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Trade policy uncertainty and innovation: Firm level evidence from China's WTO accession

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ABSTRACT

This study proposes a novel channel through which trade liberalization may induce innovation through the reduction of trade policy uncertainties (TPU) in destination markets. To verify this linkage, we utilize the significant reduction of TPU engendered by China's accession to the World Trade Organization (WTO) in 2001 as a quasi-natural experiment. We find that reduction in TPU significantly encourages firms' patent application: firms in sectors with a larger reduction in uncertainty filed more invention patent applications after China's WTO accession. We also find that firms' innovation responses to TPU reduction vary by productivity, ownership, exporting status, and the irreversibility of investment.

1. Introduction

Recent studies have documented that a surge of innovations often follows major episodes of trade liberalization. These studies emphasize that international trade can enhance innovation through competition (Bloom et al., 2016), widened access to foreign markets (Bustos, 2011), or the complementarity between imported intermediates and investment in research and development (R&D) (Bøler et al., 2015). In this paper, we propose a novel channel through which trade liberalization encourages innovation activities through the removal of trade policy uncertainties (TPU) in the export destination markets.

Innovation demands enormous and irreversible investments before commercialization and is deterred by uncertainty. Therefore, trade agreements can induce innovation because they reduce TPU and make market conditions more transparent and predictable. To confirm this, we exploit a quasi-natural experiment brought about by China's accession to the WTO. Specifically, the United States granted China permanent normal trade relationship (PNTR) status on January 1, 2002. Prior to that, Chinese exporters were at risk of being burdened with punitive "non-NTR" tariffs.[1] In a testimony to Congress, Robert Lighthizer, the current

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[1] Also known as Column 2 tariffs, the "non-NTR" tariffs were originally set under the Smoot-Hawley Tariff Act of 1930 against a few communist countries. Had China lost its temporary NTR status, the average tariff it would have faced would possibly increase from the ongoing 4% in 2000 to 31% (Handley and Limão, 2017).

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0022-1996/

U.S. trade representative, explained that the threat of high non-NTR tariffs was real. Every year, during the 1990s, the U.S. Congress fiercely debated to overriding the Presidential waiver that renewed China's temporary NTR status.[2] Thus, the conferment of PNTR status to China puts an end to the uncertainty associated with the annual review by Congress and implied higher expected payoffs for the Chinese exporters.

We examine the extent to which the reduction in TPU can explain the recent surge in Chinese firms' innovation activities. In 2002, China filed around 50,000 applications for invention patents (ranked 7th in the world), while in 2012, the number of applications increased more than tenfold and surpassed that of the United States, the European Union, and Japan, who are recognized as the most innovative nations in the world.[3] A few studies have already shown that a reduction in TPU substantially promotes Chinese exports (Pierce and Schott, 2016; Handley and Limão, 2017; Feng et al., 2017). We show that TPU reduction also contributes substantially to patent applications by Chinese firms.

More specifically, we assembled a large and unique panel of Chinese firms with information on their production, trade, and patent applications before and after China's WTO accession. We focus on invention patents since they are a more reliable measure of innovation quality. We measure TPU for each industry as the pre-WTO gap between the non-NTR tariff and the observed Most Favored Nation (MFN) tariff, following Handley and Limão (2017). Given substantial variations in this uncertainty measure across industries, we adopt a difference-in-differences (DID) estimation approach for identification. We compare the patent filing behavior of manufacturers in industries experiencing greater uncertainty reduction (i.e., the treatment group) to that of manufacturers in industries experiencing less uncertainty reduction (i.e., the control group) before and after China's entry into the WTO in 2001. The results show that uncertainty reduction significantly encourages patent applications: sectors with a larger reduction in uncertainty experienced faster growth in innovation after the WTO accession. Interestingly, reducing uncertainty not only induces innovation through expansion of the export market, but also exerts a direct effect on innovation. The overall effect of reducing market uncertainty is sizeable: a back-of-the-envelope calculation based on the benchmark model finds that for a firm in a sector with average level of pre-WTO TPU, removing the associated uncertainty would increase its filings of invention patents by 0.0064, which is about one third of the actual increase in the average patent filings per firm from the pre-WTO to the post-WTO period.

Our work suggests an important channel through which trade liberalization can stimulate innovation, and ultimately promote economic growth. In a departure from existing studies, we directly connect firms' innovation incentives to their expectations about the market environment. The literature has emphasized that efficiency loss can be caused by market uncertainty. For instance, Bloom et al. (2007) document that stock market volatility leads firms to delay investment. We view TPU as an important source of market uncertainty and provide rigorous empirical evidence to show that the existence of TPU not only hinders export growth (as confirmed by the literature), but also discourages firms' investment in innovation. Our results are robust when we control for other determinants of innovation, such as domestic and import competition, input trade liberalization, and domestic reforms. Moreover, we find that firms' response to TPU reduction is heterogeneous, depending on their productivity, ownership, exporting status, and the irreversibility of investment.

We examine possible channels through which TPU reduction affects innovation. First, studies on specific industries suggest a positive effect of expected market size on innovation, such as Dubois et al. (2015) on the pharmaceutical industry. Is the TPU effect completely captured by a market size effect? If so, we would expect the differential impact of TPU reduction on firms with different exposure to disappear once we control for firms' export volume. The results, however, show that the differential effect of TPU is still present after we have explicitly controlled for market size. Secondly, patenting can be viewed as the outcome variable of innovation, while expenditures on R&D, fixed capital investment on machinery and equipment, and imported inputs are considered the input variables of innovation. How would TPU reduction stimulate inputs in innovation? Our results show that TPU reduction significantly increases the treated firms' capital investment and imported inputs. We also find stronger effect of TPU reduction in R&D-intensive sectors.

To the best of our knowledge, this is the first paper to identify the causal effects of TPU on firms' innovation activities. Our paper contributes to the broad literature on the effect of uncertainty on investment. In particular, theoretical work such as Dixit and Pindyck (1994) highlights a "wait and see" strategy of firms facing uncertainty when investment is irreversible. Rob and Vettas (2003) illustrate how demand uncertainty induces multinationals to both export and do FDI. A few empirical studies, including Guiso and Parigi (1999) and Bloom et al. (2007), confirm the negative relation between investment and uncertainty. Closely related, Pierce and Schott (2018) examine the effect of TPU reduction on the investment behavior of U.S. industries and plants. They find that industries more exposed to TPU reduction experience declines in investment but the effect is heterogeneous within industries. Our work differs in our focus on the impact of TPU reduction on firm innovation. In this sense, we make a novel contribution to two strands of literature.

First, our study contributes to understanding the impact of trade on firms' innovation incentives. Drawing on firm level data, recent studies show that international trade can promote innovation by either intensifying competition or enlarging access to foreign markets. Bloom et al. (2016) find that import competition from China induced the technical upgrading of European firms, in terms of patenting, usage of information technology, and productivity. Based on a Melitz-type heterogeneous model with technology choice, Bustos (2011) shows that increasing export sales can induce Argentinean exporters to upgrade technology. Aghion et al. (2019) show that a positive export shock spurs innovation for productive firms, because the positive *market size* effect

[2] Lighthizer (2010) continued to explain: "While none of the annual waivers was overridden, the ongoing controversy certainly resulted in uncertainty about the long-term future of U.S.-China trade."

[3] The R&D expenditures barely accounted for about 0.7% of China's GDP in 1995, but by 2014, it had reached 2.05% of GDP. See Wei et al. (2017) for an in-depth discussion about China's innovation growth.

dominates the negative *competition* effect. Coelli et al. (2016) exploit *ex ante* variations in firms' exposure to different markets and provide evidence that trade liberalization encourages firms' patent filings. Regarding the prevalence of trade in intermediate goods, Bøler et al. (2015) point out that imported intermediates may complement investment in R&D, so improved access to imported inputs promotes innovation and technological change, while Liu and Qiu (2016) find that input tariff reduction may discourage indigenous innovation by Chinese enterprises. The study closest to ours is Coelli (2018), who explores variations in cross-country industry-level patent filings to show that the granting of PNTR by the United States reduced TPU across sectors and encouraged innovation in China. In comparison, our paper employs firm-level data of Chinese manufacturing firms, therefore we are able to examine the heterogeneous response of firms to TPU reduction.

Second, our work contributes to the increased attention on the impact of TPU. Most previous studies, however, focus on the direct impact of TPU on trade. The pioneering work by Baldwin and Krugman (1989) adopts a real options approach to explain the hysteresis of trade during large swings in the exchange rate. In a series of studies, Handley (2014), and Handley and Limão (2015, 2017) emphasize the uncertainty induced by trade policies and examine its impact on trade and welfare. Following their approach, Feng et al. (2017) examine the effect of TPU reduction on the extensive margin (i.e., entry of firms) of Chinese exports to the United States. Taglioni and Zavacka (2013) find that importer uncertainty imposes a strongly negative but nonlinear impact on foreign suppliers. Beestermöller et al. (2018) study the uncertainty due to the possibility of border rejection of Chinese agri-food exports. Besides the trade effect, TPU reduction also has a substantial impact on employment and regional economic development. Pierce and Schott (2016) link the sharp drop in U.S. manufacturing employment to changes in U.S. trade policy that removed the tariff uncertainty on Chinese imports. On the other hand, Cheng and Potlogea (2015) show that Chinese cities experienced a larger increase in their exports to the United States if they were exposed to TPU reduction, resulting in a faster growth in population, output, and employment.

The rest of the paper is structured as follows. Section 2 describes the policy background and data; it also lays out our empirical strategy. Section 3 presents the estimation results. Section 4 discusses extensions and possible mechanism. We conclude in Section 5.

2. Policy background, data, and empirical strategy

2.1. Exceptional export growth after China's accession to the WTO

China's integration into the global trading system is regarded as one of the most important economic developments of the last two decades (Branstetter and Lardy, 2008). Fig. 1 plots the surge in Chinese exports to the United States and to the rest of the world (ROW) between 1995 and 2013, expressed as an index number relative to 1995. The nominal value of Chinese exports has increased ten-fold between 1995 and 2008, far outpacing the growth of global trade during the same period. Importantly, there is an obvious acceleration of export growth around 2001, when China officially entered the WTO. Before the WTO, from 1995 to 2001, the annual nominal growth rate of exports to the US was about 14%; after the WTO, from 2002 to 2008, the annual rate reached 25%, which is strikingly high. The export growth to the ROW shows a similar pattern.

A substantial proportion of the soaring Chinese exports can be attributed to the elimination of the high tariff threat after the country's WTO entry. Before China joined the WTO in December 2001, it was granted the status of temporary Normal Trade Relations (temporary NTR) and this was subject to an annual review by the U.S. Congress. In fact, Congress passed a bill to revoke China's NTR status thrice. If the the temporary NTR had indeed been revoked, Chinese exporters would have faced the punitive non-NTR tariffs. The non-NTR tariffs, also known as Column 2 tariffs, were originally set under the Smoot-Hawley Tariff Act of 1930 and were substantially higher than the MFN tariffs applicable under NTR status. If China had lost its MFN status, the average tariff would have increased from the ongoing 4% to 31% in 2000 (Handley and Limão, 2017).[4] Thus, before 2001, Chinese exporters faced substantial uncertainty. This perturbed U.S. business leaders too, because "the imposition of conditions upon the renewal of MFN as virtually synonymous with outright revocation. Conditionality means uncertainty." [5] The policy uncertainty varies substantially across 6-digit HS products, as shown in Fig. 2.

After China joined the WTO on December 11, 2001, the United States effectively enacted the PNTR on January 1, 2002, which completely alleviated Chinese exporters' concerns about sudden tariff spikes (Pierce and Schott, 2016). Since the US Congress passed the bill granting PNTR status to China on October 2000, in our baseline analysis, we treat the years from 2001 onwards as being the post period. Due to the historic root of the Column 2 tariffs, the uncertainty measure can plausibly be regarded as exogenous. Furthermore, the pre-WTO degree of uncertainty varies substantially across industries, thereby creating large variations across industries for our empirical identification. Fig. 3 shows that after 2001, exports in sectors with above-median pre-PNTR Column 2 tariffs grew much faster than those in sectors with below-median pre-PNTR Column 2 tariffs. The same pattern holds for Chinese exports both to the US and the ROW.

2.2. A surge of patent applications in China

China established its patent system in 1985, when its first patent law took effect and its patent office, the State Intellectual Property Office (SIPO), started to accept patent applications. In practice, patents are classified into three categories: invention, utility model, and design. According to China's patent law, invention patents refer to technical innovation made to a product or a method, or both; utility model patents refer to technical proposals on the shape and/or structure of a product; and design patents

[4] Pierce and Schott (2016) provides affluent evidence on the uncertainty caused by the annual review of China's NTR status.

[5] Tyco Toys CEO "China's MFN Status" , Hearing before the committee on Finance, U.S. Senate, June 6, 1996, p. 97.

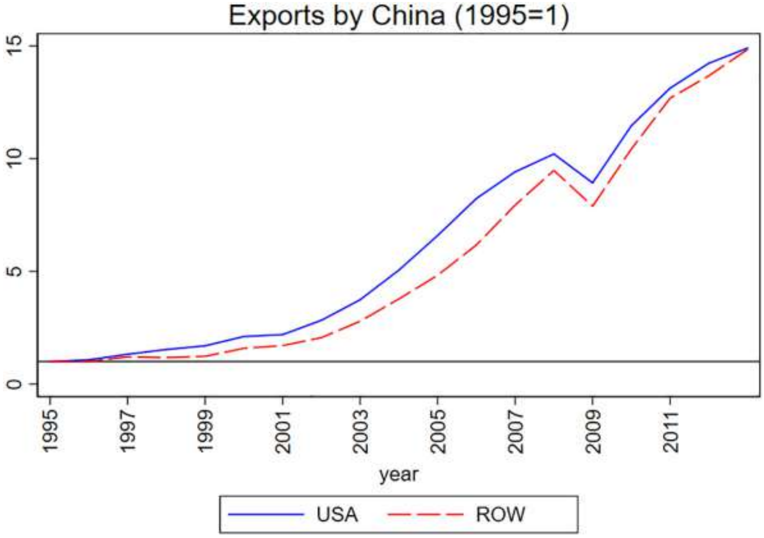

Fig. 1. Remarkable export growth: 1995-2012. Data Source: China Customs General Office. Chinese exports are expressed as an index number relative to 1995.

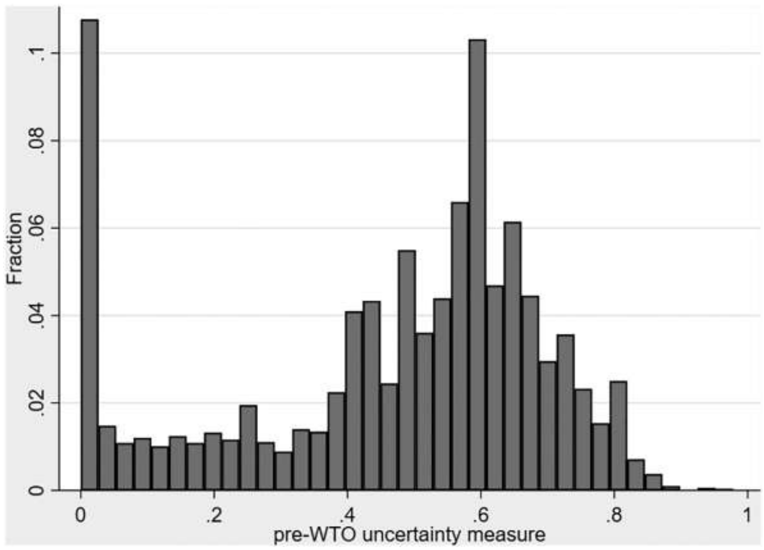

Fig. 2. TPU measure across products. Note: This figure presents the distribution of trade policy uncertainty (TPU) prior to China's accession into the WTO, across all 6-digit HS product categories. TPU is measured following Handley and Limão (2017) using Column 2 tariffs.

refer to changes in the shape and/or color of a product. The three types of patents differ in their application procedure and official requirements. An invention patent is subject to stricter examinations based on its utility, novelty, and non-obviousness.[6] Thus in this paper, we will focus on filings of invention patents only.

Fig. 4 describes the overall trend of invention patent applications submitted to the SIPO since 1995. The growth in invention patent applications submitted to the SIPO was relative stable before 2000, but began to accelerate after 2000, with an annual growth rate at about 30% from 2001 to 2008.[7] At the same time, the fraction of the invention patents out of total applications also rose from less than 12% to over 22%.

To show that the growth in invention patent applications differs across industries, Fig. 5 compares sectors in the top tercile of TPU with sectors in the bottom tercile. It shows differential trends over time of average patent filings per firm in the high TPU industries versus the low TPU industries. To ease comparison, we normalize the number of patents in 2001 for both groups to

[6] An invention innovation must have "prominently substantive characteristics and significant improvement" compared with the existent technologies. In comparison, the utility model and the design patents are incremental innovations. Both are granted on registration, and are not subject to novelty and non-obviousness examinations.

[7] The total number of invention patent applications was around 10 thousands in 1995, it increased to 30 thousands in 2001, and further jumped to about 200 thousands in 2008.

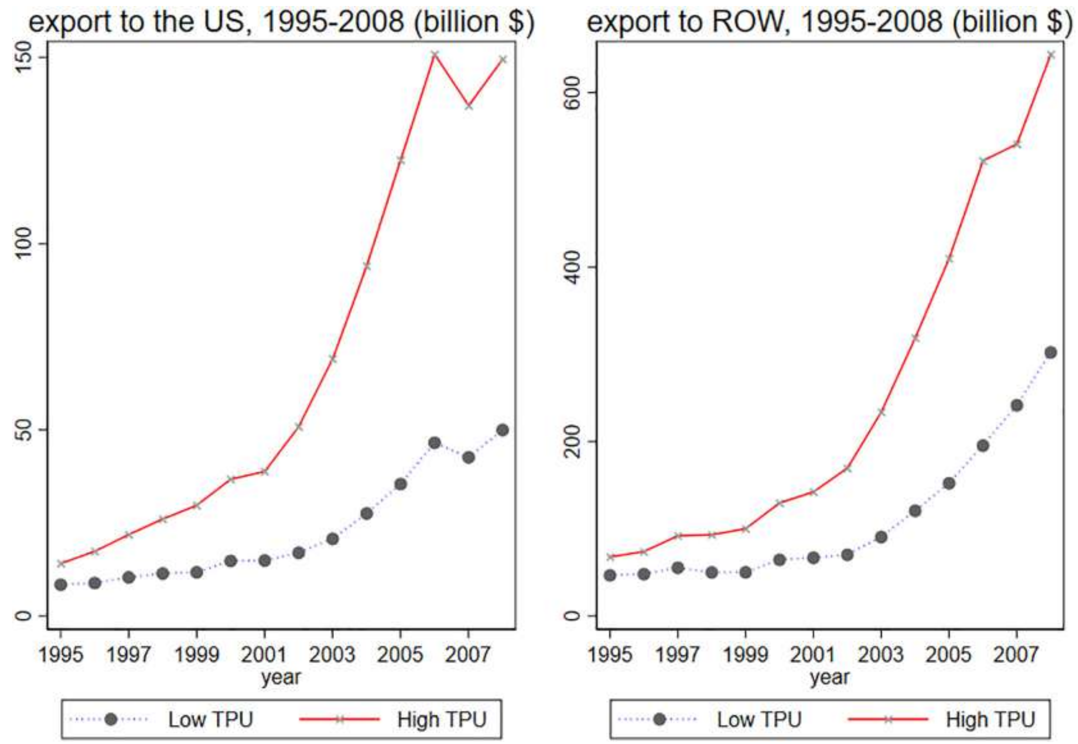

Fig. 3. Export growth by exposure to TPU: 1995–2008. Note: this figure shows the export growth of the high pre-WTO TPU product categories versus the low pre-WTO TPU product categories.

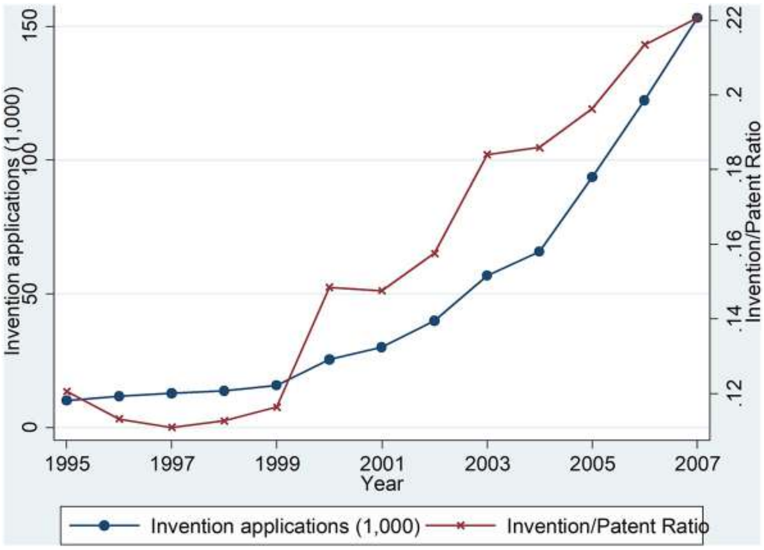

Fig. 4. Growth of patent applications in China. Note: This figure shows the growth in the number of invention patent applications (left axis, in 1,000) and the fraction of invention patents over total number of filings.

be one. Clearly the pre-WTO trends of the high TPU group and the low TPU group are comparable, while they diverge in the post-WTO period. The high TPU group experienced a larger reduction in uncertainty and exhibited a more impressive growth in patent filings. This divergence suggests positive impact of TPU reduction on firms' innovation incentives.

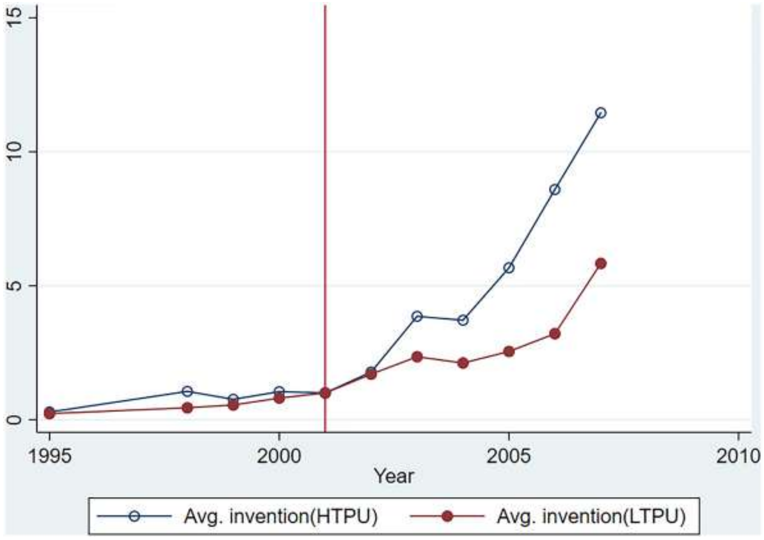

Fig. 5. Patent applications by high- and low-TPU industries. Note: This figure shows the growth in patent applications by Chinese firms in the high pre-WTO TPU product categories versus these in the low pre-WTO TPU product categories.

2.3. Estimation strategy

We examine the link between a reduction in TPU, in particular the removal of the punitive non-NTR tariffs, and Chinese manufacturing firms' patenting behavior. We exploit the fact that after China joined the WTO, industries that had higher pre-WTO TPU (i.e., industries with higher column 2 tariffs) would experience larger growth in exports after the WTO entry; whereas industries with low pre-WTO TPU would experience lower export growth after liberalization. The cross-sectional variation in pre-WTO uncertainty dates back to the 1930 Smoot-Hawley Tariff Act and therefore is plausibly exogenous to the current export patterns across industries. The differential degree of uncertainty reduction allows us to conduct a DID specification. Essentially, we compare patent applications of firms in industries experiencing greater reduction in uncertainty (i.e., the treatment group) to those in industries experiencing less reduction in uncertainty (i.e., the control group) before and after China entered the WTO in 2001.

We estimate the following equation:

$$\ln\left(PATENT_{ijt}\right) = \alpha_i + \beta TPU_j \cdot Post01_t + \mathbf{X}_{ijt}^{'}\ \gamma + \mathbf{Z}_{jt}^{'}\ \delta + \lambda_t + \varepsilon_{ijt}, \tag{1}$$

where the dependent variable $ln(PATENT_{ijt})$ is the innovation activity of firm *i* in industry *j* in year *t*. TPU_j measures the TPU faced by industry *j* before the WTO accession. $Post01_t$ denotes the post-WTO period, which takes a value of 1 for the years from 2001 onward and 0 otherwise. α_i is the firm fixed effects, controlling for all time-invariant firm characteristics. It also controls for industrial and regional differences that do not vary over time but may affect the industry's propensity to innovate. For example, certain industrial features may make firms in one industry more likely to innovate than other industries. Our estimation would be biased if both innovation and uncertainty reduction are related to business cycles or other common shocks. Thus, we add a year dummy, λ_t. We also include a set of time-varying firm-level variables ($\mathbf{X}_{ijt}$), and a set of time-varying industry-level variables ($\mathbf{Z}_{jt}$) that may affect innovation. ε_{ijt} is the error term. As suggested by Bertrand et al. (2004), standard errors are clustered at 4-digit industry level to deal with potential heteroskedasticity and serial autocorrelation.

We use the number of invention patent applications as a direct measure for innovation, following innovation literature (Aghion et al., 2005; Hu and Jefferson, 2009; and Aghion et al., 2019). Because of the zeros in patents we use the transformation $PATENT = 1 + Invention$ where Invention is the count of invention patent applications.[8] Our key explanatory variable is the change in industry-level market uncertainty TPU_j, which is essentially the difference between the Column 2 tariff (what can possibly be imposed) and the MFN tariff (what is actually imposed) in 2000.

Note that our TPU measures are constructed with the Column 2 tariffs imposed by the U.S. government, while firms that innovate may not necessarily export to the United States. We consider this specification for three reasons. First, the United States is the world's largest economy and the most important export destination market for Chinese manufacturers. Any change in the uncertainty of the U.S. market will, to a large extent, reflect the general conditions of the international market for Chinese exporters.

[8] To test the sensitivity of using $ln(1+y)$, we experiment with $ln(c+y)$ in the online appendix Table A.1, where c=0.1, 0.01, or 0.001 and y is the number of inventions. We also use the inverse hyperbolic sine transformation, which is given by $ln[y+(1+y^2)^{0.5}]$. The inverse hyperbolic sine equals 0 when $y=0$, and its slope tracks that of lny more closely than $ln(1+y)$ when y is small. The results are robust. To address the concern on the count data nature of invention filings, we explore fixed effects Poisson and negative binomial estimations in Table 8.

Secondly, even if a firm does not export *ex post*, it may still be induced to invest *ex ante* in innovation while expecting a growing potential market due to reduced uncertainty. Finally, a firm may also increase its innovation activities due to learning and technology spillover from those firms that do export to the United States. Nevertheless, since the policy shock is more relevant for firms exporting to the U.S. market, we expect that TPU reduction has stronger impact on these exporters. To verify that this is indeed the case, we further include an indicator for exporters to the United States and its interaction with the TPU measures in the following specification:

$$\ln PATENT_{ijt} = \alpha_i + \beta_1 TPU_j \cdot Post01_t + \beta_2 TPU_j \cdot Post01_t \cdot USEXP_i + \mathbf{X}'_{ijt}\gamma + +\mathbf{Z}'_{jt}\ \delta + \lambda_t + \varepsilon_{ijt}, \tag{2}$$

where $USEXP_i$ is one for a firm that has ever exported to U.S. prior to 2001, and zero otherwise. We expect a positive coefficient estimate β_2 for the interaction term, while a significant and positive β_1 captures the more general effect of TPU reduction on all firms.

2.4. Data

Our empirical analysis relies on data that include firm-level information on production, trade, and innovation, as well as industry-level information on market uncertainty and other industrial characteristics. To this end, we construct a unique dataset by merging three major data sources.

First of all, patent data comes from China's SIPO. This dataset contains detailed information of all patent filings since 1985, including the date of filing, the official name and address of the applicant, and the name and type of patent. Patents are dated by the year of application. As mentioned earlier, according to China's patent law, patents are classified into three categories: invention, utility model, or design. We will use invention patent as our main measure of innovation. An alternative measure is R&D expenditure, which reflects the input that goes into the innovation process. Although firm-level R&D expenditure is only available for a subsample from 2001 to 2007, we find that the patent filings and the R&D expenditure are strongly correlated.

Second, firm-level production and financial information are collected from *the Annual Survey of Industrial Production* (ASIP), provided by the National Bureau of Statistics of China (NBSC). The ASIP data is the most comprehensive firm-level dataset in China, including all non-state-owned enterprises with annual sales above 5 million RMB (around US $600,000 at the 2002 exchange rate) and all state-owned enterprises. It covers all 31 mainland provinces and 425 manufacturing industries at the 4-digit Chinese Industrial Classification (CIC) level from 1998 to 2007. We further extend the data back to 1995 by including the 1995 industrial census and the annual surveys of manufacturing firms for 1996 and 1997.[9] Based on the 2004 census for industrial firms, firms in the ASIP surveys account for 90% of industrial output and 97.5% of exports (Brandt et al., 2012). The ASIP also survey firms in the mining and public utility sectors, but we will focus on manufacturing firms. The ASIP data provides detailed firm-level information, including location, ownership, and accounting information such as employment, capital stock, material inputs, wage bills, total revenue, and export revenue. We further cleaned the data according to the basic rules of the Generally Accepted Accounting Principles (Cai and Liu, 2009).

The third dataset that we use is the firm level export and import data, collected by the General Administration of Customs of China (GACC), from 2000 to 2006. This dataset provides information on an exporting firm's products and destinations and an importing firm's products and sources. We also know the value and quantity exported or imported by a firm at the 6-digit HS product level. In addition, the export and import data enables us to identify processing firms. Owing to their specific production arrangement with foreign buyers, we follow Liu and Qiu (2016) and drop these processing firms in our main regressions.[10]

We merge the three datasets by carefully matching firms' names and locations. Our matched sample accounts for about 31.5% of total filings of invention patents and about a quarter of all firms that have filed at least one invention patent in the SIPO database for the period 1995-2007.[11] There may be concerns about possible mis-matches; however, our matching approach, which is based on the names and location of firms, applies to all firms across industries and in the whole sample period. The degree of mismatch across industries does not seem to be correlated with the degree of market uncertainty reduction across industries.

Following Handley and Limão (2017), we construct the TPU measure as the difference between the Column 2 tariff and the MFN tariff in 2000. That is, $TPU_j = 1 - (\tau_j^{col2}/\tau_j^{mfn})^{-\sigma}$, where σ is the substitutability coefficient.[12] Alternatively, we construct a second measure as the log difference between the Column 2 tariff and the MFN tariff in 2000 (i.e., $log(\tau_j^{col2}/\tau_j^{mfn})$). Both types of tariffs are extracted from Feenstra et al. (2002). We construct both measures for each 6-digit HS product, then aggregate to obtain an 4-digit CIC industry-level measure of TPU, by taking a simple average.

After the matching and data cleaning, we have an unbalanced panel of 576,105 firms and a total of around 1.4 million observations, spanning 266 4-digit CIC industries between 1995-2007. Table 1 presents the summary statistics and definitions of the main variables used in this study. The most important variables are patents and TPU. On average, each firm filed 0.014 invention

[9] Unfortunately, the annual surveys for 1996-1997 are incomplete, so we also prepare a whole set of estimations using 1998-2007 data. We have also specified a first-difference regression model, which examines whether the filings of invention patents grew significantly faster during 2000 to 2005 than the filings during 1995 to 2000 for sectors that experienced larger TPU reduction. Both sets of results confirm our main findings and are available upon request.

[10] Nevertheless, these processing firms account for a small proportion of patent filings in the manufacturing sector and their exclusion will not affect our results.

[11] The SIPO data does not include industry codes, so we do not know the exact number of patents filed by manufacturing firms.

[12] Handley and Limão (2017)'s measure of trade policy uncertainty is based on firm decisions under general equilibrium. We follow their method and set $\sigma = 3$.

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Variable definition	Min	Max
Firm level variables						
Invention	1,436,698	0.014	0.910	Number of invention patents	0	878
Citation-weighted (3 years)	1,145,953	0.001	0.046	Citation-weighted invention patent filings	0	10
Citation-weighted (5 years)	1,145,953	0.003	0.081	Citation-weighted invention patent filings	0	12
ln(age)	11,431,767	2.03	0.96	Logarithm of firm age	0	5.65
ln(employment)	1,336,230	4.70	1.18	Logarithm of firm employment	2.08	13.32
ln(K/L)	1,120,633	3.22	1.39	Logarithm of capital-labor ratio	−8.23	11.66
Foreign share	1,390,411	0.04	0.18	Foreign share of total equity	0.00	1.00
Industry level variables						
TPU (Handley & Limão)	3,422	0.49	0.19	TPU measure 1	0.00	0.84
TPU (log difference)	3,422	0.25	0.12	TPU measure 2	0.00	0.62
log(S/L)	2,630	−1.27	0.36	Industry level skill intensity	−2.44	−0.45
log(K/L)	2,630	4.49	0.76	Industry level capital intensity	2.84	6.89
Output tariff	3,407	0.15	0.11	Output tariff	0.00	0.75
Input tariff	3,422	0.11	0.06	Input tariff	0.02	0.41
SOE share	3,406	0.24	0.25	Share of the number of SOEs	0.00	1.00
FIE share	3,368	0.27	0.21	Share of the number of FIEs	0.00	1.00
MFN export tariff	3,283	1.03	0.04	Applied tariff by export destinations	1.00	1.81

Data Sources: Authors' own calculation based on merged data set from China National Bureau of Statistics, China's State Intellectual Property Office (SIPO), and China's Customs General Office. The details about the construction of variables are described in Section 2.4.

patents during each year of the sample period. The mean of TPU is 0.49 while the alternative measure is 0.25. However, the two TPU measures are highly correlated, with a correlation coefficient of 0.97.

3. Empirical analysis and findings

3.1. Baseline results

Our baseline estimation examines the link between TPU and the innovation activities of Chinese manufacturing firms. Fig. 5 has already shown that the trend of invention patent filings diverges for high- versus low- TPU industries, after 2001. For more rigorous empirical examinations, we specify a DID estimation approach in equation (1) and examine the heterogeneous responses of firms with varied uncertainty levels to trade liberalization. The baseline results are reported in Table 2, with robust standard errors clustered at the industry level. For all regressions, we include a year dummy λ_t and the firm-specific fixed effects α_i that controls all time-invariant cross-firm heterogeneity, and we are using variations within sectors to identify the impact of TPU reduction.

Column (1) considers only the key interaction term between TPU and an indicator for the post-treatment period: $TPU_j \cdot Post01_t$. Its coefficient is positive and statistically significant, suggesting that firms in industries with high pre-WTO uncertainty experienced a larger increase in invention patent applications after WTO entry, than firms in industries with low pre-WTO uncertainty. As high pre-WTO uncertainty industries experienced a larger reduction in uncertainty due to the grant of PNTR status, our results imply that reduction in market uncertainty induces innovation.

Column (2) includes a set of firm characteristics that may affect a firm's patenting behavior, including firm age and its squared term, firm size (employment), capital-labor ratio, and foreign equity share. The regression results show that larger and more capital intensive firms innovate more, on average, while firm age and foreign ownership do not have statistically meaningful impacts. The coefficient for $TPU_j \cdot Post01_t$ remains significant and similar in magnitude.

Our TPU measure is largely determined by the historic Smoot-Hawley tariff, which implies plausible exogeneity because it was set several decades ago. However, there are concerns that those tariffs may coincide with other industry level characteristics that could affect the destination demand. In particular, it may not be reduction in uncertainty *per se* but other industry characteristics that cause export growth from China. If these industries with high pre-WTO uncertainty happened to be industries in which China has comparative advantages, our conclusion about the impact of uncertainty reduction on innovation may be misleading. For this reason, Column (3) follows Pierce and Schott (2016) and includes additional interaction terms between initial year (i.e., 2000) capital and skill intensity ($(K/L)_j$ and $(S/L)_j$) in U.S. industries and the *Post*01 dummy.[13] These two interaction terms account for the possible impacts of the comparative advantage factors on innovation after China's WTO accession. As indicated by Column (3), however, skill-intensive sectors experienced a faster rise in invention patent filings after 2001. Our main variable of interest, $TPU_j \cdot Post01_t$, keeps its magnitude and statistical significance.

[13] Note we use subscript j to distinguish this industry level measure from firm level capital intensity. Sector-level factor intensities are from the US NBER-CES database and are matched to the Chinese industrial classification.

Table 2
Trade policy uncertainty and innovation: Benchmark results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent var: $ln(1 + Patents)$				Citation-weighted patents	
TPU × Post01	0.0069***	0.0070**	0.0132***	0.0180**	0.0016***	0.0024***
	(0.0033)	(0.0032)	(0.0047)	(0.0076)	(0.0004)	(0.0006)
$(S/L)_j$ × Post01			0.0116**	0.0118**	0.0012***	0.0016***
			(0.0046)	(0.0047)	(0.0004)	(0.0006)
$(K/L)_j$ × Post01			0.0017	0.0013	0.0002	0.0003**
			(0.0011)	(0.0010)	(0.0001)	(0.0002)
$ln(Age_{ijt})$		−0.0024***	−0.0022***	−0.0022***	−0.0009***	−0.0016***
		(0.0009)	(0.0009)	(0.0009)	(0.0003)	(0.0004)
$ln(Age_{ijt})^2$		0.0004	0.0004	0.0004	0.0002***	0.0003***
		(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$ln(Employment_{ijt})$		0.0038***	0.0039***	0.0039***	0.0008***	0.0013***
		(0.0007)	(0.0007)	(0.0007)	(0.0001)	(0.0002)
$ln(K/L)_{ijt}$		0.0015***	0.0015***	0.0015***	0.0003***	0.0003***
		(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0001)
$Foreign_{ijt}$		0.0001	0.0001	0.0001	0.0004	0.0010
		(0.0012)	(0.0012)	(0.0012)	(0.0005)	(0.0007)
Constant	−0.0014	−0.0220***	−0.0218***	−0.0218***	−0.0044***	−0.0070***
	(0.0014)	(0.0055)	(0.0052)	(0.0052)	(0.0009)	(0.0013)
Observations	1,436,698	1,317,330	1,313,963	1,313,963	1,132,437	1,132,437
R-squared	0.4563	0.4580	0.4582	0.4582	0.3156	0.3497

Note: All regressions include year dummies and the firm-specific fixed effects. Robust standard errors in parentheses, clustered on 4-digit CIC industries level. Trade Policy Uncertainty(TPU) measure follows Handley and Limão (2017). $(K/L)_j$ and $(S/L)_j$ are sectoral level capital intensity (in log) and skill intensity (in log), measured using the US NBER-CES productivity dataset. Firm level controls are from the China Annual Surveys of Industrial Production (ASIP). Details are presented in Section 2.4.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

In Columns (1) to (3), we measure TPU following the structural method of Handley and Limão (2017). Column (4), as a double check, uses a simple log difference between Column 2 tariff rates and the corresponding MFN tariff rates (i.e., $log(\tau_i^{col2}/\tau_i^{mfn})$). The impact of TPU remains highly significant.

We use invention patents as a measure of firms' innovation activity since it captures the quality of innovation better than patents in utility model or design. To further account for the quality of invention patents, Columns (5) and (6) use citation-weighted invention patents as dependent variables, where the weights are the number of citations within three or five years of the publication of the relevant patent. The results are similar.

In summary, across all estimation specifications, estimates of β are positive and statistically significant, implying that market uncertainty reduction leads to an increase in firms' innovation activity. The estimated effects are also economically significant. Taking the coefficient estimate in the preferred specification (Column (3)) as an example, a back-of-the-envelope calculation shows that for a firm in a sector with average level of pre-WTO TPU, removing the associated uncertainty would increase its filings of invention patents by 0.0064, which is about one third of the actual increase in the average patent filings per firm from the pre-WTO to the post-WTO period.

3.2. Other determinants of innovation

Table 3 considers competing explanations on the determinants of innovation that vary by industry and year and may correlate with the outcome variable (patent filings) and regressors of interest (trade liberalization and the associated reduction in market uncertainty). More specifically, Columns (1) considers the effect of domestic competition, while Column (2) considers foreign competition. Column (3) considers liberalized access to imported inputs. Column (4) considers the domestic reforms that are concurrent during the WTO entry period. Column (5) considers the effect of a reduction in MFN tariff faced by Chinese exporters in the destination markets. Column (6) considers the effect of better protection for intellectual property due to WTO. Finally, Column (7) considers all these determinants of innovation together in one regression. Note that in all cases, we have controlled for the industry comparative advantage variables interacting with Post01, and the full set of firm level characteristics that may affect a firm's patenting behavior, as we do in the benchmark Table 2.

3.2.1. Industrial competition

The discussion about the relationship between competition and innovation dates back to Schumpeter (1943), who argues that competition lowers price-cost margins, thereby reducing the quasi-rents from innovation. On the other hand, the empirical work by Nickell (1996) and Blundell et al. (1999), among others, show that competition can induce innovation. More recent studies

Table 3
TPU and innovation: Other determinants of innovation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent var: $ln(1 + Patents)$						
TPU × Post01	0.0131***	0.0133***	0.0128***	0.0136***	0.0140***	0.0130***	0.0139***
	(0.0046)	(0.0047)	(0.0046)	(0.0047)	(0.0046)	(0.0045)	(0.0046)
$(S/L)_j$ × Post01	0.0116**	0.0116**	0.0115**	0.0112**	0.0106**	0.0113**	0.0095**
	(0.0046)	(0.0046)	(0.0046)	(0.0044)	(0.0047)	(0.0045)	(0.0043)
$(K/L)_j$ × Post01	0.0017	0.0017	0.0016	0.0015	0.0019*	0.0015	0.0015*
	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0008)
HHI_{jt}	−0.0003						−0.0004
	(0.0006)						(0.0007)
Output tariff_{jt}		0.0080					−0.0006
		(0.0064)					(0.0066)
Input tariff_{jt}			0.0253				0.0347*
			(0.0185)				(0.0192)
SOE share_{jt}				−0.0168			−0.0190
				(0.0108)			(0.0120)
FIE share_{jt}				0.0127**			0.0113**
				(0.0049)			(0.0052)
Export MFN tariff_{jt}					−0.0042		−0.0148**
					(0.0065)		(0.0071)
Length_j × Post01						−0.0043**	−0.0043**
						(0.0019)	(0.0021)
$ln(Age_{ijt})$	−0.0022***	−0.0022**	−0.0022**	−0.0021**	−0.0021**	−0.0021**	−0.0018**
	(0.0009)	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
$ln(Age_{ijt})^2$	0.0004	0.0004	0.0004	0.0004	0.0004	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
$ln(Employment_{ijt})$	0.0039***	0.0039***	0.0039***	0.0040***	0.0039***	0.0040***	0.0041***
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
$ln(K/L)_{ijt}$	0.0015***	0.0015***	0.0015***	0.0015***	0.0015***	0.0016***	0.0015***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Foreign_{ijt}$	0.0001	0.0001	0.0001	0.0000	0.0002	0.0002	0.0003
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Constant	−0.0235***	−0.0239***	−0.0265***	−0.0280***	−0.0174*	−0.0227***	−0.0202**
	(0.0062)	(0.0056)	(0.0061)	(0.0067)	(0.0091)	(0.0055)	(0.0093)
Observations	1,313,963	1,312,631	1,313,963	1,313,235	1,276,169	1,233,009	1,194,791
R-squared	0.4582	0.4583	0.4583	0.4587	0.4628	0.4596	0.4648

Note: All regressions include year dummies and the firm-specific fixed effects. Robust standard errors in parentheses, clustered on 4-digit CIC industries level. Trade Policy Uncertainty(TPU) measure follows Handley and Limão (2017). Besides TPU, other determinants of innovation are considered, including industrial competition (HHI), import competition (output tariff), access to imported inputs (input tariff), domestic reforms (SOE share and FIE share), length of product cycle, and finally reduction in export tariffs (MFN export tariffs). $(K/L)_j$ and $(S/L)_j$ are sectoral level capital intensity (in log) and skill intensity (in log), measured using the US NBER-CES productivity dataset. Firm level controls are from the China Annual Surveys of Industrial Production (ASIP). Details are presented in Section 2.4.
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

include Aghion et al. (2005), who suggest an inverted-U shape between competition and innovation, and Hashmi (2013), who finds only a mildly negative relationship.Therefore, the net effect of competition on innovation is inherently ambiguous.

To measure competition, we construct a Herfindahl-Hirschman Index (HHI) at the 4-digit industry level using each manufacturing firms' domestic sales. A higher value of the HHI indicates a more concentrated market and thus less competition. Column (1) shows that a higher HHI translates to lower innovation, thus competition promotes innovation though the coefficient is not statistically significant.

3.2.2. Import competition

Competition may also come from foreign producers through imports. Importantly, coinciding with China's WTO entry, import tariffs on final goods (i.e., output tariffs) dropped substantially: the average import tariff dropped from 15.3% in 2000 to 9.8% in 2007. Thus, reduction in output tariff is expected to intensify domestic competition and consequently affect innovation (Liu et al., 2019). In Column (2), we include industry-level average import tariffs, $OutputTariff_{jt}$. Interestingly, higher protection from foreign competition, as indicated by a higher import tariff, is positively associated with firm innovation.

3.2.3. Access to imported inputs

Trade liberalization may affect domestic firms by easing their access to foreign intermediate inputs. It is been widely accepted that increasing imports of intermediate inputs, due to lower tariffs, can raise firms' productivity (Amiti and Konings, 2007; Liu and Ma, 2020). On the one hand, lower input tariffs may promote domestic innovation as the cost of innovation falls, especially when it relies on imported equipment and components. On the other hand, however, since foreign technology is often embodied in imported inputs, firms may simply purchase cheaper foreign technology to substitute for indigenous innovation. To this end, we consider the reduction in industrial input tariffs ($InputTariff_{jt}$) in Column (3), which are calculated using the 2002 Chinese input-output table following the approach by Goldberg et al. (2010).[14] The result shows a positive (though not significant) coefficient for input tariff, implying that imported inputs are substituting rather than complementing indigenous innovation, which is consistent with findings by Liu and Qiu (2016).

3.2.4. Domestic reforms

Besides joining WTO, China has also been engaged in domestic reform to deregulate the market. Column (4) considers two important policy reforms in the early 2000s: the privatization of state-owned enterprises (SOEs) and the deregulation of foreign direct investment (FDI). China embarked on a very large-scale privatization reform on SOEs in the late 1990s, which resulted in the privatization or closure of small and medium SOEs and stimulated the entry of many private firms (Berkowitz et al., 2017). To see whether this privatization campaign has any effect on innovation, we add an additional control variable *SOE share*, measured as the fraction of SOEs in each industry (Lu and Yu, 2015). Meanwhile, to conform to WTO rules, China undertook a major regulatory reform regarding foreign trade and investment in 2002, with the goal of encouraging foreign firms to compete on an equal basis with Chinese companies (Branstetter and Lardy, 2008). Entry of multinationals intensifies local competition. Multinational firms may also bring in more advanced technology, which may spillover to domestic firms. Accordingly, we use the fraction of foreign invested firms (FIEs), *FIE share*, to control for FDI liberalization. We find that FDI liberalization substantially promote innovation while SOE reform has a negative but insignificant impact.

3.2.5. Export tariff reduction

Along with the reduction in TPU, Chinese exporters also faced decreasing tariffs in importing destinations. The response of innovation to export growth may simply be due to lower tariffs. Therefore, Column (5) controls for the MFN tariffs imposed on Chinese exporters, *Export MFN tariff*, which is measured by the average MFN tariff rate across destination markets and 6-digit HS products within the same industry. Column (5) shows that declining MFN tariffs increases firms' patenting activities.

3.2.6. Intellectual property rights protection

China's WTO accession also led to the strengthening of intellectual property rights (IPR) protection as required by the Trade-Related Aspects of Intellectual Property Rights (TRIPs), which might also affect firms' patenting incentives. By using year fixed effects, the overall effect of TRIPs on patent filings has been controlled for. However, TRIPs may be exerting differentiated influences across industries with different length of product life cycle (Bilir, 2014). In particular, this differentiated effect may be correlated with the impact of TPU reduction, which may bias our estimation. Therefore, in column (6), we use a measure of the average industry life-cycle length constructed by Bilir (2014) and interact this measure with the WTO accession indicator, following Liu and Qiu (2016). The results show that the impact of TPU reduction remains significant.

3.2.7. Full-fledged model

Columns (1) to (6) adds additional determinants of innovation one by one, and the results show that the impact of TPU on innovation remains significant and stable. Finally, Column (7) runs a full-fledged model with the complete set of controls, confirming the results we have shown in previous columns. In summary, across all specifications, the coefficient for $TPU * Post01$ remains similar to the benchmark result and statistically significant, implying a robust result that TPU reduction leads to a substantial increase in firm innovation.

3.3. Validity of the DID Specification

In this subsection, we test the econometric validity of our DID specification with a battery of robustness checks in Table 4.

3.3.1. Expectation effect

First, we check whether firms changed their innovation behavior in anticipation of the coming WTO accession. For example, China and the US reached an agreement about China's accession of the WTO on November 15, 1999. Therefore, if some firms have already anticipated the entry, our treated and comparison group may not be *ex ante* comparable. Column (1) of Table 4 includes two additional controls $TPU_j \cdot Year2000$ and $TPU_j \cdot Year1999$. The coefficients for these two interaction terms are negative and insignificant, suggesting no expectation effect, while the effect of TPU reduction after 2001 remains significant.

3.3.2. Pre-WTO period

Column (2) runs a placebo test with time-varying TPU measures for the whole pre-WTO period (i.e., we restrict the sample to the period between 1995 and 2000). The premise is that we should not expect significant impact of TPU during this period since it did not change much (Topalova, 2010). Otherwise, it may imply some unobserved confounding factors are indeed taking effect

[14] Specifically, the input tariff for industry j in year t is defined as the weighted average of the tariffs of goods that are used as inputs for industry j, where the weight is the cost share of each input in the production of a good in industry j based on the 2002 Chinese Input-Output Table.

Table 4
TPU and innovation: Validity tests.

	(1)	(2)	(3)	(4)	(5)
	Dependent var: $ln(1 + Patents)$				
TPU × Post01	0.0144***		0.0110***		0.0126*
	(0.0047)		(0.0040)		(0.0074)
Annual TPU (1995-2000)		−0.0038			
		(0.0043)			
TPU × YR1996				−0.0172**	
				(0.0068)	
TPU × YR1997				−0.0063	
				(0.0075)	
TPU × YR1998				−0.0066	
				(0.0043)	
TPU × YR1999	0.0007			−0.0050	
	(0.0019)			(0.0042)	
TPU × YR2000	0.0018			−0.0039	
	(0.0018)			(0.0037)	
TPU × YR2001				0.0024	
				(0.0048)	
TPU × YR2002				0.0051	
				(0.0044)	
TPU × YR2003				0.0094*	
				(0.0051)	
TPU × YR2004				0.0124**	
				(0.0054)	
TPU × YR2005				0.0166***	
				(0.0063)	
TPU × YR2006				0.0253***	
				(0.0073)	
TPU × YR2007				0.0283***	
				(0.0084)	
Constant	−0.0198**	−0.0012	−0.0013	−0.0196*	−0.0427*
	(0.0095)	(0.0055)	(0.0341)	(0.0100)	(0.0256)
Observations	1,194,791	382,880	1,194,791	1,194,791	525,112
R-squared	0.4648	0.5282	0.4648	0.4649	0.8427

Note: All regressions include year dummies and the firm-specific fixed effects. Robust standard errors in parentheses, clustered on 4-digit CIC industries level. Trade Policy Uncertainty (TPU) measure follows Handley and Limão (2017). All regressions include interactions of factor intensity ($(K/L)_j$ and $(S/L)_j$) and Post01, and the full vector of control variables from Column (7) of Table 3, including industrial competition (HHI), import competition (output tariff), access to imported inputs (input tariff), domestic reforms (SOE share and FIE share), length of product cycle, and finally reduction in export tariffs (MFN export tariffs).
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

and therefore bias our results. The insignificant coefficient estimate for the annual TPU variable confirms that the TPU has no effect prior to China's WTO entry.

3.3.3. Industry time trend

The DID estimation assumes that, conditional on $(\mathbf{X}'_{ijt}, \alpha_i, \lambda_t)$, innovation activities of the treatment and the control group follow the same time trend. This assumption allows us to use innovation activities of the control group as the counterfactual of the treatment in the post-WTO period. However, it may not hold because of some industry-specific confounding factors. To check this, we add an industry-specific linear time trend, $\lambda_j \cdot t$, which enables us to control for all unobserved industry characteristics that vary over time. Column (3) presents the result, which remains strongly significant with the magnitude similar to the baseline results.

3.3.4. Flexible estimations

Column (4) adopts the most flexible specification, which replaces the interaction term $TPUj \times Post01$ with a set of interaction terms between TPU_j and the year dummies, i.e., $\sum_{t=1996}^{2007} \beta_t TPU_j \times Year_t$. The estimated coefficients are mostly insignificant for years before 2001, indicating a pre-WTO similarity between the treatment (i.e. the high uncertainty industries) and comparison groups (i.e., the low uncertainty industries).[15] The interactions become positive but insignificant from 2001 to 2002, and turn significant since 2003. Obviously, the effect becomes stronger over time, reflecting the fact that innovation responds with lags.

[15] The coefficient for 1996 is significantly negative, probably due to a much smaller number of observations.

3.3.5. Two-period estimation

The statistical inference of the DID estimation crucially depends on the accuracy of the standard errors. We have followed Bertrand et al. (2004) to cluster the standard errors at the industry level to correct serial correlation. We now use an alternative approach, also suggested by Bertrand et al. (2004), to collapse the panel data in two periods, one before WTO (1995–2000) and one after (2001–2007). We then use the White-robust standard errors and cluster at the 4-digit CIC industry level. The regression results are presented in Column (5), with qualitatively similar results.

3.4. Robustness checks

Table 5 provides a set of robustness checks using various subsets of our sample. First, Column (1) considers a sample of firms whose products belong to a single industry. Column (2) restricts the sample to surviving firms and excludes firms that enter or exit. Columns (3) to (6) separately consider firms based on their ownership. Finally, as a placebo test, Column (7) considers processing exporters.

3.4.1. Single-product firms

In our sample, some firms produce multiple products spanning different industries while our TPU measure is industry specific.[16] To check whether our results are contaminated by multi-industry firms, Column (1) is restricted to a subsample of firms whose products belong to the same industry. We show a strong and significant impact of TPU reduction on firm innovation for this subsample.

3.4.2. Incumbent firms

Another issue is firms' entry and exit, which may be jointly determined with their innovation activities by unobservables such as productivity. This means that firms that entry or exit may exhibit different innovation behaviors. To circumvent this selection effect, Column (2) focuses on a subsample of surviving firms who operate in both pre- and post-WTO periods. Again this regression generates results that are very similar to our main findings.

3.4.3. Ownership

Columns (3) to (5) separately consider the heterogeneous responses of firms with different ownership. We consider three types of firms: state owned enterprises (SOEs), domestic privately-owned firms (POEs), and foreign invested enterprises (FIEs), including both Sino-foreign joint ventures and wholly foreign-owned enterprises. Interestingly, TPU reduction has a significant effect on innovation by SOEs and POEs, while the effect is not significant for FIEs. The insignificant response from FIEs is understandable given the fact that within multinational enterprises foreign affiliates usually specialize in less innovation-intensive parts of production and sales, with most innovation activities being undertaken by the headquarters (Antràs and Yeaple, 2014). Column (6) includes the interactions of all three ownership dummies with $TPU * Post01$. The results are similar.

3.4.4. Processing firms

Column (7) provides a placebo test using a subsample of processing firms. Such firms mainly engage in process and assembly work for foreign buyers by importing duty-free intermediate inputs. [17] Due to this special arrangement, processing firms may not respond to the reduction in TPU in the same way as normal trade firms (Liu and Qiu, 2016). Indeed, Column (6) shows that processing firms do not respond actively to the policy shock.

3.5. Heterogenous effects

In previous sections, we established the average effect of TPU reduction on firms' patent applications, by exploring the differential effect on firms exposed to high TPU reduction versus those exposed to low TPU reduction. However, firms with different characteristics may respond differently. Table 5 shows that firms with different types of ownership respond differently to the reduction in TPU. In Table 6, we further explore three important dimensions of firms' heterogeneity.

3.5.1. Distance from the technology frontier

First, as shown in Aghion et al. (2009), firms' response to competition is crucially dependent on their current distance to the technology frontier. Firms will respond by increasing innovation only when they are close to the frontier. Since distance to the technology frontier is an essential determinant of the cost of innovation, we explore whether firms also respond differently to TPU reduction according to this parameter. More specifically, we divide firms into quantiles based on their total factor productivity (TFP) before the WTO accession. We estimate firm level TFP using the Levinshon and Petrin (2003) method.[18] Quantiles are

[16] Each firm is categorized into one 4-digit industry, however, they may manufacture products that belongs to different 4-digit industries. We obtain firm-product information from the NBSC, which contains information about each 5-digit product produced by a firm, for the period 2000-2006.

[17] A firm is defined as a processing firm if its processing exports account for more than 50% of its total exports. The results are not sensitive to this choice of processing export share.

[18] Firm level TFP is estimated within each 2-digit CIC industry. We deflate firm value added, employment, fixed assets, and intermediate inputs using deflators provided in Brandt et al. (2012). We do not have investment and material input data for 1995-1997, so here we focus on a sample of firms from 1998 to 2007.

Table 5
TPU and innovation: Robustness.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent var: $ln(1+Patents)$						
	Single-product	Incumbent	SOE	POE	FIE	All	Processing
TPU × Post01	0.0112**	0.0150***	0.0104*	0.0108***	0.0124	0.0120***	0.0018
	(0.0047)	(0.0046)	(0.0055)	(0.0037)	(0.0114)	(0.0041)	(0.0146)
TPU × Post01 × SOE						−0.0021	
						(0.0034)	
TPU × Post01 × FIE						0.0008	
						(0.0028)	
$(S/L)_j$ × Post01	0.0090*	0.0111***	0.0061*	0.0061*	0.0145*	0.0081**	0.0189*
	(0.0046)	(0.0041)	(0.0034)	(0.0034)	(0.0081)	(0.0037)	(0.0109)
$(K/L)_j$ × Post01	0.0012	0.0015*	0.0027	0.0009	0.0028	0.0012*	0.0062
	(0.0009)	(0.0009)	(0.0017)	(0.0008)	(0.0021)	(0.0007)	(0.0037)
HHI_{jt}	−0.0004	0.0001	−0.0010	−0.0006	−0.0006	−0.0007	0.0014
	(0.0007)	(0.0007)	(0.0010)	(0.0009)	(0.0011)	(0.0008)	(0.0023)
Output tariff$_{jt}$	0.0048	−0.0043	−0.0068	0.0048	−0.0289	0.0004	−0.0425
	(0.0051)	(0.0086)	(0.0111)	(0.0055)	(0.0195)	(0.0082)	(0.0521)
Input tariff$_{jt}$	0.0278	0.0432**	0.0292	0.0383*	0.0710	0.0453*	0.1734**
	(0.0182)	(0.0210)	(0.0246)	(0.0202)	(0.0550)	(0.0244)	(0.0737)
SOE share$_{jt}$	−0.0167	−0.0194	0.0084	−0.0234	−0.0600	−0.0306*	−0.0682**
	(0.0129)	(0.0118)	(0.0068)	(0.0151)	(0.0374)	(0.0172)	(0.0297)
FIE share$_{jt}$	0.0111**	0.0131**	0.0137	0.0130**	−0.0007	0.0162**	0.0471
	(0.0043)	(0.0060)	(0.0101)	(0.0059)	(0.0115)	(0.0078)	(0.0358)
Export MFN tariff$_{jt}$	−0.0167***	−0.0116	−0.0129*	−0.0186	0.0004	−0.0237	−0.0010
	(0.0060)	(0.0082)	(0.0074)	(0.0120)	(0.0223)	(0.0153)	(0.0306)
Length$_j$ × Post01	−0.0036*	−0.0049**	−0.0019	−0.0045***	−0.0033	−0.0037**	0.0050
	(0.0020)	(0.0021)	(0.0039)	(0.0017)	(0.0047)	(0.0018)	(0.0057)
$ln(Age_{ijt})$	−0.0014	0.0024**	−0.0027	−0.0019*	−0.0021	−0.0027***	−0.0101*
	(0.0009)	(0.0011)	(0.0027)	(0.0010)	(0.0032)	(0.0010)	(0.0058)
$ln(Age_{ijt})^2$	0.0002	−0.0006**	0.0004	0.0004	−0.0003	0.0005*	0.0007
	(0.0003)	(0.0003)	(0.0006)	(0.0003)	(0.0015)	(0.0003)	(0.0019)
ln(Employment$_{ijt}$)	0.0042***	0.0051***	0.0037***	0.0043***	0.0068***	0.0053***	0.0085***
	(0.0009)	(0.0011)	(0.0012)	(0.0008)	(0.0019)	(0.0011)	(0.0024)
ln(K/L)$_{ijt}$	0.0014***	0.0023***	0.0024***	0.0012***	0.0028**	0.0014***	0.0052***
	(0.0004)	(0.0005)	(0.0008)	(0.0003)	(0.0011)	(0.0003)	(0.0017)
Foreign share$_{ijt}$	0.0003	0.0003	−0.0227	0.0024	0.0017	0.0005	−0.0010
	(0.0013)	(0.0018)	(0.0178)	(0.0049)	(0.0014)	(0.0013)	(0.0015)
Constant	−0.0186**	−0.0308***	−0.0261*	−0.0178	−0.0453*	−0.0229	−0.1061**
	(0.0085)	(0.0106)	(0.0153)	(0.0128)	(0.0259)	(0.0186)	(0.0469)
Observations	1,120,030	395,835	157,478	882,523	155,061	1,034,287	96,101
R-squared	0.4688	0.3376	0.4372	0.4781	0.5591	0.4752	0.4747

Note: Column (1) considers a sample of firms whose products belong to a single industry. Column (2) restricts the sample to surviving firms and excludes firms that enter or exit. Columns (3) to (6) separately consider firms based on their ownership. Column (7) considers processing exporters. All regressions include year dummies and the firm-specific fixed effects. Robust standard errors in parentheses, clustered on 4-digit CIC industries level. Trade Policy Uncertainty(TPU) measure follows Handley and Limão (2017).

*** $p<0.01$.

** $p<0.05$.

* $p<0.1$.

constructed within each CIC 4-digit industry. Column (1) presents regression results using the sample of the fifth quantile (i.e., firms that are farthest from the frontier), while Column (2) presents the results for the first quantile (i.e., firms that are closest to the frontier). Consistent with the insight of Aghion et al. (2009), firms in the first quantile respond much more sensitively to TPU shock, while those in the fifth quantile do not innovate in response to TPU reduction; that is, the coefficient is much smaller and less significant.

3.5.2. Irreversible investment

Facing policy uncertainty, a forward-looking firm is reluctant to invest in innovation, especially when the investment is highly irreversible. The literature offers two measures for investment irreversibility at the industry level. The first is the gap between the purchase and resale prices of capital goods. Secondly, when resale market is limited, firms have to rely on depreciation to reduce unwanted capital, which is more difficult in industries with low depreciation rates.

Since the purchase and resale prices of capital goods are hardly available, we use the depreciation rate to measure irreversibility. More specifically, we follow Chirinko and Schaller (2009) and Guariglia et al. (2012) and assume a firm is more (less) likely to face irreversibility if the average depreciation rate of the industry in which this firm operates is below (above) the median depreciation rate of all industries. We run the same regression separately on firms in the high irreversibility industries and those in low

Table 6
TPU and innovation: Heterogenous effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var:	ln(1+Patents)						
	Tech frontier		Irreversibility		Exporter Interaction		
	5th quantile	1st quantile	High	Low	Exporter	US exporter	New exporter
TPU × Post01	0.0032*	0.0397***	0.0164**	0.0023	0.0107**	0.0094**	0.0058*
	(0.0019)	(0.0140)	(0.0082)	(0.0034)	(0.0041)	(0.0040)	(0.0033)
TPU × Post01 × Exporter					0.0072***	0.0042**	
					(0.0021)	(0.0017)	
TPU × Post01 × US exporter						0.0057***	
						(0.0018)	
TPU × Post01 × New exporter							0.0110***
							(0.0034)
$(S/L)_j$ × Post01	0.0015*	0.0277**	0.0091	0.0061***	0.0112***	0.0113***	0.0083***
	(0.0009)	(0.0126)	(0.0066)	(0.0021)	(0.0042)	(0.0042)	(0.0030)
$(K/L)_j$ × Post01	0.0001	0.0045	0.0000	0.0016	0.0016*	0.0013	0.0003
	(0.0006)	(0.0029)	(0.0012)	(0.0011)	(0.0009)	(0.0009)	(0.0007)
HHI_{jt}	0.0004	0.0001	-0.0014	-0.0007	0.0001	0.0002	-0.0006
	(0.0005)	(0.0020)	(0.0020)	(0.0010)	(0.0007)	(0.0007)	(0.0007)
Output tariff_{jt}	-0.0018	-0.0087	0.0033	-0.0184	-0.0040	-0.0040	0.0000
	(0.0030)	(0.0221)	(0.0080)	(0.0143)	(0.0085)	(0.0084)	(0.0086)
Input tariff_{jt}	0.0103	0.0923	0.0562	0.0574	0.0437**	0.0431**	0.0442**
	(0.0091)	(0.0601)	(0.0366)	(0.0385)	(0.0210)	(0.0208)	(0.0195)
SOE share_{jt}	-0.0035	-0.0255	-0.0345	-0.0218	-0.0194	-0.0196*	-0.0213
	(0.0033)	(0.0255)	(0.0232)	(0.0184)	(0.0118)	(0.0118)	(0.0132)
FIE share_{jt}	0.0017	0.0333*	0.0146	0.0276***	0.0132**	0.0125**	0.0084
	(0.0031)	(0.0178)	(0.0239)	(0.0084)	(0.0059)	(0.0058)	(0.0087)
Export MFN tariff_{jt}	-0.0063*	-0.0163	-0.0330	-0.0006	-0.0121	-0.0119	-0.0147
	(0.0034)	(0.0204)	(0.0264)	(0.0162)	(0.0084)	(0.0082)	(0.0222)
Length × Post01	0.0007	-0.0134*	-0.0102**	-0.0003	-0.0047**	-0.0047**	-0.0041**
	(0.0009)	(0.0070)	(0.0049)	(0.0013)	(0.0020)	(0.0020)	(0.0017)
(Age_{ijt})	0.0028*	0.0027	-0.0038**	-0.0013	0.0030***	0.0026**	0.0015
	(0.0014)	(0.0035)	(0.0015)	(0.0011)	(0.0011)	(0.0011)	(0.0014)
$(Age_{ijt})^2$	-0.0005*	-0.0009	0.0009*	0.0001	-0.0007**	-0.0006**	-0.0003
	(0.0003)	(0.0009)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
$\ln(\text{Employment}_{ijt})$	0.0021***	0.0074***	0.0052***	0.0046***	0.0052***	0.0051***	0.0067***
	(0.0005)	(0.0020)	(0.0020)	(0.0009)	(0.0011)	(0.0011)	(0.0015)
$\ln(\text{K/L})_{ijt}$	0.0007**	0.0040***	0.0013**	0.0012***	0.0023***	0.0023***	0.0013***
	(0.0003)	(0.0011)	(0.0005)	(0.0003)	(0.0005)	(0.0005)	(0.0004)
Foreign_{ijt}	-0.0035	-0.0045	0.0001	0.0011	0.0003	0.0003	0.0024
	(0.0043)	(0.0044)	(0.0032)	(0.0015)	(0.0018)	(0.0018)	(0.0039)
Constant	-0.0062	-0.0682**	0.1172**	-0.0179	-0.0307***	-0.0294***	-0.0283
	(0.0066)	(0.0284)	(0.0512)	(0.0221)	(0.0107)	(0.0104)	(0.0209)
Observations	78,658	98,811	450,133	583,883	395,835	395,835	174,810
R-squared	0.2809	0.3799	0.4717	0.5047	0.3376	0.3383	0.3298

Note: Columns (1) and (2) compare patent applications by firms with frontier productivity with firms in the bottom quintile productivity level. Columns (3) and (4) compare patent applications by firms with high irreversible investment with firms with low irreversible investment. Columns (5)-(7) examine the heterogeneous effects on exporters. All regressions include year dummies and the firm-specific fixed effects. Robust standard errors in parentheses, clustered on 4-digit CIC industries level. Trade Policy Uncertainty(TPU) measure follows Handley and Limão (2017).

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

irreversibility industries. The results are reported in Columns (3)-(4), showing strong and positive impact of TPU reduction on innovation of firms in industries with highly irreversible investment. By contrast, for firms in low irreversibility industries, the effect is not significant.

3.5.3. Exporters

Columns (5)-(6) of Table 6 consider the heterogeneous responses of exporters, compared with non-exporting firms. Our general specification in Eq. (1) considers all firms, regardless of their observed export status. Since foreign trade policy shock directly affects firms that export, we expect TPU reduction to have a stronger impact on exporters. A related study by Bustos (2011) introduces technology choice in a Melitz trade model with heterogeneous firms. The author finds that trade integration can induce both continuing exporters and new entrants to upgrade technology, while non-exporters continue to use old technology. Feng et al. (2017) find that the reduction in TPU induces entry of new exporters. Therefore, both exporting and innovating could be the result of TPU reduction.

To address the endogeneity of the exporting decision, we construct an exporter indicator EXP_i, which equals one when a firm has ever exported during the period prior to 2001 and zero otherwise. Following the empirical model specified in Eq. (2), Column (5) adds an additional interaction term between $TPU_j \cdot Post01_t$ and EXP_i to the baseline model. Here, we focus on the sample of firms that have been operating before and after 2001 and split the sample based on initial export status. The first sample includes firms that were been exporting prior to 2001 and the second includes firms that were not. If innovation was dominantly driven by new entrants into exporting, we would not see a significant effect of TPU on continuing exporters. Instead, Column (5) shows that exporters respond more to TPU.

Similarly, Column (6) specifically looks at firms that export to the United States, with an additional interaction term between $TPU_j \cdot Post01_t$ and an exporter indicator $USEXP_i$, which equals one when a firm has ever exported to the United States in 2000 and zero otherwise.[19] Since the TPU shock is more relevant for firms that export to the US market, we expect TPU reduction to have a stronger impact on these exporters. The results shown in Columns (5)-(6) confirm that, first, TPU reduction has greater impact on firms in high pre-WTO TPU sectors. Second, within these sectors, exporters respond more. Third, the effect is even stronger for firms that directly export to the United States.

Finally, we construct a comparison between firms who became new exporters after 2001 versus incumbent firms who have never exported throughout the sample period. The idea is to directly test whether removing policy uncertainty encourages new entrants into the exporting market with simultaneous innovation. Column (7) reports the result, that is, new exporters increase their innovation more compared to never-exporters. This is consistent with Bustos (2011) who shows that new exporters spend significantly more on technology upgrading than never-exporters.

4. Mechanism and further discussions

4.1. Mechanism

We now extend our discussion to investigate the possible mechanisms that TPU shock could affect firms' innovation behavior.

4.1.1. Market expansion

One important hypothesis regarding the effect of TPU reduction is that it enlarges the exporters' market. As confirmed by Handley and Limão (2017) and Pierce and Schott (2016), TPU reduction induces export growth disproportionately in sectors that were exposed to high TPU prior to WTO. Therefore the effect of TPU reduction on innovation may simply be a market expansion effect. Studies on specific industries, for example Dubois et al. (2015), suggest a positive effect of expected market size on innovation. If so, we would then expect that after controlling for firms' export or export growth, the TPU effect will largely disappear. Thus, in Columns (1)-(2 of Table 7, we examine whether the realized export growth (due to reduced TPU) can completely explain the surge in innovation. More specifically, Column (1) directly controls for firm-level export value. Conditional on firms' export scale, the TPU effects remain substantial and significant. However, firms' export status may be endogenous due to the reverse causality between innovation and export. Hence, Column (2) instead controls for the average export at the industry level. In both specifications, the reduction in TPU remains an important determinant of firm innovation. Thus, the removal of uncertainty does not simply reflect growing market size. Instead, it also implies other subtle effects that are worthy of further exploration.

4.1.2. Technological input

Patent applications measure the output of innovation, while on the other hand, innovation can be realized by different types of inputs. It is therefore worthwhile to examine how TPU reduction affects firms' inputs to innovation. Due to data availability, Columns (3) to (5) of Table 7 focus on three major inputs. First, capital intensity can be used as an alternative measure of technology (Bernard et al., 2006). Hence, in Column (3), we consider firms' fixed investment.[20] The result implies TPU reduction induces substantially more capital investment by firms in the high TPU industries. Second, Column (4) finds that reduction in uncertainty also leads firms to import more intermediate capital equipment. Finally, Column (5) considers firms' expenditure on R&D. Unfortunately, the ASIP data does not include R&D expenditure until 2001. Thus, we cannot directly compare the change in R&D expenditure by firms in the high TPU sectors with those in the low TPU sectors before and after 2001. Instead, Column (5) investigates whether firms in R&D-intensive industries have benefited more from TPU reduction, where R&D intensity is calculated as the industry level R&D expenditure over sales. More specifically, we interact R&D intensity in the initial year (2001) with our main explanatory variable ($TPU \times Post01$) to capture the heterogeneity across industries. The result suggests that firms in R&D-intensive industries innovate more.[21]

[19] We have firm's export destination information from 2000 to 2006, so we use 2000 as the initial year to identify an exporter to the U.S. market.

[20] Following Liu and Lu (2015), we construct firm's fixed investment by using perpetual inventory method with firms' book values of fixed assets (reported in the ASIP dataset) and assuming a constant depreciation rate.

[21] In the online appendix (Table A.2), we directly test whether industries experiencing larger TPU reduction have larger increase in R&D intensity. The results confirm that TPU reduction increases R&D intensity, at both the industry and the firm level.

Table 7
Market expansion or technology investment.

Variables	(1) ln(1+Patents)	(2)	(3) ln(Investment)	(4) ln(Imported Inputs)	(5) ln(1+Patents)
TPU × Post01	0.0125***	0.0126***	0.1857***	0.3752***	0.0054**
	(0.0043)	(0.0043)	(0.0677)	(0.1203)	(0.0025)
ln(Firm exports)	0.0005***				
	(0.0001)				
ln(Industrial exports)		0.0013**			
		(0.0006)			
TPU × Post01 × R&D/sales					3.7828***
					(1.1734)
$(S/L)_j$ × Post01	0.0087**	0.0089**	0.0035	0.2146***	0.0038*
	(0.0040)	(0.0039)	(0.0514)	(0.0669)	(0.0022)
$(K/L)_j$ × Post01	0.0012*	0.0014*	−0.0217	0.0585*	0.0015**
	(0.0007)	(0.0008)	(0.0217)	(0.0347)	(0.0006)
HHI_{jt}	−0.0006	−0.0008	−0.0292***	0.0087	−0.0006
	(0.0008)	(0.0008)	(0.0101)	(0.0162)	(0.0007)
Output Tariff_{jt}	0.0008	0.0018	−0.0018	−0.3028	0.0001
	(0.0067)	(0.0069)	(0.1151)	(0.3397)	(0.0058)
Input Tariff_{jt}	0.0379*	0.0383*	−0.0038	0.4291	0.0332*
	(0.0198)	(0.0197)	(0.3452)	(0.5871)	(0.0175)
SOE share_{jt}	−0.0249*	−0.0235	0.2231**	0.0492	−0.0182*
	(0.0150)	(0.0152)	(0.1083)	(0.1174)	(0.0110)
FIE share_{jt}	0.0125**	0.0114**	−0.1448	0.2454*	0.0105**
	(0.0053)	(0.0052)	(0.1217)	(0.1255)	(0.0051)
Export MFN Tariff_{jt}	−0.0160*	−0.0178*	−0.1808	0.3381	−0.0146**
	(0.0082)	(0.0093)	(0.2863)	(0.3004)	(0.0068)
Length × Post01	−0.0039**	−0.0038*	−0.0805***	−0.0205	−0.0029*
	(0.0019)	(0.0020)	(0.0278)	(0.0545)	(0.0015)
(Age_{ijt})	−0.0021**	−0.0019**	−0.4039***	0.2621***	−0.0017**
	(0.0009)	(0.0009)	(0.0278)	(0.0288)	(0.0009)
$(Age_{ijt})^2$	0.0004	0.0004	0.0733***	−0.0533***	0.0003
	(0.0003)	(0.0003)	(0.0066)	(0.0064)	(0.0003)
$\ln(\text{Employment}_{ijt})$	0.0039***	0.0041***	0.8158***	0.0740***	0.0041***
	(0.0008)	(0.0008)	(0.0133)	(0.0087)	(0.0008)
$\ln(K/L)_{ijt}$	0.0014***	0.0015***	0.2901***	0.0425***	0.0015***
	(0.0003)	(0.0003)	(0.0065)	(0.0051)	(0.0003)
Foreign_{ijt}	0.0005	0.0005	−0.0102	−0.0268	0.0002
	(0.0013)	(0.0013)	(0.0280)	(0.0636)	(0.0012)
Constant	−0.0211**	−0.0262**	2.1040***	−1.2427***	−0.0203**
	(0.0107)	(0.0102)	(0.2956)	(0.3115)	(0.0089)
Observations	1,168,518	1,167,887	995,039	1,194,791	1,194,791
R-squared	0.4720	0.4720	0.7179	0.6288	0.4650

Note: Columns (1)-(2) control for firms' export market expansion. Column (1) directly controls for firm-level export value. Column (2) controls for the average export at the industry level. Columns (3)-(5) focus on three major inputs affected by TPU reduction. Column (3) considers firms' fixed investment. Column (4) looks at imports of intermediate capital equipment. Column (5) considers firms' expenditure on R&D by interacting R&D intensity with *TPU* × *Post*01 to capture the heterogeneity across industries. All regressions include year dummies and the firm-specific fixed effects. Robust standard errors in parentheses, clustered on 4-digit CIC industries level. Trade Policy Uncertainty(TPU) measure follows Handley and Limão (2017).
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

4.2. Further robustness

Our main specifications adopt linear econometric models. We further investigate whether the main results hold with count data specifications in Table 8.

Column (1) runs a fixed effects Poisson regression. While TPU reduction has a positive effect on invention patent filings, the coefficient is not significant. Column (2) runs a negative binomial regression, taking into account the inequality between sample mean and variance of the distribution of the patent filings. The result is significant and much larger in magnitude. To address possible serial correlations of the error term, Column (3) follows Bertrand et al. (2004) and collapses the sample into two subperiods, before and after 2001, and keeps firms that exist in both periods. The results also strongly support the importance of TPU reduction in promoting innovation. Column (4) runs a fixed effects Poisson regression at the 4-digit industry level, taking into account firms' entry and exiting. The result shows a strong and significant impact of TPU reduction. Column (5) runs a Poisson regression at the firm level with 2-digit industry-year fixed effects to control for any industry specific trends for innovation. The result also shows strong effects of TPU reduction.

Table 8
Poisson specification and decision to patent.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Number of patents					Decision
Method	xtpoisson	Neg. binomial	2-period xtpoisson	Industry xtpoisson	Poisson	LPM
TPU × Post01	0.1690	0.6960***	0.9734***	0.7065***	0.2003***	0.0127***
	(0.2285)	(0.2117)	(0.3353)	(0.2093)	(0.0683)	(0.0038)
$(S/L)_j$ × Post01	−0.1408	0.2667***	0.1878	0.5218***	1.3729***	0.0083**
	(0.1011)	(0.0959)	(0.1509)	(0.0944)	(0.0444)	(0.0032)
$(K/L)_j$ × Post01	−0.1457***	−0.0734	−0.3392***	−0.2127***	−0.4398***	0.0012
	(0.0534)	(0.0508)	(0.0746)	(0.0586)	(0.0185)	(0.0007)
HHI_{jt}	−0.3508***	−0.0872***	−0.0838	−0.7661***	0.0790***	−0.0004
	(0.0258)	(0.0261)	(0.0792)	(0.0309)	(0.0085)	(0.0006)
Output Tariff_{jt}	0.0852	−1.1807**	−0.5047	0.1557	0.8212***	0.0009
	(0.5254)	(0.5063)	(1.2543)	(0.5292)	(0.1585)	(0.0056)
Input Tariff_{jt}	−8.2579***	−0.6416	−16.6339***	−7.8114***	0.3919	0.0320*
	(1.4245)	(1.1267)	(3.2442)	(1.3006)	(0.6520)	(0.0171)
SOE share_{jt}	−1.1202***	−0.8669***	−1.4809***	0.2591	−1.4641***	−0.0153
	(0.2437)	(0.2645)	(0.4428)	(0.2840)	(0.1243)	(0.0094)
FIE share_{jt}	0.3024	0.5366**	3.1437***	1.1118***	2.7539***	0.0092**
	(0.2633)	(0.2502)	(0.4734)	(0.2502)	(0.0940)	(0.0044)
Export MFN Tariff_{jt}	2.9703***	−0.6408	14.4889***	1.4431***	4.7942***	−0.0165***
	(0.7259)	(0.8625)	(3.0883)	(0.4996)	(0.3318)	(0.0062)
Length × Post01	−0.2627***	−0.0477	−0.5968***	−0.1211	0.5462***	−0.0035**
	(0.0934)	(0.0839)	(0.1257)	(0.0874)	(0.0530)	(0.0016)
(Age_{ijt})	0.2005**	0.3207***	0.5544**	1.5797***	1.0773***	−0.0009
	(0.0795)	(0.0961)	(0.2376)	(0.3893)	(0.0404)	(0.0008)
$(Age_{ijt})^2$	−0.0701***	−0.0700***	−0.0937*	−0.6385***	−0.2089***	0.0001
	(0.0181)	(0.0204)	(0.0547)	(0.0914)	(0.0083)	(0.0002)
$\ln(\text{Employment}_{ijt})$	0.5989***	0.2543***	1.1976***	0.2942***	0.9328***	0.0039***
	(0.0300)	(0.0210)	(0.0961)	(0.0606)	(0.0056)	(0.0007)
$\ln(K/L)_{ijt}$	0.1561***	0.0704***	0.4895***	0.3120***	0.5191***	0.0014***
	(0.0171)	(0.0179)	(0.0631)	(0.0575)	(0.0059)	(0.0003)
Foreign_{ijt}	−0.3307***	−0.2537**	0.3652	−5.0717***	−0.4564***	−0.0006
	(0.0963)	(0.1203)	(0.3621)	(0.5783)	(0.0330)	(0.0012)
Constant		−4.1564***			−19.1885***	−0.0155*
		(0.9408)			(0.5150)	(0.0082)
Observations	28,107	28,107	2,912	2,870	1,034,016	1,194,791
R-squared						0.4138

Note: Column (1) uses a firm-level fixed effects Poisson regression while Column (2) uses a firm-level fixed effects Negative Binomial regression, both with firm and year fixed effects. Column (3) collapses the sample into a pre-WTO and a post-WTO period, and runs a firm-level fixed effects Poisson regression, with firm and period fixed effects. Column (4) examines industry-level invention patents, using a industry-level fixed effects Poisson regression with 4-digit industry and year fixed effects. Column (5) runs a Poisson regression at the firm level, with 2-digit industry-year fixed effect to control for any industry specific trends. Column (6) runs a linear probability model (LPM) to examine the impact of TPU reduction on the likelihood of patent applications, with firm and year fixed effects and the standard errors are clustered on 4-digit CIC industry level. Trade Policy Uncertainty(TPU) measure follows Handley and Limão (2017).
*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

Finally, Column (6) studies firms' decision to patent. Specifically, it examines the impact of TPU reduction on the likelihood of patent applications using a linear probability model (LPM). Compared with the number of patents a firm may file, whether the firm has ever filed a patent may send a stronger signal about the firm's ability to innovate. Column (6) shows that TPU reduction makes firms in the high uncertainty group more likely to invest in innovation after China's WTO accession, compared with firms in the low uncertainty group.

5. Conclusion

In this paper, we propose a novel channel that trade policy uncertainty may affect innovation. Past literature has emphasized that trade liberalization may stimulate innovation by expanding the market, intensifying competition, or importing intermediate inputs that are complementary to indigenous R&D. We argue that firms may delay or reduce their investment into innovation activities, simply because they are uncertain about trade policy. In this sense, major trade liberalization may reduce trade policy uncertainty (TPU), which consequently leads to more investment in innovations. To examine this linkage, we utilize the significant reduction of TPU engendered by China's accession to the WTO as a quasi-natural experiment. We find the effect of TPU reduction on innovation is sizable, for a firm in a sector with average level of pre-WTO TPU, removing the associated uncertainty would increase its filings of invention patents by 0.0059, which is about one third of the actual increase in the average patent filings per firm from the pre-WTO to the post-WTO period.

Since Schumpeter (1943), economists have emphasized the importance of paving the way for firm innovation. Our paper implies an important channel that trade liberalization may promote economic growth by removing policy uncertainties and consequently encouraging innovation. Understanding the impact of policy uncertainty has important implications for economists and policy makers to evaluate the effectiveness of economic policies. For example, the post 2008 global financial crisis period saw an insurgence of trade protectionism. Many countries resort to non-tariff measures such as Anti-dumping investigations or label other countries as “currency manipulator”. Recently, the Brexit vote and the outright calls for protectionist measures by the U.S. government all implied rising uncertainty surrounding the future of the world trading system. Such protectionism measures may not only impose higher trade costs, but also harm firm innovations since it creates concerns of uncertainty on the market.

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Appendix A. Supplementary data

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References

Aghion, P., Bloom, N., Blundell, R., Griffth, R., Howitt, P., 2005. Competition and innovation: An inverted U relationships. Quart. J. Econ. 120 (2), 701–728.
Aghion, P., Blundell, R., Griffith, R., Howitt, P., Prantl, S., 2009. The effects of entry on incumbent innovation and productivity. Rev. Econ. Stat. 91 (1), 20–32.
Aghion, P., Bergeaud, A., Lequien, M., Melitz, M., 2019. The heterogeneous impact of market size on innovation: Evidence from French firm-level exports. Working Paper. Harvard University.
Amiti, M., Konings, J., 2007. Trade liberalization, intermediate inputs, and productivity: Evidence from Indonesia. Am. Econ. Rev. 97, 1611–1638.
Antràs, P., Yeaple, S.R., 2014. Multinational firms and the structure of international trade. In: Gopinath, G., Helpman, E., Rogoff, K. (Eds.), Handbook of International Economics. 4, pp. 55–130.
Baldwin, R., Krugman, P., 1989. Persistent trade effects of large exchange rate shocks. Quart. J. Econ. 104 (4), 635–654.
Beestermöller, M., Disdier, A.-C., Fontagné, L., 2018. Impact of European food safety border inspections on agri-food exports: Evidence from Chinese firms. China Econ. Rev. 48 (C), 66–82.
Berkowitz, D., Ma, H., Nishioka, S., 2017. Recasting the iron rice bowl: The reform of China's state-owned enterprises. Rev. Econ. Stat. 99 (4), 735–747.
Bernard, A., Jensen, J., Schott, P., 2006. Survival of the best fit: Exposure to low-wage countries and the (uneven) growth of U.S. manufacturing plants. J. Int. Econ. 68 (1), 219–237.
Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Quart. J. Econ. 119 (1).
Bilir, L.K., 2014. Patent laws, product lifecycle lengths, and multinational activity. Am. Econ. Rev. 104 (7), 1979–2013.
Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. Rev. Econ. Stud. 74 (2), 391–415.
Bloom, N., Draca, M., Van Reenen, J., 2016. Trade induced technical change: The impact of Chinese imports on innovation diffusion and productivity. Rev. Econ. Stud. 83 (1), 87–117.
Blundell, R., Griffith, R., van Reenen, J., 1999. Market share, market value and innovation in a panel of British manufacturing firms. Rev. Econ. Stud. 66 (3), 529–554.
Bøler, E.A., Moxnes, A., Ulltveit-Moe, K.H., 2015. R&D, international sourcing, and the joint impact on firm performance. Am. Econ. Rev. 105, 3704–3739.
Brandt, L., Van Biesebroeck, J., Zhang, Y., 2012. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. J. Dev. Econ. 97 (2), 339–351.
Branstetter, L., Lardy, N., 2008. China's embrace of globalization. In: Brandt, L., Rawski, T. (Eds.), China's Economic Transition: Origins, Mechanisms, and Consequences. Cambridge University Press.
Bustos, P., 2011. Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms. Am. Econ. Rev. 101, 304–340.
Cai, H., Liu, Q., 2009. Competition and corporate tax avoidance: Evidence from chinese industrial firms. Econ. J. 119, 764–795.
Cheng, W., Potlogea, A., 2015. Trade liberalization and economic development: Evidence from China's WTO accession. Working Paper.
Chirinko, R., Schaller, H., 2009. The irreversibility premium. J. Monetary Econ. 56, 390–408.
Coelli, F., 2018. Trade Policy uncertainty and innovation: Evidence from China. Working Paper.
Coelli, F., Moxnes, A., Ulltveit-Moe, K.H., 2016. Better, faster, stronger: Global innovation and trade liberalization. NBER Working Paper 22647.
Dixit, A., Pindyck, R., 1994. Investment Under Uncertainty. Princeton University Press, Princeton, NJ, USA.
Dubois, P., de Mouzon, O., Scott-Morton, F., Seabright, P., 2015. Market size and pharmaceutical innovation. Rand J. Econ. 46 (4), 844–871.
Feenstra, R.C., Romalis, J., Schott, P.K., 2002. U.S. imports, exports and tariff data, 1989-2001. NBER Working Paper 9387.
Feng, L., Li, Z., Swenson, D.L., 2017. Trade policy uncertainty and exports: Evidence from China's WTO accession. J. Int. Econ. 106, 20–36.
Goldberg, P.K., Khandelwal, A.K., Pavcnik, N., Topalova, P., 2010. Imported intermediate inputs and domestic product growth: Evidence from India. Quart. J. Econ. 125 (4), 1727–1767.
Guariglia, A., Tsoukalas, J., Tsoukas, S., 2012. Investment, irreversibility, and financing constraints: Evidence from a panel of transition economies. Econ. Lett. 117 (3), 582–584.
Guiso, L., Parigi, G., 1999. Investment and demand uncertainty. Quart. J. Econ. 114 (1), 185–227.
Handley, K., 2014. Exporting under trade policy uncertainty: Theory and evidence. J. Int. Econ. 94, 50–66.

Handley, K., Limão, N., 2015. Trade and investment under policy uncertainty: Theory and firm evidence. Am. Econ. J. Econ. Policy 7 (4), 189–222.
Handley, K., Limão, N., 2017. Policy uncertainty, trade and welfare: Theory and evidence for China and the U.S. Am. Econ. Rev. 107 (9), 2731–2783.
Hashmi, A.R., 2013. Competition and innovation: The inverted-U relationship revisited. Rev. Econ. Stat. 95 (5), 1653–1668.
Hu, A.G., Jefferson, G.H., 2009. A great wall of patents: What is behind China's recent patent explosion? J. Dev. Econ. 90 (1), 57–68.
Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Rev. Econ. Stud. 70 (2), 317–341.
Lighthizer, R., 2010. Testimony before the U.S.-China Economic and Security Review Commission: Evaluating China's Role in the World Trade Organization Over the Past Decade. p. 2010.
Liu, Q., Lu, Y., 2015. Firm investment and exporting: Evidence from China's value-added tax reform. J. Int. Econ. 97, 392–403.
Liu, Z., Ma, H., 2020. Input trade liberalization and markup distribution: Evidence from China. Econ. Inquiry forthcoming.
Liu, Q., Qiu, L.D., 2016. Intermediate input imports and innovations: Evidence from Chinese firms' patent filings. J. Int. Econ. 103, 166–183.
Liu, Q., Lu, R., Lu, Y., Luong, T.A., 2019. Import competition and firm innovation: Evidence from China. Working Paper.
Lu, Y., Yu, L., 2015. Trade liberalization and markup dispersion: Evidence from China's WTO accession. Am. Econ. J. Appl. Econ. 7 (4), 221–253.
Nickell, S.J., 1996. Competition and corporate performance. J. Polit. Econ. 104 (4), 724–746.
Pierce, J.R., Schott, P.K., 2016. The surprisingly swift decline of U.S. manufacturing employment. Am. Econ. Rev. 106 (7), 1632–1662.
Pierce, J.R., Schott, P.K., 2018. Investment responses to trade liberalization: Evidence from US industries and plants. J. Int. Econ. 115, 203–222.
Rob, R., Vettas, N., 2003. Foreign direct investment and exports with growing demand. Rev. Econ. Stud. 70 (3), 629–648.
Schumpeter, J.A., 1943. Capitalism, Socialism, and Democracy. 6th ed. George Allen & Unwin, London and New York.
Taglioni, D., Zavacka, V., 2013. Innocent bystanders: How foreign uncertainty shocks harm exporters. Working Paper.
Topalova, P., 2010. Factor immobility and regional impacts of trade liberalization: Evidence on poverty from India. Am. Econ. J. Appl. Econ. 2 (4), 1–41.
Wei, S.-J., Xie, Z., Zhang, X., 2017. From "Made in China" to "Innovated in China": Necessity, prospect, and challenges. J. Econ. Perspect. 31 (1), 49–70.