Is Free Trade Good or Bad for Innovation?

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Abstract

This paper investigates whether trade liberalization affects firm innovation. Using China's World Trade Organization accession as a quasi-natural experiment, firms in industries experiencing more liberalization are compared with those in industries experiencing less liberalization. The analysis finds that trade liberalization reduces firms' overall innovation. However, the effects of trade liberalization differ for different types of innovation. Specifically, trade liberalization reduces firms' invention innovation and utility model invention (with a larger effect on the former), but increases firms' design innovation. These results are rationalized with a model in which trade generates a negative Schumpeterian effect and a positive spillover effect.

Keywords: Trade liberalization; Firm innovation; WTO; Difference-in-differences; Schumpeterian effect; Spillover effect

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

1 Introduction

The world has witnessed an unprecedented degree of globalization in the past decades. For example, the world's total merchandise trade reached US$17,816 billion in 2011 (WTO 2012). However, the recent progress of multilateral free trade negotiations seems to have lost its momentum, and criticisms of free trade have resurfaced and are gaining some support. The free trade debate centers on questions like whether free trade is good or bad for a nation's economy, and whether a nation can remain competitive in the integrated world market.

This paper contributes to the above debate by investigating whether trade affects innovation, an important factor determining a country's economic growth and long-term competitiveness.[1] We examine two research questions: whether import competition (induced by trade liberalization) increases (or decreases) the degree of innovation, and whether import competition has differential effects on different types of innovation (e.g., on invention, utility model, and design innovation).

The innovation-based growth literature yields mixed answers to the first question. For instance, Rivera-Batiz and Romer (1991) suggest that economic integration provides incentives for industrial research, a result of economies of scale. However the conclusion might be different when countries are asymmetric. Grossman and Helpman (1993) show that a country with a small endowment of human capital will stay away from R&D activities that are skill intensive in response to trade liberalization. Indeed, according to these authors, these countries (mostly developing countries) are at the wrong side of the comparative advantage in R&D and will invest less in innovation. Moreover, trade policies on different sectors can have opposite impact on innovation: protecting the labor-intensive sectors or the ones where the effect of learning by doing is strong will boost innovation (Grossman and Helpman 1990, Grossman and Helpman 1991). Meanwhile, as far as we know, the second question is a new one that we are the first to address.[2]

Our research setting exploits China's World Trade Organization (WTO) accession at the end of 2001. After 15 years of applying, China successfully joined the WTO in November 2001 and started to fulfill its tariff reduction responsibilities in 2002 (e.g., the unweighted average tariff dropped from 15.3% in 2001 to 12.3% in 2004). However, China's tariff reduction upon WTO accession exhibited great heterogeneity across industries. Those industries with higher initial tariffs in 2001 experienced more tariff reduction after the WTO accession (for more details, see Section 2.2). Such a disparity in the degree of trade liberalization 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 experiencing more trade liberalization before and after the WTO accession with that in industries with less trade liberalization during the same period.

Manually matching three data sets (i.e., tariff data, patent filing data, and firm-level data), we find that trade liberalization reduces firms' overall innovation: overall patent filings fell in industries experiencing more liberalization upon WTO accession relative to those having less liberalization. The findings are robust to a battery of validity checks on

[1] Grossman and Helpman (1994) provide convincing arguments to support the idea that innovation and technological progress, rather than capital accumulation, is the real engine of long-run economic growth.

[2] In Dhingra (2013) a related but different question has been addressed: how trade liberalization affects the nature of innovation, namely product variety expansion and cost reduction.

our DD estimation, including controlling for the non-random selection of pre-WTO tariffs, checking the expectation effect, and controlling for other ongoing policy reforms. They also remain robust to checks on other econometric concerns, such as the aggregation issue, the multi-industry issue, and the cross-product within-industry tariff variations issue.

Meanwhile, with detailed information about the innovation type of each firm (i.e., invention, utility model, and design innovation according to China's patent classification), we are able to uncover differential effects of trade liberalization on innovation. Specifically, we find that the WTO accession significantly reduced firms' invention innovation and utility model innovation (with the former experiencing the larger effect), but significantly increased firms' design innovation.

To rationalize these findings, we extend the standard trade model to allow an endogenous selection of product quality (see also Dhingra 2013). Our model entails two effects from trade on firm innovation. First, the increase in competition reduces firms' future profits from innovation and hence dampens firms' incentives to innovate. This is the standard Schumpeterian competition effect identified in the industrial organization literature (see, e.g., Aghion et al. 2005). The second effect from trade is the spillover effect—that is, firms can share the knowledge stock possessed by foreign firms through learning from observing and competition. Hence, the overall effect of trade liberalization on firm innovation depends on the relative importance of these two effects. Meanwhile, the Schumpeterian competition effect does not vary across different types of innovation; but the spillover effect on design innovation is larger than that on invention innovation, given the specifics and requirements of innovation types (for details, see Section 2.3). Combined, the model explains the average and differential innovation effects of trade liberalization that we have identified from the data.

Literature.—Our work is related to a growing and important literature that investigates how globalization affects the incentives for innovation.[3] This growing literature is helped by new insights and new micro data that have become available only recently. In an important work, Bustos (2011) suggests that innovation is subject to economies of scale. Only firms with large sales can afford to pay for innovative activities. Therefore, when trade liberalization occurs, firms with expanding sales (exporters) innovate more, while others (non-exporters) have to lower their investment. A similar idea is found in Burstein and Melitz (2013): trade liberalization implies more innovation activities among future exporters, as they expect more export opportunities. Trade liberalization can also release some trapped factors, reducing the costs of innovation, an idea proposed by Bloom et al. (2013).

About the relationship between trade liberalization and innovation, a particularly interesting topic is the impact of import competition on innovation. Bloom, Draca and Van-Reenen (forthcoming) investigate the effect of import competition on the innovation behavior of European firms. They find that import competition from China leads to more innovations of European firms, but imports from other developed countries have no significant effect. Autor et al. (2016) study how the import competition from China affects U.S. manufacturing firms innovation. Using all U.S. utility patent filings data, they find that import competition from China significantly reduces patenting and global R&D expenditure.

Different from the papers above, we show in this paper that trade liberalization leads

[3] For a recent review of this literature, see Grossman and Helpman (2015).

to different outcomes of innovation. In this regard, our paper is closely related to Aghion et al. (2007) and Dhingra (2013). Aghion et al. (2007) suggest that the impact of competition depends on the technological distance: competition induced by trade liberalization has a positive impact on innovation in sectors that are close to the world's technological frontier, but a negative one on innovation in sectors that are distant from the world's technological frontier. Dhingra (2013) combines the economies of scale effect that is used in Bustos (2011) and the cannibalization effect. With these two forces, she is able to generate different reactions on two types of R&D activities: product and process innovation. While Dhingra (2013) focuses on the demand side of innovation (the profitability of R&D determines the impact of international trade), our focus here is on the supply side: trade liberalization will bring down the costs of R&D activities via the spillover effect.[4] In this regard, our paper is also different from Bloom, Draca and Van-Reenen (forthcoming) and Autor et al. (2016), which emphasize the within- and between-firms adjustment and the role of global supply chains in firms' response to import competition. In addition, we look at the impact of import competition on a developing economy while they both look at the impact on developed economies.

Knowledge spillover in the literature occurs essentially under the expanding varieties model (Romer 1990) or quality ladder model (Grossman and Helpman 1993). In the former type of model, the scale effect is at work as more varieties reduce the entry costs of firms. In the latter type of model, the firm learns from the frontier technology to upgrade its quality. We differ from these models in the sense that although our model is a quality ladder type of model, the scale effect is at work here. Instead of learning from the frontier technology or the right tail of the distribution, the firm learns from the mass of foreign firms. This idea is similar to what is used in Atkeson and Burstein (2010). In their model, investment in research creates new intermediate firms. By the love of variety effect, the final good producers benefit from this firm creation as they use intermediate goods for their production. The idea that firms learn from the whole distribution of technologically advanced competitors has also been used in other studies (see for example Eeckhout and Jovanovic 2002 or Luttmer 2007). Several reasons could explain this idea. It is not always easy to find out the best technology, especially in the presence of information asymmetry. Moreover, the best technology is not always suitable to the searching firm, due to the needs of the company, the capacity to absorb the new technology, or intellectual property protection.

2 Background

2.1 China's WTO Accession

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,

[4]The role of the spillover effect in the discussion of technological transfer should not be ignored. Indeed, the knowledge stock in the world has been mostly created in only a few rich, advanced countries. For example, in 1995 the seven largest industrialized countries accounted for more than 80% of the world's R&D spending (Keller 2005). Moreover, it is reported that most manufacturing R&D was conducted by multinationals (NSF 2005). And a large part of international technology diffusion occurs via externalities or spillovers (see McNeil and Fraumeni 2005).

as China was debating the direction of its economic reforms, the 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 regarding China's WTO accession was New Zealand. However, the negotiations between China and the United States took 25 rounds and four years for an agreement to be reached in November 1999. After that, China reached agreements with 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 commitment for joining the WTO, China carried out large-scale tariff reductions between 1992 and 1997. Specifically, in 1992, China's (un-weighted) average tariff was as high as 42.9%. Shortly after the GATT Uruguay Round negotiations, China substantially reduced 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 fulfill 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), and the average tariffs on agricultural and manufacturing goods would be reduced to 15% and 8.9%, respectively.

Figure 1 plots China's (un-weighted) average tariffs during the period 1996–2007. It can be seen that tariff rates dropped substantially in 1996, remained relatively stable in 1997–2001, and gradually reduced in 2002 until reaching a steady state in 2005. The un-weighted 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 1 Here]

Interestingly, tariff reduction on accession to the WTO exhibited great heterogeneity across products. As shown in Figure 1, the ratio of tariffs at the 25th percentile over those at the 75th percentile also had a sharp drop in 2002 and then stabilized after 2005. In Figure 2, we further plot the relation between tariffs in 2001 (the year just before the WTO accession) and the changes in tariffs between 2001 and 2005 across 3-digit industries (the level used in the main regression analysis).[5] Clearly, there is a strong, positive correlation, implying that industries with higher tariffs before the WTO accession experienced more tariff reductions after the WTO accession. Presumably, China had to reduce it tariffs to the WTO-determined levels, which are quite uniform across products, whereas China's pre-WTO tariffs differed a lot across products.

[Insert Figure 2 Here]

[5]A similar pattern was uncovered at the HS-6 product level (results available upon request).

2.2 The Patent System in China

The Chinese patent system has some similarities and some differences compared with that 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 design for an article of manufacture), and plant patents (distinct and new plant varieties). China does not recognize plant patents and divides the utility patent concept into two categories: 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 the Patent Law of China). The application for an invention patent in China requires the submission of information by the applicant much like what is required in the United States for a utility patent, and, like the Patent and Trademark Office (PTO) in the United States, SIPO conducts a thorough investigation as to the novelty, inventiveness, and usefulness of the innovation before issuing the patent. On average, the process takes 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, the structure, or their combination, of a product which is fit for practical use" (Article 2 in the Patent Law of China). It is not subject to a substantive examination as in the case of an invention patent. Although a utility model patent does not have to meet the 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 a new solution as in the case of an invention patent. Therefore, a utility patent can be granted as quickly 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 it protects "any new design of the shape, pattern, color, or their combination, of a product, which creates an aesthetic feeling and is fit for industrial application" (Article 2 in the Patent Law of China). The requirements for design patents are lower compared with 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 up to 10 years.

Table 1 shows, for each of the 29 2-digit industries, the total number of patent filings, the average number of patent filings per firm, and the proportion of firms that ever filed a patent. Electric Equipment (30, 793 filings), Electric Machinery (26, 267 filings), and Transport Equipment (10, 707 filings) are the top three industries for 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 have larger numbers, 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 labor-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 labor-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 Beverage are the top three industries in the average design patent filings per firm. Electric Equipment, Medical, and Electric Machinery have the largest average invention patent filings per firm.

3 Theoretical Analysis

In this section, we use a simple model to illustrate how trade liberalization affects firms' innovation behavior 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). We do not intend to claim this model as the only channel through which trade liberalization affects firm innovation, but will test the feasibility of the model using data later.

3.1 Model Setup

Demand.—There is a continuum of horizontally differentiated varieties. Let us denote Θ 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:

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

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

$$D = \left(\frac{P_D}{P}\right)^{-\mu} \frac{E}{P}, M = \left(\frac{\tau P_M}{P}\right)^{-\mu} \frac{E}{P} \tag{2}$$

where $P = \left[(P_D)^{1-\mu} + (\tau P_M)^{1-\mu}\right]^{\frac{1}{1-\mu}}$ is the Home price index, E indicates the Home aggregate expenditure, and τ 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 θ_i represents product quality. Hence, the demand for each product is given by

$$q_i = \theta_i \left(\frac{p_i}{P_D} \right)^{-\sigma} D, \tag{3}$$

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

Production.—Labor is our only factor in the 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 φ from a distribution $G(\varphi)$, which is assumed to be a Pareto distribution for ease of illustration.[6] Specifically, we assume

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

where φ_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. 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.[7]

Innovation, Learning, and Patenting.—In our model, we allow the firm to invest in innovation to improve its product quality θ. Specifically, we follow Grossman and Helpman (1993) to model the costs of innovation: resources (in terms of labor) 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 to make 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:

$$I(\theta) = v(\theta) * f(\alpha, X), \tag{4}$$

where $v(\theta)$ is the cost of the committed labor for quality θ. 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 next, where X captures the set of firms/products that the firm can learn from; and α is the strength of the spillover effect.[8]

[6] All our results will go through with any general form of $G(.)$.

[7] 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 3)

[8] 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).

A challenge in analyzing the endogenous technological change is how to model the learning effect. For example, the firm acquires more necessary information if it invests more resources (Romer 1990) or if it has access to a wider pool of knowledge (Grossman and Helpman 1993). We generalize their setup by adding a parameter that captures the extent to which more resources or a larger pool of knowledge helps the firm to acquire new information. What is new in our framework is that we provide a micro-foundation for this parameter, which then enables us to use this parameter to differentiate different types of innovation in the empirical exercises.

We assume that domestic firms mainly learn from their foreign competitors, which suits our empirical setting. Specifically, we look at the Home country as a developing country, where the technological state is inferior to that of its trading partner. Meanwhile, we analyze whether trade liberalization changes the innovation activities of the Home firms, where the learning from domestic counterparts remains largely unchanged.

In our setup, domestic firms are able to learn from foreign firms via observation. Instead of learning from the frontier technology as is conventional in the quality-upgrading literature (see Grossman and Helpman 1993) due to information asymmetry or adoption capacity, firms learn from the entire distribution of foreign firms. Similarly, Eeckhout and Jovanovic (2002) assume that firms learn from the entire distribution of firms that are technologically more advanced. In Luttmer (2007), new entrants draw one random incumbent and adopt a scaled-down version of this incumbent's technology.

To formalize our idea of learning, we assume that each time a domestic firm observes a foreign firm, there is a probability p of successfully discovering the trick to pass the test required for its patent application and, as a result, the firm does not need to commit any resources to raise its product quality. With probability $1-p$, the firm has to invest $v(\theta)$ to improve its quality and pass the patent application test. Therefore, after observing one particular foreign firm, the expected cost of raising quality is $(1-p)\, v(\theta)$.

Assume that the success of learning from one foreign firm is independent of the experiment with the other foreign firms. In this case, we can apply the binomial distribution to calculate the expected cost of quality investment, which equals $(1-p)^X\, v(\theta)$, with X being the number of experiments.[9]

Denote $\alpha = 1-p$, and let this parameter vary across different types of innovation, as there are different levels of quality requirements corresponding to the types of patent applications. Specifically, as discussed in Section 2.3, according to Chinese law, the requirement for an invention patent is much higher than that of a design patent. Since the test for design patents is almost nonexistent while the firm has to take a stringent test if it applies for invention patents, it is more difficult for the invention-type firms to prove that their innovation is distinctively different from other existing goods, especially the foreign goods from which they learned. Indeed, it takes from three to five years to approve an invention application, while approval for a design patent is much faster. Therefore, we assume that the probability of passing the test, p, is high for design patents but low for invention patents. This assumption is consistent with the fact that the nature of a design application, relative to an invention application, is more similar to imitation or technology diffusion. Consequently, the parameter α is lowest for design patents and

[9] The idea that the number of firms is used as the spillover vehicle can be found in Atkeson and Burstein (2010). In particular, in their set-up the final producer can benefit from the creation of new intermediate input suppliers via the love of variety.

highest for invention patents.

To summarize, the learning effect is formulated as $f(\alpha, X) = \alpha^X$, where X is the number of foreign firms, i.e., $X = \int_{\varphi_x}^{+\infty} dG(\varphi) = \frac{\varphi_m^k}{\varphi_x^k}$.[10]

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.

3.2 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 the quality does not affect the firm's variable cost, the firm chooses its pricing strategy to maximize its profit given a level of quality θ:

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

where the demand q is given from Equation (3). This yields the optimal price, which equals the variable cost multiplied by the constant markup:

$$p = \frac{\sigma}{\sigma - 1} c. \tag{5}$$

Quality Selection.—With the above pricing strategy (Equation 5), the profit of a domestic firm is given by

$$\pi_d(\varphi_i) = B\theta_i \varphi_i^{\sigma-1} - I(\theta_i), \tag{6}$$

where

$$B = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} P_D^{\sigma-1} D. \tag{7}$$

Recall that the innovation cost $I(\theta) = \theta^n \alpha^X$. Maximizing the firm's profit (Equation 6) by choosing the quality level yields:

$$\theta_i = \left(\frac{B\varphi_i^{\sigma-1}}{\alpha^X n} \right)^{\frac{1}{n-1}}. \tag{8}$$

Equation 8 demonstrates the effect of economies of scale. A firm generates more sales when the market is large (high B) and its productivity level (φ) is high, resulting in more investment to upgrade its product quality. The new element we want to emphasize

[10] 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 parameter α. Both approaches lead to the same result. Our approach is chosen purely because it allows us to have a microfoundation for the parameter α.

here is the spillover effect $f(\alpha, X) = \alpha^X$. Equation 8 shows that the scope of learning is another factor that determines the extent to which the firm upgrades its product quality.

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

$$\int_{\varphi_0} \left(B\theta\varphi^{\sigma-1} - I(\theta) - f\right) dG(\varphi) = f_e \tag{9}$$

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

$$B\theta_0\varphi_0^{\sigma-1} - I(\theta_0) = f \tag{10}$$

Inserting the quality level θ_0 in Equation 8, the two conditions (9) and (10) yield market demand B and domestic cut-off φ_0. Specifically, the formula for the domestic cut-off is given by:

$$\varphi_0 = \left(\frac{n^{\frac{1}{n-1}}}{\left(1-\frac{1}{n}\right)} f\right)^{\frac{n-1}{(\sigma-1)n}} B^{\frac{-1}{\sigma-1}} \alpha^{\frac{X}{(\sigma-1)n}}. \tag{11}$$

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

$$\varphi_x = \left(\frac{n^{\frac{1}{n-1}}}{\left(1-\frac{1}{n}\right)} f_x^*\right)^{\frac{n-1}{(\sigma-1)n}} (B^*)^{\frac{-1}{\sigma-1}} \alpha^{\frac{X}{(\sigma-1)n}} \tau, \tag{12}$$

where τ is the iceberg shipping cost to the foreign market.

Quality Distribution.—We can draw the quality distribution from Equation 8. Given the zero profit condition (10), 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 σ 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 commits to raise the quality of its product, while the former depends on the domestic cut-off φ_0.

As in Bustos (2011) and Dhingra (2013), equation (8) shows that more productive firms in large market (i.e., B) tend to invest more on innovation and apply for more patents. Their decision, however, also depends on the learning effect (i.e., α^X): the higher the learning scope X, the more innovation investment and hence, patents, the firms apply.

3.3 The Effect of Trade Liberalization

In this section, we analyze 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, depends 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 (2)), resulting in less demand for domestic goods D. Therefore, effective market demand B drops (see Equation (7)).

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 12 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 α 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 generates two effects: the Schumpeterian effect, which reduces the number of patents, and the spillover effect, which increases the number of patents. Whether the former effect dominates the latter depends on the value of the parameter α.

Proof. From Equation 8, 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. As the latter is amplified by parameter α, the firm invests more in quality in response to a cut in tariffs if this parameter is large enough.

4 Estimation Strategy

4.1 Estimation Specification

To identify the impact of trade liberalization 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 more tariff reductions, due to the WTO agreement, and hence higher degrees of liberalization, whereas other previously more open industries (i.e., industries with lower tariffs in 2001) had smaller changes in tariffs and hence less liberalization. The timing of the tariff reductions (2002) and the disparity in the degree of liberalization provide an opportunity to conduct a 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).

The specification of our DD estimation is

$$y_{fit} = \alpha_f + \beta Tariff_{i2001} \cdot Post02_t + \mathbf{X}'_{fit}\gamma + \lambda_t + \varepsilon_{fit}, \tag{13}$$

where f, i, and t represent firm, 3-digit industry, and year, respectively; y_{fit} measures the innovation made by firm f in industry i in year t; $Tariff_{i2001}$ is the tariff rate of industry i in 2001; $Post02_t$ is an indicator of post-WTO period, taking a value of 1 if it is 2002 and onward, and 0 otherwise; α_f is the firm fixed effect, controlling for all time-invariant differences across firms (as well as industries and regions); λ_t is the year fixed effect, controlling for all yearly shocks common to industries such as business cycles; and ε_{fit} is the error term. To deal with the potential heteroskedasticity and serial autocorrelation, we cluster the standard errors at the firm level (see Bertrand, Duflo and Mullainathan 2004).

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

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

where Y_{fit} is the total number of patent filings by firm f in industry i in year t.[11]

To isolate the effect of trade liberalization, we control for several time-varying firm characteristics ($\mathbf{X}_{fit}$) that may affect firms' innovation, such as firm age, firm size, capital–labor ratio, exporting status, share owned by foreign investors, and share owned by the state.

In the main specification, we define an industry at the 3-digit Chinese Industrial Classification (CIC) level. Presumably there are relatively more observations within such defined industries and hence smaller measurement errors in the outcome variable. However, to address concern about any potential aggregation bias, we conducted a robustness check at the 4-digt CIC level, the finest definition in our data.

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

[11]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 larget set of firm and year dummies.

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 trade liberalization from other industries in which firms have production but that are not reported in the data. To check whether our estimates are biased because of this multiple-industry issue, we first conducted a robustness check at the 2-digit industry level, in which the multiple-industry issue is less severe. Moreover, we obtained product-level data from the National Bureau of Statistics of China for the period 2000–2006, which contains information about each product (defined at the 5-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 data sets, and we conducted a robustness check by focusing on a subsample of firms producing all goods within only one 3-digit industry.

Note that we use the interaction of tariffs in 2001 ($Tariff_{i2001}$)[12] and the post-WTO indicator ($Post02_t$) as our regressor of interest, instead of yearly tariffs ($Tariff_{it}$). One motivation is that the schedule of tariff reduction upon WTO accession in China 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 the expected effects of trade liberalization.

4.2 Identifying Assumption and Checks

The identifying assumption associated with our DD estimation specification (Equation 13) is that conditional on a whole list of controls ($\alpha_f, \mathbf{X}_{fit}, \lambda_t$), our regressor of interest, $Tariff_{i2001} \cdot Post02_t$, is uncorrelated with the error term, ε_{fit}, i.e.,[13]

$$E\left[\varepsilon_{fit} | Tariff_{i2001} \cdot Post02_t, \alpha_f, \mathbf{X}_{fit}, \lambda_t\right] = E\left[\varepsilon_{fit} | \alpha_f, \mathbf{X}_{fit}, \lambda_t\right]. \tag{14}$$

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.

However, there may be other challenges to our identifying assumption, specifically, the nonrandom selection of tariffs in 2001, the timing of the WTO accession, and some other simultaneous policy reforms.

Nonrandom Selection of Tariffs in 2001.—Tariffs in 2001 were not set randomly, creating concerns that our treatment and control groups could be systematically different *ex ante*. To address the concern that some preexisting differences between the treatment and the control groups may also differentially affect the degree of innovation by these two groups even after the WTO accession (and hence contaminate our DD estimates), we augment our DD equation (13), following an approach by (Gentzkow 2006). Specifically, Lu and Yu (forthcoming) show three significant determinants of tariffs at the industry

[12] Using average tariffs over 1997–2001 or tariffs in 1997 generates similar results (available upon request), presumably because tariffs did not change much between 1997 and 2001.

[13] Note that the identification does not require our control variables to be exogeneous, e.g.,

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

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

level in 2001: output share of SOEs, average wage per worker, and export intensity. We then add to our DD regression the interactions between a fourth−order polynomial function of time and these significant determinants of tariffs, i.e., $\mathbf{Z}_{i2001} \cdot f(t)$. This allows us to control flexibly for post-WTO differences in the time path of the degree of innovation between our treatment and control groups that are generated by these preexisting differences. As a further robustness check, we include an industry-specific linear time trend (i.e., $\alpha_i \cdot t$) to control for the underlying differences between our treatment and control groups in a restricted way—that is, assuming these potential confounding factors affect our outcome variable in the specification of the linear trend.

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 behavior even before the tariff reduction happened after 2002. However, China's WTO accession process was very lengthy, taking about 15 years to complete, and the approval required a consensus by all WTO member countries. Despite China's having achieved important breakthroughs by signing agreements with the United States in 1999 and the European Union in 2000, there were still many leftovers unresolved until mid-2001. Hence, the timing of China's WTO accession was largely uncertain before 2001. Nonetheless, as a first robustness check, we include in the DD regression an additional control, $Tariff_{i2001} \times A\ Year\ Before\ WTO_t$ (where $A\ Year\ Before\ WTO_t$ indicates that the WTO accession would happen next year), to examine whether firms changed their innovation behavior in anticipation of the WTO accession in the next year.

Furthermore, we estimate flexibly 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 the WTO accession, and hence further exclude any expectation effects.

Other Policy Reforms.—If there were other policy reforms differentially targeting our treatment and control groups around the time of the WTO accession (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 reforms in the early 2000s, the SOE reform and the relaxation of foreign direct investment (FDI) regulations (which allowed more wholly-owned FDI rather than equity joint ventures). 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 number of domestic firms) and FDI (measured by the logarithm of the number of foreign invested firms)[14].

Further Robustness Checks.—To check our identifying assumption further, we conduct two placebo tests. The first one follows Topalova (2010) in using only the pre-WTO period data. The premise of this test is that as tariffs in China barely changed before the WTO accession, regressions of our outcomes on tariffs in the pre-WTO period shall produce no treatment effect; otherwise, the test indicates the existence of some omitted variables in the regression specification.

[14] As discussed in the introduction, the alternative channel of spillovers beside imports is investment from foreign firms.

In our second placebo test, we randomly assign the degree of tariff reduction upon the WTO accession to industries. Specifically, we randomly distribute tariff values in 2001 to industries, and randomly select a year between 1999 and 2004 as a false year for WTO accession. Then, we construct a false regressor of interest, $Tariff_i^{false} \cdot Post_t^{false}$. Given the random generating process of the data, $Tariff_i^{false} \cdot Post_t^{false}$ is expected to cast zero effects; otherwise, it may indicate the misspecification of equation (13). We repeat the exercise 500 times to increase the power of the placebo test.

5 Data

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

We first used the *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 from 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 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.

As our outcome variable (i.e., degree of firm innovation) can only be linked to the tariff change at the industry level, we need to aggregate tariffs from the HS product level to the industry level. To this end, we first matched the HS classification to the Chinese Industrial Classification using the concordance table from the National Bureau of Statistics of China.[15] 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 an industry, which may underestimate the effect of trade liberalization. To address this concern, in a robustness check, we add an interaction between our regressor of interest and the number of products within a 3-digit industry, to check whether industries with more HS-6 products (and hence potentially more tariff variations) behave differently from those with fewer products.

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, e.g., Aghion et al. 2005; Hashmi 2013). By construction, 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. Autor et al. (2016) further discuss three attractive features of using patent filing data to capture the degree of innovative activities. However, it is important to be aware of the issues of using such a measure. First, patents could underestimate technology because the innovation must be important enough to be registered as a patent and some part of technology cannot be codified in

[15]We thank Yifan Zhang for sharing this concordance table.

the patents. Second, some patents are more important and therefore more cited than the others.

The patent filing data were downloaded from the State Intellectual Property Office of China (SIPO). The data contain 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).

In addition to the problems with patents as we mentioned above, another 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), maintained by the National Bureau of Statistics of China, for the period 1998 to 2005. This is the most comprehensive firm-level data set 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 an invaluable national representativeness. The data set 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.

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.[16] This may raise a concern of the matching quality, which may then bias our estimation. Specifically, if the mismatching degree changed discontinuously across industries with different degrees of trade liberalization at the time of the WTO accession, our estimator would then reflect the mimatching errors rather than the trade liberalization effect. While we cannot directly examine the quality of matching, several threads evidence largely dispels 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 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 firms in China. Concerning 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 2004–2005, there were about 4% of firms that applied for patents. Given that the patent filings increased quickly in the 2000s, we should have obtained a reasonably good match. Furthermore, we have used consistent rules for the data matching through the whole sample period (from 1998 to 2005) and there is no reason to expect that there are discontinuities in the degree of mis-match across industries with different degrees of trade liberalization at the time of the WTO accession, thereby alleviating concern about estimation biases arising from the

[16]Due to differente firm identity codes used by different ministries in China, using the official name of firms to match different data sources is a widely used method. For similar practise, see, for example, Yu (2015).

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.

6 Empirical Findings

6.1 Graphical Results

Figures 4 and 5 contain plots of the time trends of 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]

In the pre-WTO period, we find two points worth noting here. First, while the most protected sectors possess more design patents, they have the same number of invention and utility patents as the least protected sectors. Second, it is clear that in the pre-WTO period (1998–2001, i.e., the pre-treatment period), the two groups have 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 the trends of firm innovation after 2002, the time when China started to reduce its tariffs upon the WTO accession. The consistency in timing between the divergence in firm innovation and the WTO accession suggests that trade liberalization affects firm innovation. Specifically, trade liberalization has a visible, negative effect on overall innovation and invention innovation; a visible, positive effect on design innovation; and a modest, negative effect on utility model innovation.

In the remaining parts of this section, we use a regression analysis to establish formally these innovation effects of trade liberalization (via the WTO accession).

6.2 Main Results

The regression results of the DD specification (13) are presented in Table 2. We start with a simple DD specification with the inclusion of 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 innovate 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 after 2002, these results imply that trade liberalization reduces firm innovation.

[Insert Table 2 Here]

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

In column 3, we further address the concern that our estimates may capture the effects of two ongoing policy reforms in the early 2000s (the SOE reform and the lifting of some FDI regulations). Specifically, we add two control variables (the number of foreign-invested firms, and the share of SOEs among domestic firms). Our main findings still remain robust.

One prominent concern of our DD estimation is that tariffs in 2001 were nonrandomly determined, and hence our treatment and control groups could be systematically different *ex ante*, which may spuriously generate the negative effect of trade liberalization on firm innovation. However, as displayed in Figure 4, firm innovation in high 2001-tariff industries and in low 2001-tariff industries has similar time trends in the pre-WTO period and the trend starts to diverge upon the WTO accession, implying that our treatment and control groups are largely comparable. To alleviate the concern that the nonrandom determination of tariffs in 2001 may bias our estimates, we conduct a robustness check following Gentzkow (2006). Specifically, in column 4, we add the interaction terms between a fourth-order polynomial function of time and three significant determinants of tariffs in 2001 to control for flexible time trends in firm innovation generated by these tariff determinants. Clearly, the coefficient of our regressor of interest remains negative and statistically significant.

In columns 5 and 6, we further disentangle the trade liberalization effect on innovation at the extensive and intensive margins. Specifically, we investigate whether the effect comes from that fewer firms apply for patents (the extensive margin) or firms apply for fewer patents (the intensive margin). To this end, we regress the total number of patent filing firms on our regressor of interest at the industry level in column 5 (with the control variables as the industrial average), and find a small and statistically insignificant effect. Meanwhile, we focus on the sample of firms that applied for patent before China's WTO accession to shed light on the intensive margin effect. The estimation results in column 6 show a consistently negative and statistically significant effect. These results suggest that much of the trade liberalization effect on innovation comes from the intensitve margin rather than the extensive margin.

In summary, the results in Table 2 show that trade liberalization (via China's WTO accession) causes firms to innovate less. And this effect is not contaminated by the nonrandom tariff selection in the pre-WTO period or other ongoing policy reforms. Referring to our theoretical model in Section 3 (Proposition 1), these findings imply that the negative Schumpeterian competition effect dominates the positive spillover effect of trade, which then dampens firms' incentives to innovate.

6.3 Different Types of Innovation

The previous sub-section focuss on the total number of patent filings, without differentiating types of patents. However, our patent filing data contain information about patent types. Specifically, patents are classified into three categories at the filing stage—that is, invention, utility model, and design patents. With such detailed patent type information, we are able to test whether trade liberalization has different effects on different types of innovations.

The regression results are presented in Table 3. Interestingly, we find differential effects of trade liberalization on different types of innovations. Specifically, the effect of trade liberalization on design innovation is positive and statistically significant, but negative and statistically significant on invention and utility model innovations, with the former having a larger effect. These results are consistent with the literature: for example, Gorodnichenko, Svejnar and Terrell (2010) find that firms in European developing countries engage in more small-step innovations in response to imports.

[Insert Table 3 Here]

To explain these differential results, we argue that the positive spillover effect from trade liberalization works strongest for design innovation, followed by utility model innovation and then invention innovation. According to the Patent Law of China, 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 focuses 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. As shown in Proposition 1 in Section 3, the interaction between the negative Schumperterian effect and different degrees of the positive spillover effect may then explain the differential results of trade liberalization on the three types of innovations.

An alternative explanation lies in the theory of comparative advantage. Specifically, if China possesses comparative advantage in design innovation but the rest of the world has comparative advantage in utility model and invention innovations, trade liberalization results in an explosion of design patent applications and, through resource reallocation, a drop in the other types of innovations, including invention and utility model. However, this theory is inconsistent with what we observe in China. Figure 4 shows that before trade liberalization took place in China, the total number of design patents in the more protected sectors was lower than that in the less protected sectors. This is not a result of the scale effect, because both types of sectors had relatively the same amount of patents in the form of invention and utility. Moreover, with the presence of international spillover, the effect of trade liberalization in a developing country can be ambiguous. Suppose the invention activities are more skill intensive than the design activities. On the one hand, knowledge spillovers from abroad reduce the costs of research, especially for invention activities. On the other hand, the comparative advantage in the labor-intensive activity (design) causes the country to allocate more human resources to the skill-intensive activity.

6.4 Checks on the Identifying Assumption

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 4. To save space, we focus on the total number of patent filings, and report the checks for the three different types of patent filings in Tables A1-A3 in the Appendix.

[Insert Table 4 Here]

Industry-Specific Linear Time Trend.—The analyses above controlled for flexible time trends in firm innovation generated by the significant pre-WTO differences between the treatment and control groups. However, there may still be a concern about some unobserved industry characteristics that might compromise the comparability between the treatment and control groups. To check whether these unobserved industry factors could bias our estimates, we include an industry-specific linear time trend, e.g., $\alpha_i \cdot t$. This enables us to control for all 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 unobserved underlying industry characteristics.

Expectation Effect.—In column 2, we add to the regression an additional control, $Tariff_{i2001} \times A\ Year\ Before\ WTO_t$, to check whether firms changed their innovative behavior in anticipation of the coming WTO accession, which might in turn have made our treatment and control groups *ex ante* noncomparable, thus biasing our estimates. The coefficient of $Tariff_{i2001} \times A\ Year\ Before\ WTO_t$ is 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.

Flexible Estimation.—We use a flexible estimation specification, that is, replacing the post-treatment period indicator ($Post02_t$) with year dummies (λ_t). This exercise allows us to check whether the treatment and control groups were comparable up to the time of the WTO accession and became different after that event. As shown in column 3, in the pre-WTO period, all the estimated coefficients are positive, insignificant, and small in magnitude. However, right after the WTO accession, the estimated coefficients become negative and continuously increase in magnitude. 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.—As the first placebo test, we follow Topalova (2010) in looking at the effect 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, we would not expect any significant effects; the contrary might indicate the existence of some underlying confounding factors. As shown in column 4, we indeed find that tariffs had no significant effect on firm innovation in the pre-WTO period.

Placebo Test II: 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, and conduct a regression analysis using the specification (13) We repeat the exercise 500 times to increase the power of the placebo test. The mean and standard deviation of the 500 coefficients are reported in column 5. Evidently, the mean value is small in magnitude and highly insignificant, leading further support to the validity of our research design.

6.5 Other Robustness Checks

In this subsection, we present another series of robustness checks on other econometric concerns. The regression results are presented in Table 5. To save space, we focus on the total number of patent filings, and report the checks for the three different types of patent filings in Tables A4-A6 in the Appendix.

[Insert Table 5 Here]

Finer Industry Definition.—Thus far, our analysis is based on the 3-digit CIC industry level. To alleviate concern about aggregation biases, we conducted a robustness check at the 4-digit CIC industry level (note that a trade-off is that there are fewer observations within each industry-year cell and hence potentially higher measurement errors). The regression results are presented in column 1. Clearly, our results are robust to this finer industry definition, albeit less precisely estimated.

Check on Cross-Product, Within-Industry Tariff Variations.—As noted in Section 2,1, one drawback of our empirical data is that tariff information is at the HS-6 product level, while the firm innovation information can only be linked to tariffs at the CIC 3-digit industry level. Hence, the mapping from the HS-6 product to the CIC 3-digit industry level may conceal variations of tariff reductions across different HS-6 products but within the same 3-digit industry, which may lead to an underestimate of the effect of trade liberalization. As a check on this issue, we add an interaction between our regressor of interest ($Tariff_{i2001} \times Post02_t$) with the number of products within a 3-digit industry. As shown in column 2, the triple interaction term is not statistically significant, implying that industries with more HS-6 products (and hence potentially more variations of tariffs within the industry) do not behave differently from those with fewer products.

Checks on the Multi-Industry Issue.—Another potential concern is that firms could produce multiple products spanning different 3-digit industries, and hence our aforementioned DD estimation may miss the liberalization effect from other related 3-digit industries. To check this concern, we first investigated the effect at the 2-digit industry level, where the multi-product issue is less severe. As shown in column 3, the innovation effect of trade liberalization remains negative and statistically significant. Meanwhile, in column 4, we focus on a subsample of firms producing only in one 3-digit industry, and continue to find a negative innovation effect of trade liberalization.

Using New Product Share as a Measure of Firm Innovation.—To measure the degree of firm innovation, we follow the literature by using patent filings. To check whether our findings of the negative innovation effect of trade liberalization are sensitive to the choice of the measure of firm innovation, we could use some alternative measures of firm innovation. Ideally, we want to use firm R&D expenditure share; however, our ASIF data only have such information for a few years in the post-WTO period, precluding the use of the DD identification. Instead, we use the share of new product output over total output. The regression results are presented in column 5. Consistent with our previous findings, trade liberalization is found to reduce the share of new product output, albeit the effect is imprecisely estimated.

Two-Period Estimation.—One concern with the DD estimation is how to 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 firm 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 using the White-robust standard errors. Meanwhile, this exercise also allows us to compare the long-run average effect of trade liberalization on firm innovation. The regression results are presented in column 6. Clearly, we obtain similar (but larger) results.

6.6 Underlying Mechanisms

In this subsection, we investigate potential underlying mechanisms through which trade liberalization might affect firm innovation. Our perceived channels, as illustrated in the theoretical model in Section 3, are that trade liberalization generates two opposing effects, the negative competition effect and the positive spillover effect from the increase in imports. To check whether this argument is supported by our data, we first investigate whether imports increase after the tariff reduction; second, we exclude other channels like foreign market access brought about by the WTO accession; and finally, we examine the existence of positive spillover effects.

Tariff Reduction and Imports.—With import and tariff information both available at the HS-6 product level, we conduct the analysis of import response to trade liberalization at the HS-6 product 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 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 6. We find that imports increase in those product categories experiencing more tariff reduction, corroborating our import competition argument.

[Insert Table 6 Here]

Market Access Effect.—The WTO accession is multilateral, that is, China's trading partners may also reduce their tariffs on imports from China. 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 $Export\ Tariff_{p2001} \times Post02_t$ to control for access to foreign markets. The regression results are presented in column 2. Our main findings remain robust to this additional control, lending support to the import competition argument.

Spillover Effect.—The innovative part of our theoretical analysis to explain the differential innovation effects of trade liberalization is the existence of a spillover effect from imports. To provide further support for this argument, we carry out a formal test of the spillover effect. Ideally, to capture the spillover effect, the data on patent citation shall be used. However, the patent filing data in China do not contain information on patent citation. Instead, we regress firm innovation on the stock of industrial patents following the work by Coe and Helpman (1995) and Coe, Helpman and Hoffmaister (2009). The regression results are presented in columns 3–5 of Table 6. It is found that the stock of industrial patents has a positive and statistically significant effect on firm innovations; and the estimated magnitudes increase from invention innovation, to utility model innovation, to design innovation (e.g., the t-statistic of the difference between the invention innovation and design innovation coefficients has a p-value of 0.0399). These findings confirm our argument that there are spillover effects, and that design innovation benefits more than the other types of innovation from such spillovers.

7 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-run 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, China's accession to the WTO generated industrial heterogeneity in tariff reduction, based on which, we compared firms in industries experiencing more liberalization with those in industries experiencing less liberalization.

We have found that trade liberalization reduces a firm's overall innovation, and this finding is robust to a series of checks. Furthermore, with detailed information about types of innovation, we have found different effects of trade liberalization on the different types of innovation. Specifically, WTO accession reduced firms' invention innovation and utility model invention, but increased firms' design innovation. As far as we know, the present paper is the first to uncover the differential effects of trade liberalization on different innovation types.

We also showed that these findings can be rationalized in an extended trade model with endogenous selection of product quality. On the one hand, increased competition due to trade liberalization dampens firms' incentives to innovate (i.e., the standard Schumpeterian effect, see Aghion, et al., 2005). On the other hand, the increased stock of knowledge accompanying trade liberalization lowers the cost of innovation, which helps boost innovation (i.e., the spillover effect, see Coe and Helpman (1995) and Coe, Helpman and Hoffmaister (2009)). Given the specific requirements of the specific types of innovation, it is expected, and also confirmed by our data, that the spillover effect is larger for design innovation than for invention innovation. The combination of the two effects then drives the differentiation of the effects on innovation.

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. 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.

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Appendix: Figures and Tables

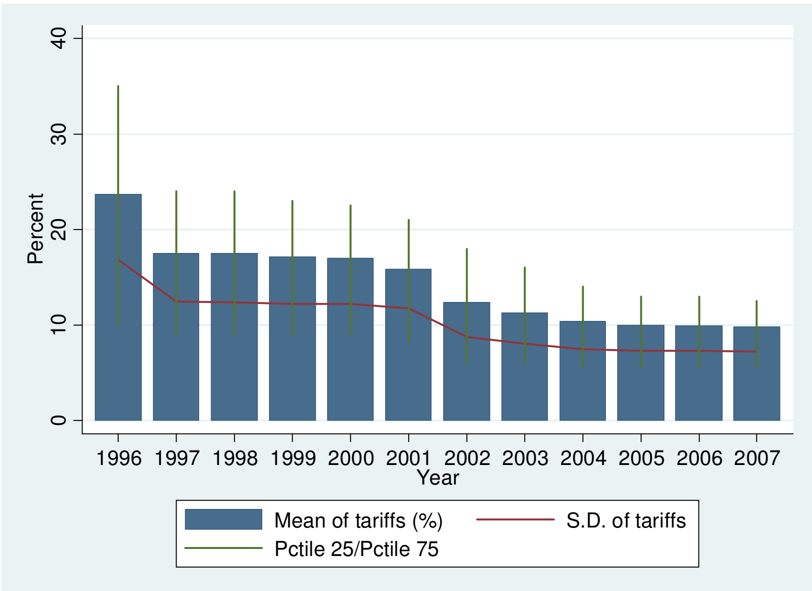

Figure 1: Tariffs: 1996-2007

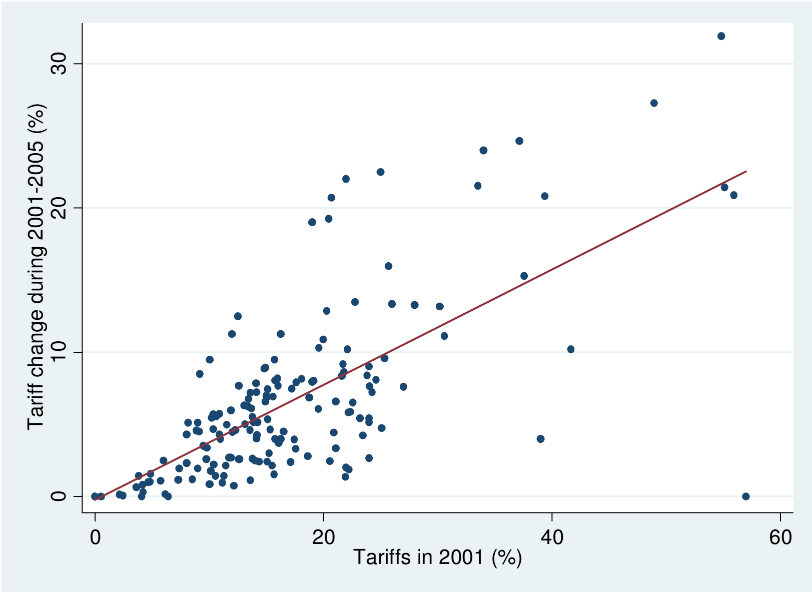

Figure 2: The correlation between tariffs in 2001 and tariff changes during 2001-2005

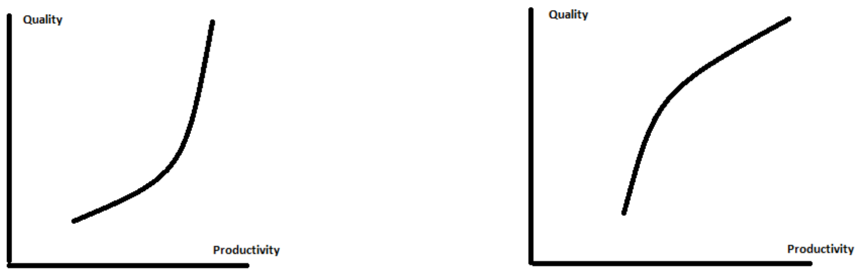

Figure 3: The distribution of quality. The left figure corresponds to the case when $\sigma > n$ while the right figure corresponds to the case when $\sigma < n$

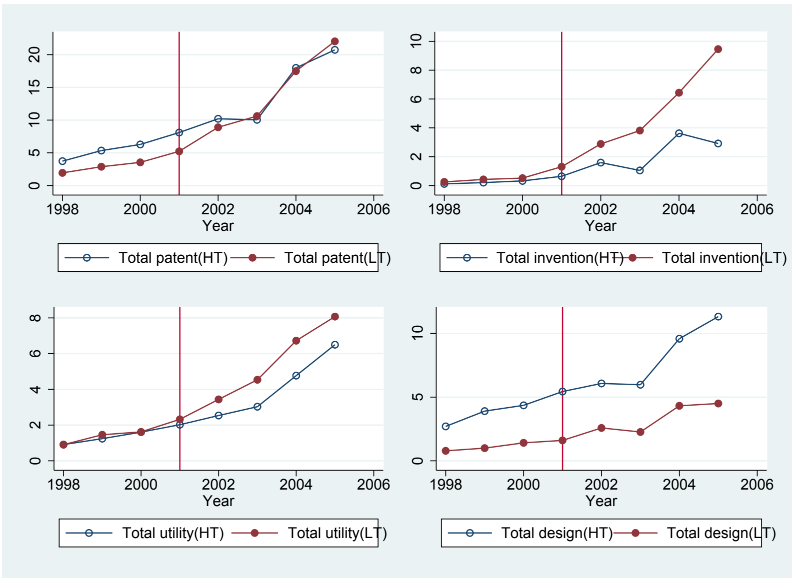

Figure 4: Time trends in innovation for high- and low-tariff industries: total number (thousands of patents)

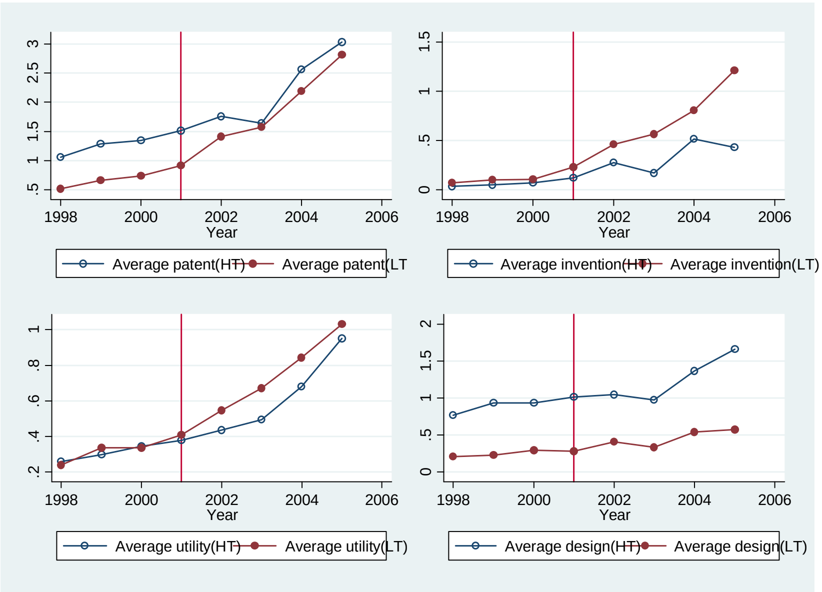

Figure 5: Time trends in innovation for high- and low-tariff industries, thousands of patents per firm

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

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

Table 2, Main Results

Specification	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) No. of Patenter	(6) Patent
Tariff2001*Post2002	-0.0216***	-0.0217***	-0.0282***	-0.0156**	-0.3744	-0.2685***
	(0.0072)	(0.0072)	(0.0075)	(0.0075)	(0.3797)	(0.0913)
Firm controls						
Firm age		-0.0007***	-0.0006***	-0.0006***	-0.0652	-0.0093***
		(0.0002)	(0.0002)	(0.0002)	(0.0545)	(0.0020)
Firm age squared		0.0000***	0.0000***	0.0000***	0.0012	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0012)	(0.0000)
Export status		0.0067***	0.0067***	0.0068***	-0.2899	0.0533***
		(0.0013)	(0.0013)	(0.0013)	(0.4806)	(0.0161)
ln(employment)		0.0149***	0.0150***	0.0148***	-0.0343	0.1378***
		(0.0009)	(0.0009)	(0.0009)	(0.1962)	(0.0138)
ln(capital/labor)		0.0030***	0.0030***	0.0029***	-0.0006	0.0246***
		(0.0004)	(0.0004)	(0.0004)	(0.1470)	(0.0087)
Foreign share holding		-0.0007	-0.0007	-0.0008	-2.0190**	-0.0226
		(0.0028)	(0.0028)	(0.0028)	(0.9528)	(0.0351)
State share holding		-0.0043**	-0.0037*	-0.0033	1.9448**	-0.0032
		(0.0021)	(0.0021)	(0.0021)	(0.7459)	(0.0207)
Industrial controls						
SOE share			-0.0383***	-0.0279**	-1.1124	-0.1585
			(0.0090)	(0.0112)	(0.6760)	(0.0996)
ln(FIEs)			0.0027***	0.0022**	0.5386***	0.0180
			(0.0009)	(0.0009)	(0.1063)	(0.0125)
Year Dummy	X	X	X	X	X	X
Firm Dummy	X	X	X	X		X
Industry Dummy					X	
Time Polynomial Interactions				X	X	X
Observations	1,339,899	1,323,158	1,322,956	1,322,956	1,234	40,404
R-squared	0.5437	0.5451	0.5452	0.5455	0.9217	0.4466

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3, Different Types of Innovation

Specification	(1) Invention	(2) Utility Model	(3) Design
Tariff2001*Post2002	-0.0164***	-0.0095**	0.0136**
	(0.0030)	(0.0044)	(0.0059)
Year Dummy	X	X	X
Firm Dummy	X	X	X
Firm Controls	X	X	X
Industry Controls	X	X	X
Time Polynomial Interactions	X	X	X
Observations	1,322,956	1,322,956	1,322,956
R-squared	0.5206	0.5190	0.5135

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4, Checks on the Identifying Assumption

Specification	(1) Industry linear trend	(2) Expectation effect	(3) Flexible estimation	(4) Pre-WTO period	(5) Random treatment
Tariff2001*Post2002	-0.0166**	-0.0160*			0.0002
	(0.0084)	(0.0085)			(0.0120)
Tariff2001*Next Year		-0.0011			
		(0.0072)			
Tariff rate				0.0126	
				(0.0143)	
Tariff2001*Year1999			-0.0003		
			(0.0070)		
Tariff2001*Year2000			0.0050		
			(0.0079)		
Tariff2001*Year2001			0.0007		
			(0.0085)		
Tariff2001*Year2002			-0.0078		
			(0.0094)		
Tariff2001*Year2003			-0.0176*		
			(0.0103)		
Tariff2001*Year2004			-0.0102		
			(0.0122)		
Tariff2001*Year2005			-0.0287**		
			(0.0128)		
Year Dummy	X	X	X	X	X
Firm Dummy	X	X	X	X	X
Firm Controls	X	X	X	X	X
Industry Controls	X	X	X	X	X
Time Polynomial Interactions	X	X	X	X	X
Observations	1,322,956	1,322,956	1,322,946	520,017	
R-squared	0.5457	0.5455	0.5454	0.6159	

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5, Other Robustness Checks

Specification	(1) 4-digit industry	(2) Number of products	(3) 2-digit industry	(4) New product share	(5) Two periods
Tariff2001*Post2002	-0.0201**	-0.0155*	-0.0584***	-0.0017	-0.0284***
	(0.0086)	(0.0090)	(0.0115)	(0.0048)	(0.0092)
Tariff2001*Post2002*ProdNum2001		0.0000			
		(0.0001)			
Post2002*ProdNum2001		-0.0025*			
		(0.0015)			
post02					0.0080***
					(0.0021)
Year Dummy	X	X	X	X	X
Firm Dummy	X	X	X	X	X
Firm Controls	X	X	X	X	X
Industry Controls	X	X	X	X	X
Time Polynomial Interactions	X	X	X	X	X
Observations	1,242,998	1,321,174	1,286,045	1,079,438	630,227
R-squared	0.5454	0.5455	0.5479	0.7813	0.7820

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6, Underlying Mechanism

Specification	(1) Import	(2) Patent	(3) Invention	(4) Utility model	(5) Design
Tariff2001*Post2002	0.0205***	-0.0232***			
	(0.0000)	(0.0087)			
ExportTariff2001*Post2002		0.0004			
		(0.0003)			
Stock of Patents (ln)			0.0002***	0.0004***	0.0006***
			(0.0001)	(0.0001)	(0.0001)
Year Dummy	X	X	X	X	X
Product/Firm Dummy	X	X	X	X	X
Firm Controls		X	X	X	X
Industry Controls		X	X	X	X
Time Polynomial Interactions		X			
Observations	35,252	1,187,297	1,217,085	1,217,085	1,217,085
R-squared	5,036	0.5443	0.0029	0.0021	0.0006

Note: Standard errors, clustered at HS-6 product level for column (1) and the firm level for the rest

Appendix Table A1, Checks on the Identifying Assumption: Invention

Specification	(1) Industry linear trend	(2) Expectation effect	(3) Flexible estimation	(4) Pre-WTO period	(5) Random treatment
Tariff2001*Post2002	-0.0203***	-0.0166***			0.0003
	(0.0034)	(0.0033)			(0.0065)
Tariff2001*Next Year		-0.0007			
		(0.0024)			
Tariff rate				-0.0009	
				(0.0034)	
Tariff2001*Year1999			0.0057**		
			(0.0023)		
Tariff2001*Year2000			0.0044*		
			(0.0026)		
Tariff2001*Year2001			0.0028		
			(0.0028)		
Tariff2001*Year2002			-0.0048		
			(0.0033)		
Tariff2001*Year2003			-0.0155***		
			(0.0039)		
Tariff2001*Year2004			-0.0172***		
			(0.0047)		
Tariff2001*Year2005			-0.0260***		
			(0.0050)		
Year Dummy	X	X	X	X	X
Firm Dummy	X	X	X	X	X
Firm Controls	X	X	X	X	X
Industry Controls	X	X	X	X	X
Time Polynomial Interactions	X	X	X	X	X
Observations	1,322,956	1,322,956	1,322,956	520,017	
R-squared	0.5209	0.5206	0.5207	0.5465	

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A2, Checks on the Identifying Assumption: Utility Model

Specification	(1) Industry linear trend	(2) Expectation effect	(3) Flexible estimation	(4) Pre-WTO period	(5) Random treatment
Tariff2001*Post2002	-0.0087*	-0.0113**			0.0000
	(0.0048)	(0.0049)			(0.0082)
Tariff2001*Next Year		-0.0053			
		(0.0039)			
Tariff rate				0.0084	
				(0.0090)	
Tariff2001*Year1999			-0.0050		
			(0.0039)		
Tariff2001*Year2000			-0.0017		
			(0.0043)		
Tariff2001*Year2001			-0.0072		
			(0.0048)		
Tariff2001*Year2002			-0.0113**		
			(0.0053)		
Tariff2001*Year2003			-0.0152**		
			(0.0061)		
Tariff2001*Year2004			-0.0111		
			(0.0073)		
Tariff2001*Year2005			-0.0157**		
			(0.0079)		
Year Dummy	X	X	X	X	X
Firm Dummy	X	X	X	X	X
Firm Controls	X	X	X	X	X
Industry Controls	X	X	X	X	X
Time Polynomial Interactions	X	X	X	X	X
Observations	1,322,956	1,322,956	1,322,956	520,017	
R-squared	0.5192	0.5190	0.5190	0.5812	

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A3, Checks on the Identifying Assumption: Design

Specification	(1) Industry linear trend	(2) Expectation effect	(3) Flexible estimation	(4) Pre-WTO period	(5) Random treatment
Tariff2001*Post2002	0.0163**	0.0145**			-0.0001
	(0.0065)	(0.0066)			(0.0066)
Tariff2001*Next Year		0.0029			
		(0.0060)			
Tariff rate				0.0059	
				(0.0114)	
Tariff2001*Year1999			-0.0026		
			(0.0057)		
Tariff2001*Year2000			0.0012		
			(0.0064)		
Tariff2001*Year2001			0.0023		
			(0.0069)		
Tariff2001*Year2002			0.0086		
			(0.0076)		
Tariff2001*Year2003			0.0146*		
			(0.0081)		
Tariff2001*Year2004			0.0216**		
			(0.0096)		
Tariff2001*Year2005			0.0170*		
			(0.0100)		
Year Dummy	X	X	X	X	X
Firm Dummy	X	X	X	X	X
Firm Controls	X	X	X	X	X
Industry Controls	X	X	X	X	X
Time Polynomial Interactions	X	X	X	X	X
Observations	1,322,956	1,322,956	1,322,956	520,017	
R-squared	0.5136	0.5135	0.5135	0.6154	

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A4, Other Robustness Checks: Invention

	(1)	(2)	(3)	(4)
Specification	4-digit industry	Number of products	2-digit industry	Two periods
Tariff2001*Post2002	-0.0194***	-0.0137***	-0.0331***	-0.0184***
	(0.0036)	(0.0036)	(0.0044)	(0.0035)
Tariff2001*Post2002*ProdNum2001		-0.0001		
		(0.0001)		
Post2002*ProdNum2001		0.0001		
		(0.0010)		
post02				0.0052***
				(0.0009)
Year Dummy	X	X	X	X
Firm Dummy	X	X	X	X
Firm Controls	X	X	X	X
Industry Controls	X	X	X	X
Time Polynomial Interactions	X	X	X	X
Observations	1,242,998	1,321,174	1,286,045	630,227
R-squared	0.5205	0.5209	0.5232	0.7730

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A5, Other Robustness Checks: Utility Model

	(1)	(2)	(3)	(4)
Specification	4-digit industry	Number of products	2-digit industry	Two periods
Tariff2001*Post2002	-0.0115**	-0.0110**	-0.0253***	-0.0155***
	(0.0049)	(0.0047)	(0.0050)	(0.0055)
Tariff2001*Post2002*ProdNum2001		0.0000		
		(0.0000)		
Post2002*ProdNum2001		-0.0033***		
		(0.0008)		
post02				0.0048***
				(0.0014)
Year Dummy	X	X	X	X
Firm Dummy	X	X	X	X
Firm Controls	X	X	X	X
Industry Controls	X	X	X	X
Time Polynomial Interactions	X	X	X	X
Observations	1,242,998	1,321,174	1,286,045	630,227
R-squared	0.5215	0.5190	0.5210	0.7625

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<p<0.05, * p<0.1

Appendix Table A6, Other Robustness Checks: Design

Specification	(1) 4-digit industry	(2) Number of products	(3) 2-digit industry	(4) Two periods
Tariff2001*Post2002	0.0138**	0.0133*	-0.0109	0.0033
	(0.0067)	(0.0074)	(0.0097)	(0.0070)
Tariff2001*Post2002*ProdNum2001		0.0000		
		(0.0001)		
Post2002*ProdNum2001		-0.0003		
		(0.0008)		
post02				-0.0006
				(0.0014)
Year Dummy	X	X	X	X
Firm Dummy	X	X	X	X
Firm Controls	X	X	X	X
Industry Controls	X	X	X	X
Time Polynomial Interactions	X	X	X	X
Observations	1,242,998	1,321,174	1,286,045	630,227
R-squared	0.5137	0.5134	0.5163	0.7699

Note: Standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1