the above pricing strategy (Equation 7), the profit of a domestic firm is given by:

$$\pi_d(\varphi_i) = B\theta_i\varphi_i^{\sigma-1} - I(\theta_i), \quad (8)$$

where  $\varphi_i$  is the productivity of the firm and:

$$B = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} P_D^{\sigma-1} D. \quad (9)$$

Recall that the innovation cost is  $I(\theta) = \theta^n \alpha^X$ . Maximizing the firm’s profit (Equation 8) by choosing the quality level yields:

$$\theta_i = \left( \frac{B\varphi_i^{\sigma-1}}{\alpha^X n} \right)^{\frac{1}{n-1}}. \quad (10)$$

Equation 10 is the key theoretical result of our model. First it demonstrates the *negative* effect of economies of scale. A firm generates more sales when the market is large (high  $B$ ) and its productivity level ( $\varphi$ ) is high, resulting in more investment to upgrade its product quality. Second and more importantly it illustrates the spillover effect via the term  $\alpha^X$ . More precisely, more foreign firms (i.e., greater  $X$ ) bring with them new products and new technologies. As a result, there is more scope for learning

for the Home firms, which implies a fall in innovation cost (see equation 6). This spillover effect explains the *positive* effect of import liberalization on innovation.

*Market Demand and Domestic Cut-off.*—Firms enter the market as long as their expected profits are higher than the entry cost, and the free-entry condition implies:

$$\int_{\varphi_0} (B\theta\varphi^{\sigma-1} - I(\theta) - f) dG(\varphi) = f_e \quad (11)$$

Marginal domestic firms (indicated by the subscript 0), by definition, only have sufficient profits to cover their production fixed costs. In other words, the zero-profit condition implies:

$$B\theta_0\varphi_0^{\sigma-1} - I(\theta_0) = f \quad (12)$$

Inserting the quality level  $\theta_0$  in Equation 10, the two conditions (11) and (12) yield market demand  $B$  and domestic cut-off  $\varphi_0$ . Specifically, the formula for the domestic cut-off is given by:

$$\varphi_0 = \left( \frac{n^{\frac{1}{n-1}}}{\left(1 - \frac{1}{n}\right)} f \right)^{\frac{n-1}{(\sigma-1)n}} B^{\frac{-1}{\sigma-1}} \alpha^{\frac{X}{(\sigma-1)n}}. \quad (13)$$

*Foreign Cut-off.*—The foreign cut-off is also determined by the zero-profit condition, with the fixed cost being the export fixed cost  $f_x^*$  and the market demand  $B^* = \frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma} P_M^{\sigma-1} M$ . In particular, we have:

$$\varphi_x = \left( \frac{n^{\frac{1}{n-1}}}{\left(1 - \frac{1}{n}\right)} f_x^* \right)^{\frac{n-1}{(\sigma-1)n}} (B^*)^{\frac{-1}{\sigma-1}} \alpha^{\frac{X}{(\sigma-1)n}} \tau, \quad (14)$$

where  $\tau$  is the iceberg shipping cost from the foreign country to the domestic market.

*Quality Distribution.*—We can draw the quality distribution from Equation 10. Given the zero profit condition (12), the lowest quality for a domestic firm is given by:

$$\theta_0 = \left( \frac{f}{(n-1)\alpha^X} \right)^{1/n}.$$

Figure 3 shows the distribution of quality before trade liberalization takes place. The form of the distribution can be convex or concave depending on the elasticity of substitution  $\sigma$  and the convexity of the quality investment  $n$ . In particular, the distribution is convex when  $\sigma > n$ .

[Insert Figure 3 Here]

*Number of Patents.*—The total number of patents for which domestic firms apply is the product of the number of firms and the number of patents per firm. The latter clearly



depends on the amount of R&D the firm undertakes to raise the quality of its product, while the former depends on the domestic cut-off  $\varphi_0$ .

As in [Bustos \(2011\)](#) and [Dhingra \(2013\)](#), equation (10) shows that more productive firms in a large market (i.e.,  $B$ ) tend to invest more in innovation and apply for more patents. Their decision, however, also depends on the learning effect (i.e.,  $\alpha^X$ ); the higher the learning scope  $X$ , the more innovation investment, and hence patents, the firms apply.

### 6.3 The Effect of Trade Liberalization

In this section, we analyse the impact of a unilateral tariff cut from the Home country on the domestic innovation effort. As the number of patents at the firm and industry levels depend on the effective market size  $B$  and the learning scope  $X$ , we focus on how import tariffs affect these two variables.

**Lemma 1.** Lowering import tariffs leads to smaller domestic market demand.

**Proof.** When import tariffs are cut, consumers switch their expenditure toward imported goods (see Equation (4)), resulting in less demand for domestic goods  $D$ . Therefore, effective market demand  $B$  drops (see Equation (9)).

**Lemma 2.** Lowering import tariffs raises the learning ability of domestic firms. Moreover, the strength of the learning effect is lowest for the invention type and highest for the design type.

**Proof.** When trade liberalization takes place, the market demand for imported goods  $B^*$  rises. Equation 14 implies that the cut-off for foreign firms to enter the Home market falls. As a result, the number of foreign firms  $X$  increases, which brings more information to domestic firms and helps them learn more. In other words, the costs of upgrading the quality of the products is reduced (note that  $f(\alpha, X) = \alpha^X$  decreases with  $X$  as  $\alpha < 1$ ). Moreover, as the parameter  $\alpha$  increases from the design type to the invention type, a firm that applies for a design patent benefits more from the influx of foreign firms than a firm that applies for an invention patent in terms of knowledge acquired.

We use the two lemmas above to prove the following proposition.

**Proposition 1.** A unilateral tariff cut has a *negative* impact on innovation via the Schumpeterian effect and a *positive* impact via the spillover effect.

**Proof.** From Equation 10, we can decompose the change in investment in quality per firm as:

$$\Delta \log \theta = \frac{1}{n-1} \Delta \log B + \frac{\log \alpha}{n-1} \Delta X$$

From this we have:

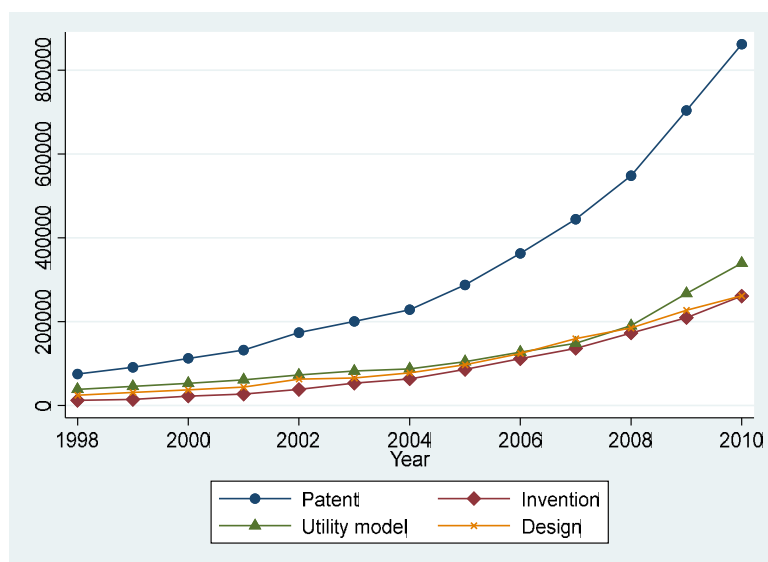
$$\frac{\partial \log \theta}{\partial \tau} = \underbrace{\frac{1}{n-1} \frac{\partial \log B}{\partial \tau}}_{\text{Schumpeterian effect}} + \underbrace{\frac{\log \alpha}{n-1} \frac{\partial X}{\partial \tau}}_{\text{spillover effect}}$$

According to Lemma 1, the Schumpeterian effect implies a reduction in the number of patents, while Lemma 2 indicates that the spillover effect increases the number of patents, after a reduction in tariffs.

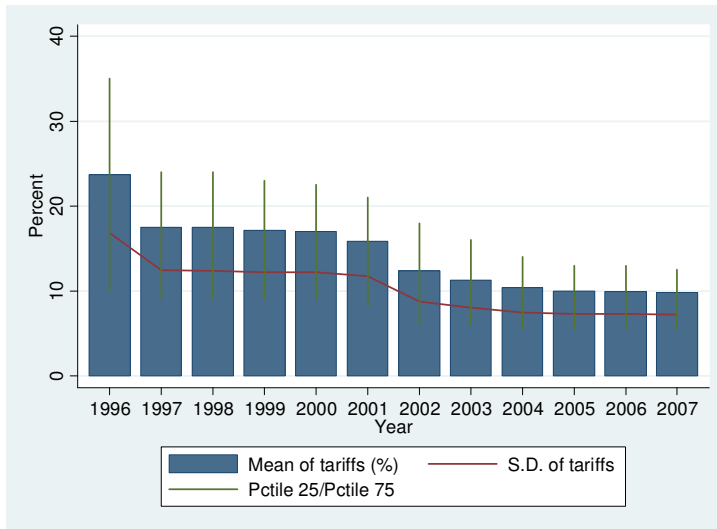
Because of the two opposing effects, the impact of import liberalization on innovation cannot be straightforwardly assessed as it depends on which effect is the dominant force. As we can see from the decomposition above, the strength of the spillover effect depends on the learning parameter  $\alpha$ . When this parameter takes a value close to 1, the spillover effect is negligible ( $\log\alpha = 0$ ). In this case, the negative Schumpeterian effect is more likely to dominate and import liberalization reduces the number of patents which is an indicator of innovation. By contrast, if  $\alpha$  is close to 0, the strength of the spillover is significant and more likely to dominate the Schumpeterian effect. Therefore when a country like China opens its market, we would expect Chinese firms to escalate their innovation efforts which in turn boosts the number of patents. This prompts us to suggest the following hypothesis:

**Hypothesis 1.** A reduction in the import tariff reduces (increases) the number of patents when the spillover effect is less (more) pronounced.

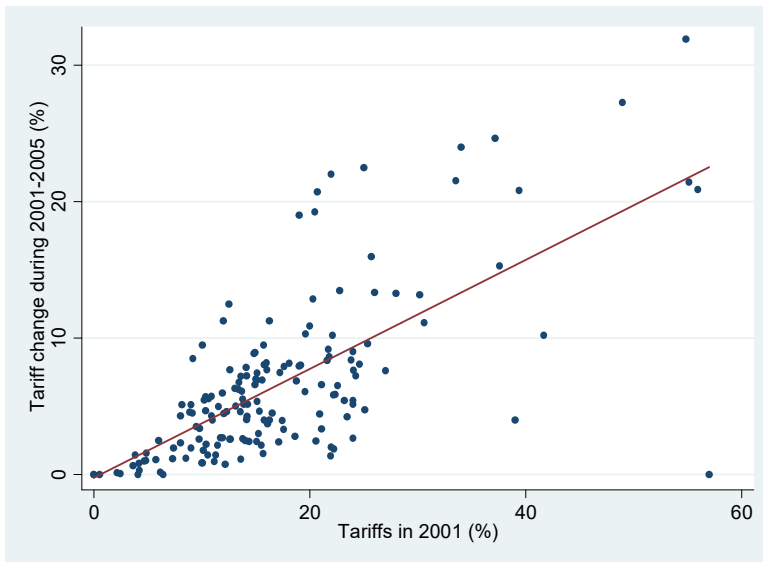
## Appendix B: Figures and Tables



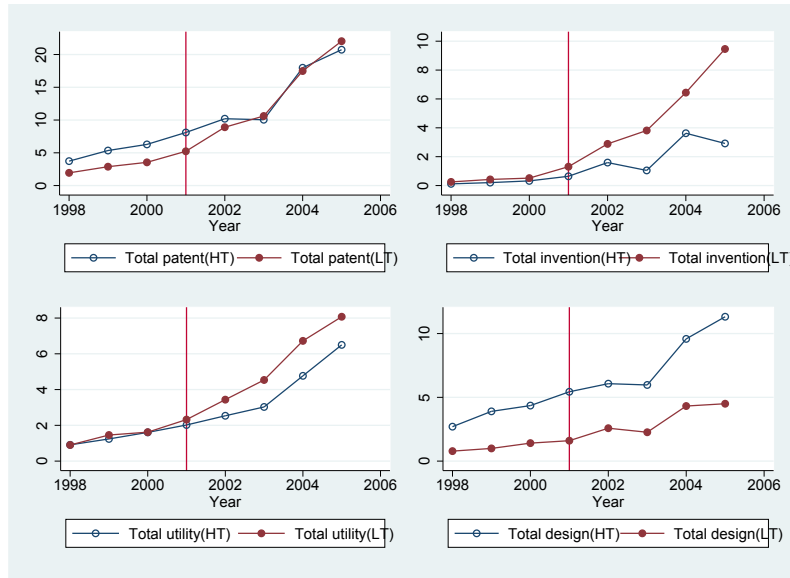
**Figure 1:** Trend for patent applications in China, 1998-2010



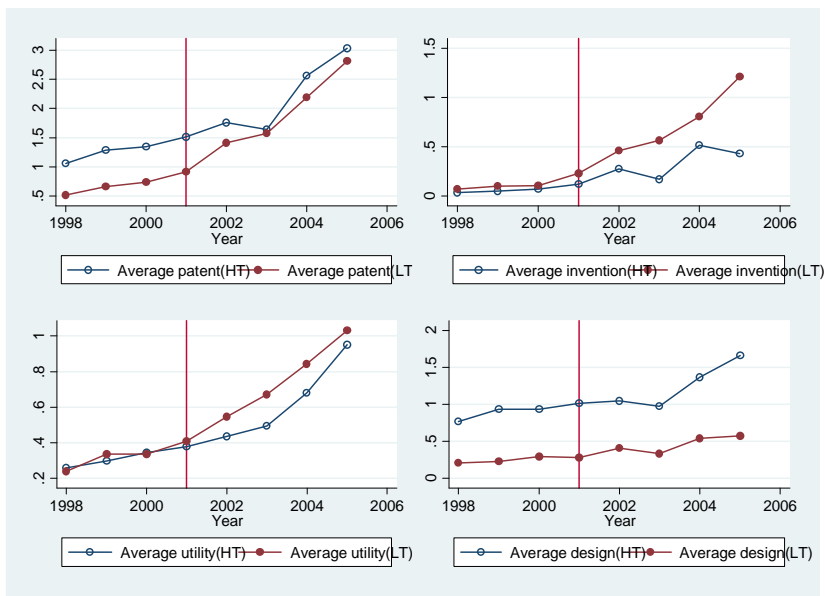
**Figure 2:** Import Tariffs in China between 1996 and 2007



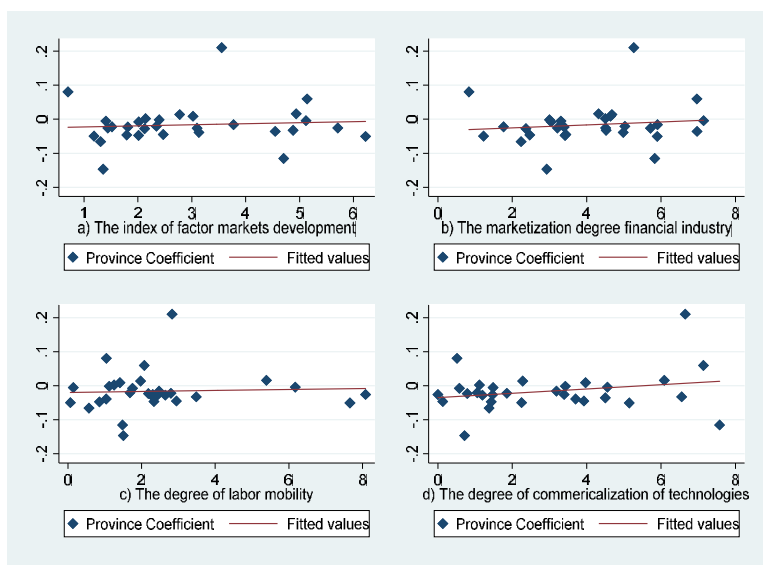
**Figure 3:** The correlation between tariffs in 2001 and tariff changes during 2001-2005



**Figure 4:** Time trends in innovation for high- and low-tariff industries: total number (thousands of patents)



**Figure 5:** Time trends in innovation for high- and low-tariff industries, average number of patents per firm



**Figure 6:** Test for the trapped factor model.

Table 1. Summary statistics of patent filings in Chinese 2-digit industries

Code	Industry	Total						Average						Ratio of Innovative Firms
		Patent	Invention	Utility	Design	Patent	Invention	Utility	Design	Patent	Invention	Utility	Design	
13	Food Processing	1462	298	88	1076	0.0168	0.0034	0.0010	0.0124	0.0068	0.0068	0.0068	0.0068	
14	Food Production	6207	316	156	5735	0.1752	0.0089	0.0044	0.1619	0.0341	0.0341	0.1619	0.0341	
15	Beverage	3877	166	103	3608	0.1642	0.0070	0.0044	0.1528	0.0352	0.0352	0.1528	0.0352	
17	Textile	3517	321	603	2593	0.0298	0.0027	0.0051	0.0219	0.0049	0.0049	0.0219	0.0049	
18	Garments	1327	70	130	1127	0.0196	0.0010	0.0019	0.0167	0.0025	0.0025	0.0167	0.0025	
19	Leather	867	19	145	703	0.0262	0.0006	0.0044	0.0213	0.0041	0.0041	0.0213	0.0041	
20	Timber	682	56	222	404	0.0255	0.0021	0.0083	0.0151	0.0070	0.0070	0.0151	0.0070	
21	Furniture	1772	11	274	1487	0.1174	0.0007	0.0182	0.0985	0.0168	0.0168	0.0985	0.0168	
22	Papermaking	920	142	295	483	0.0215	0.0033	0.0069	0.0113	0.0074	0.0074	0.0113	0.0074	
23	Print and Record Medium Reproduction	580	111	248	221	0.0199	0.0038	0.0085	0.0076	0.0072	0.0072	0.0076	0.0072	
24	Stationery, Educational and Sporting Goods	5218	98	1150	3970	0.2875	0.0054	0.0634	0.2188	0.0378	0.0378	0.2188	0.0378	
25	Petroleum Processing	494	320	99	75	0.0491	0.0318	0.0098	0.0074	0.0132	0.0132	0.0074	0.0132	
26	Raw Chemical	7126	2595	720	3811	0.0811	0.0295	0.0082	0.0434	0.0210	0.0210	0.0434	0.0210	
27	Medical	5734	2922	363	2449	0.2431	0.1239	0.0154	0.1038	0.0739	0.0739	0.1038	0.0739	
28	Chemical Fibre	315	164	140	11	0.0444	0.0231	0.0197	0.0016	0.0135	0.0135	0.0016	0.0135	
29	Rubber	853	124	406	323	0.0518	0.0075	0.0247	0.0196	0.0199	0.0199	0.0196	0.0199	
30	Plastic	3791	344	1261	2186	0.0602	0.0055	0.0200	0.0347	0.0176	0.0176	0.0347	0.0176	
31	Nonmetal Products	5604	672	1120	3812	0.0454	0.0054	0.0091	0.0309	0.0096	0.0096	0.0309	0.0096	
32	Pressing Ferrous	2904	884	1877	143	0.0865	0.0263	0.0559	0.0043	0.0113	0.0113	0.0043	0.0113	
33	Pressing of Nonferrous	1671	595	510	566	0.0648	0.0231	0.0198	0.0220	0.0162	0.0162	0.0220	0.0162	
34	Metal Products	6398	445	2688	3265	0.0975	0.0068	0.0409	0.0497	0.0243	0.0243	0.0497	0.0243	
35	Ordinary Machinery	10487	1213	6779	2495	0.1054	0.0122	0.0681	0.0251	0.0315	0.0315	0.0251	0.0315	
36	Special Equipment	10232	1208	7149	1875	0.1786	0.0211	0.1248	0.0327	0.0546	0.0546	0.0327	0.0546	
37	Transport Equipment	10707	765	4813	5129	0.1730	0.0124	0.0778	0.0829	0.0352	0.0352	0.0829	0.0352	
39	Electric Machinery	26267	5211	10251	10805	0.3245	0.0644	0.1266	0.1335	0.0471	0.0471	0.1335	0.0471	
40	Electric Equipment	30793	17088	7515	6190	0.6887	0.3822	0.1681	0.1384	0.0571	0.0571	0.1384	0.0571	
41	Electronic and Telecom	4565	476	2207	1882	0.2481	0.0259	0.1199	0.1023	0.0729	0.0729	0.1023	0.0729	
42	Instruments	2736	65	410	2261	0.0962	0.0023	0.0144	0.0795	0.0124	0.0124	0.0795	0.0124	
43	Other Manufacturing	26	24	2	0	0.0293	0.0271	0.0023	0.0000	0.0079	0.0079	0.0000	0.0079	

Table 2: Main results

VARIABLES	(1) Inpatient	(2) Inpatient	(3) Inpatient	(4) Inpatient	(5) Inpatient	(6) Inpatient	(7) Indicator	(8) Inpatient
Tariff01*Post02	-0.0218*** (0.0082)	-0.0215*** (0.0082)	-0.0202** (0.0089)	-0.0202** (0.0084)	-0.0217** (0.0089)	-0.0114* (0.0068)	-0.0237*** (0.0051)	-0.1897*** (0.0641)
InAge		-0.0007*** (0.0001)	-0.0006*** (0.0001)	-0.0007*** (0.0001)	-0.0006*** (0.0001)	-0.0005*** (0.0002)	-0.0003*** (0.0001)	-0.0039*** (0.0010)
InAge 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)	0.0001*** (0.0000)
Exporting status		0.0067*** (0.0011)	0.0066*** (0.0012)	0.0065*** (0.0012)	0.0066*** (0.0012)	0.0063*** (0.0014)	0.0042*** (0.0008)	0.0403*** (0.0096)
InLabor		0.0148*** (0.0009)	0.0146*** (0.0009)	0.0143*** (0.0009)	0.0145*** (0.0009)	0.0128*** (0.0010)	0.0094*** (0.0006)	0.1449*** (0.0074)
Capital/Labor		0.0030*** (0.0004)	0.0028*** (0.0004)	0.0028*** (0.0004)	0.0028*** (0.0004)	0.0026*** (0.0004)	0.0017*** (0.0003)	0.0246*** (0.0044)
Foreign share holding		-0.0012 (0.0025)	-0.0024 (0.0025)	-0.0025 (0.0025)	-0.0024 (0.0025)	-0.0061** (0.0030)	-0.0008 (0.0015)	-0.0416* (0.0223)
Government share holding		-0.0049*** (0.0019)	-0.0036* (0.0019)	-0.0044** (0.0019)	-0.0037** (0.0019)	-0.0029 (0.0023)	-0.0019 (0.0014)	-0.0075 (0.0132)
SOE Share01*Post02			0.0403*** (0.0081)		0.0458*** (0.0088)	0.0393*** (0.0113)	0.0234*** (0.0058)	0.1932*** (0.0393)
FIE Share01*Post02				0.0017 (0.0025)	0.0069*** (0.0027)	-0.0005 (0.0032)	0.0022 (0.0016)	-0.0017 (0.0139)
Constant	0.0141*** (0.0012)	-0.0654*** (0.0055)	-0.0643*** (0.0054)	-0.0630*** (0.0054)	-0.0637*** (0.0054)	-0.0553*** (0.0065)	-0.0362*** (0.0035)	-0.6009*** (0.0497)
Observations	1,307,718	1,291,472	1,266,886	1,266,886	1,266,886	904,075	1,266,886	86,346
R-squared	0.5475	0.5488	0.5470	0.5469	0.5470	0.5583	0.4809	0.4232

Robust standard errors in parentheses. The tariffs used in column 6 are weighted average tariffs. The Indicator in column 7 takes value 1 if the firm files any patent application in that year, 0 otherwise. In Column 8 we use the subsample of firms that ever filed for patent. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



Table 3: Checks on the Identifying Assumption

VARIABLES	(1) Inpatient	(2) Inpatient	(3) Inpatient	(4) Inpatient	(5) Inpatient	(6) Inpatient
	Linear trend	Expectation	Flexible	Pre-WTO	Processing export	Random treatment
Tariff01*Post02	-0.0218** (0.0091)	-0.0216** (0.0096)			-0.0174 (0.0449)	-0.0001 (0.0115)
Tariff01*Y2001		0.0006 (0.0107)				
Tariff01*Y1999			0.0044 (0.0104)			
Tariff01*Y2000			0.0086 (0.0111)			
Tariff01*Y2001			0.0035 (0.0122)			
Tariff01*Y2002			-0.0113 (0.0098)			
Tariff01*Y2003			-0.0219* (0.0126)			
Tariff01*Y2004			-0.0178 (0.0143)			
Tariff01*Y2005			-0.0397** (0.0181)			
Annual Tariff				0.0076 (0.0130)		
InAge	-0.0006*** (0.0001)	-0.0006*** (0.0001)	-0.0006*** (0.0001)	0.0002 (0.0002)	0.0030 (0.0030)	
InAge Squared	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	-0.0000 (0.0000)	-0.0001 (0.0001)	
Exporting status	0.0066*** (0.0012)	0.0066*** (0.0012)	0.0067*** (0.0011)	0.0088*** (0.0020)		
InLabor	0.0145*** (0.0009)	0.0145*** (0.0009)	0.0145*** (0.0009)	0.0066*** (0.0011)	0.0186*** (0.0059)	
Capital/Labor	0.0028*** (0.0004)	0.0028*** (0.0004)	0.0029*** (0.0004)	0.0012** (0.0005)	0.0057 (0.0037)	
Foreign share holding	-0.0024 (0.0025)	-0.0024 (0.0025)	-0.0019 (0.0025)	-0.0068 (0.0053)	0.0003 (0.0054)	
Government share holding	-0.0038** (0.0019)	-0.0037** (0.0019)	-0.0035* (0.0018)	0.0019 (0.0029)	0.0309 (0.0299)	
SOE Share01*Post02	0.0458*** (0.0088)	0.0458*** (0.0088)	0.0411*** (0.0081)		0.0539* (0.0287)	
FIE Share01*Post02	0.0069*** (0.0027)	0.0069*** (0.0027)	0.0069*** (0.0026)		-0.0043 (0.0048)	
Constant	-0.0638*** (0.0054)	-0.0637*** (0.0054)	-0.0640*** (0.0053)	-0.0241*** (0.0076)	-0.1125** (0.0455)	
Observations	1,266,886	1,266,886	1,302,559	374,461	37,097	
R-squared	0.5470	0.5470	0.5447	0.6281	0.6704	

Robust standard errors in parentheses. The specifications are explained in Section 4.4.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 4: Other Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Negative Binomial	3-Digit	Single product	Two period	No. of patents	No. of firms
Tariff01*Post02	-1.0439*** (0.1157)		-0.0173** (0.0082)	-0.0214*** (0.0072)	-0.9039*** (0.2982)	-0.6937*** (0.1661)
Tariff3d01post02		-0.0240*** (0.0087)				
SOE Share	0.4350*** (0.0862)	0.0411*** (0.0081)	0.0385*** (0.0075)	0.0369*** (0.0067)	0.1706 (0.2099)	-0.1489 (0.1321)
FIE Share	-0.0230 (0.0283)	0.0069*** (0.0026)	0.0076*** (0.0028)	0.0027 (0.0031)	0.1869*** (0.0603)	0.1053*** (0.0389)
InAge	-0.0113*** (0.0021)	-0.0006*** (0.0001)	-0.0005*** (0.0001)	-0.0004 (0.0002)	-0.0474*** (0.0182)	-0.0264** (0.0107)
InAge Squared	0.0002*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000 (0.0000)	0.0004* (0.0002)	0.0002* (0.0001)
Exporter	0.0773*** (0.0208)	0.0067*** (0.0011)	0.0062*** (0.0012)	0.0106*** (0.0029)	0.2546 (0.3031)	0.1366 (0.1740)
InLabor	0.1936*** (0.0095)	0.0145*** (0.0009)	0.0145*** (0.0009)	0.0195*** (0.0016)	-0.0998 (0.1219)	-0.0803 (0.0721)
Capital/Labor	0.0487*** (0.0082)	0.0029*** (0.0004)	0.0029*** (0.0004)	0.0052*** (0.0009)	-0.1056 (0.0954)	-0.0590 (0.0542)
Foreign share holding	-0.1277*** (0.0376)	-0.0019 (0.0025)	-0.0021 (0.0026)	0.0002 (0.0063)	0.5425 (0.6022)	0.4214 (0.3580)
Government share holding	0.0440 (0.0330)	-0.0035* (0.0018)	-0.0025 (0.0019)	-0.0105** (0.0041)	0.7643** (0.3451)	0.2935 (0.2142)
post02				0.0058*** (0.0021)		
Constant	-3.1455*** (0.0718)	-0.0640*** (0.0053)	-0.0641*** (0.0053)	-0.0897*** (0.0091)	2.8033*** (0.6462)	1.9772*** (0.3781)
Observations	83,953	1,302,559	1,166,718	617,527	3,223	3,223
R-squared		0.5446	0.5408	0.7693	0.8037	0.8491
Number of firmid	16,424					

Robust errors in parentheses. In Columns 5 and 6, the dependent variables are the total number of industrial patents and the number of patenting firms. The specifications are explained in Section 4.5. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 5: Import Competition Channel

VARIABLES	(1) Import	(2) Inpatent	(3) Inpatent
Tariff01*Post02	0.0205*** (0.0000)	-0.0308*** (0.0089)	-0.0230** (0.0090)
ExportTariff01*Post		0.0003 (0.0003)	0.0003 (0.0003)
Input Tariff			0.1119*** (0.0267)
InAge		-0.0006*** (0.0001)	-0.0006*** (0.0001)
InAge Squared		0.0000*** (0.0000)	0.0000*** (0.0000)
Exporter		0.0066*** (0.0012)	0.0066*** (0.0012)
InLabor		0.0130*** (0.0009)	0.0130*** (0.0009)
Capital/Labor		0.0026*** (0.0004)	0.0026*** (0.0004)
Foreign share holding		-0.0027 (0.0027)	-0.0027 (0.0027)
Government share holding		-0.0023 (0.0019)	-0.0023 (0.0019)
SOE Share01*Post02		0.0438*** (0.0098)	0.0473*** (0.0097)
FIE Share01*Post02		0.0047* (0.0027)	0.0052* (0.0027)
Constant		-0.0569*** (0.0054)	-0.0723*** (0.0066)
Observations	35,252	1,173,023	1,173,023
R-squared		0.5436	0.5437

Robust standard errors in parentheses. In Column 1, the dependent variable is the import volume.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 6: Escape Competition and Preference effects

VARIABLES	(1)	(2)	(3)	(4)
	Inpatient Q1	Inpatient Q2	Inpatient Q3	Inpatient Q4
Tariff01*Post02	-0.0109 (0.0091)	-0.0397*** (0.0112)	-0.0228* (0.0123)	-0.0326* (0.0183)
SOE Share01*Post02	0.0056 (0.0076)	0.0501*** (0.0127)	0.0695*** (0.0144)	0.0661*** (0.0160)
FIE Share01*Post02	-0.0022 (0.0035)	0.0034 (0.0045)	0.0127** (0.0061)	0.0238*** (0.0059)
lnAge	-0.0002 (0.0002)	-0.0010*** (0.0002)	-0.0009*** (0.0003)	-0.0011*** (0.0004)
lnAge Squared	0.0000* (0.0000)	0.0000*** (0.0000)	0.0000* (0.0000)	0.0000** (0.0000)
Exporter	0.0043* (0.0022)	0.0035 (0.0026)	0.0101*** (0.0026)	0.0151*** (0.0028)
lnLabor	0.0084*** (0.0012)	0.0114*** (0.0016)	0.0156*** (0.0016)	0.0177*** (0.0018)
Capital/Labor	0.0022*** (0.0006)	0.0032*** (0.0007)	0.0029*** (0.0007)	0.0047*** (0.0008)
Foreign share holding	-0.0002 (0.0049)	-0.0051 (0.0060)	-0.0013 (0.0058)	-0.0031 (0.0051)
Government share holding	-0.0027 (0.0021)	-0.0065** (0.0033)	-0.0070 (0.0044)	0.0017 (0.0058)
Constant	-0.0401*** (0.0081)	-0.0455*** (0.0096)	-0.0628*** (0.0097)	-0.0740*** (0.0106)
Observations	176,868	207,345	217,418	214,363
R-squared	0.4141	0.4232	0.4465	0.5573

Robust standard errors in parentheses. The subsamples in Columns 1-4 are the four quantiles of firms from low to high productivity, respectively. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 7: Spillover effects

VARIABLES	(1)	(2)	(3)
	Design	Utility Model	Invention
Tariff01*Post02	0.0088 (0.0067)	-0.0108** (0.0053)	-0.0150*** (0.0035)
InAge	-0.0002*** (0.0001)	-0.0003*** (0.0001)	-0.0002*** (0.0001)
InAge Squared	0.0000* (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Exporting status	0.0026*** (0.0008)	0.0033*** (0.0007)	0.0021*** (0.0005)
InLabor	0.0065*** (0.0005)	0.0077*** (0.0005)	0.0042*** (0.0004)
Capital/Labor	0.0012*** (0.0002)	0.0012*** (0.0002)	0.0012*** (0.0002)
Foreign share holding	-0.0017 (0.0022)	-0.0017 (0.0015)	0.0005 (0.0008)
Government share holding	0.0001 (0.0011)	-0.0024* (0.0013)	-0.0022** (0.0009)
SOE Share01*Post02	0.0135*** (0.0039)	0.0330*** (0.0061)	0.0180*** (0.0039)
FIE Share01*Post02	0.0004 (0.0015)	0.0075*** (0.0020)	0.0030*** (0.0011)
Constant	-0.0262*** (0.0032)	-0.0346*** (0.0034)	-0.0240*** (0.0025)
Observations	1,266,895	1,266,895	1,266,895
R-squared	0.5168	0.5209	0.5204

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1