Trade policy uncertainty and innovation:
Evidence from China [*]

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Abstract

This paper studies the effect of resolving trade policy uncertainty on investment in innovation in China during 1990-2007. It exploits exogenous and heterogeneous exposure to trade policy uncertainty resolution arising from a major change in US trade policy, which eliminated the possibility of tariff increases on Chinese imported goods, and detailed data on innovation from all sectors and countries in a triple difference-in-differences. I find that *i.* reducing tariff uncertainty has an economically and statistically significant effect on innovation; *ii.* that this effect represents actual innovation, rather than just more patent filings; *iii.* that the effect is mostly driven by an extensive margin response; *iv.* that the effect is at least in part driven by exports to the US. The results are robust to flexibly controlling for sectoral trends in innovation, contemporaneous policy changes, and the inflow of foreign technologies in China.

Keywords: Trade policy, uncertainty, innovation, patents, China, PNTR.

JEL Codes: D72, F13, F14, O19, O24, O33, P33

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1 Introduction

This paper studies the effect of trade policy uncertainty on investment in innovation in China. When the cost of investment is sunk, firms may have an option value of waiting and thus delay investment until the uncertainty is resolved or business conditions improve. This theoretical mechanism is well understood (Bernanke, 1983; Dixit, 1989; Rodrik, 1991; Dixit and Pindyck, 1994), and emerging empirical literature finds that firms' investment behavior is consistent with this basic mechanism (Baker et al., 2016; Gulen and Ion, 2016; Handley and Limão, 2015, 2017; Koijen et al., 2016; Julio and Yook, 2016).[1] However, most empirical work has focused on investment in employment, physical capital, and productivity, or on narrow economic sectors, while there is very little focus on investment in innovation. This paper aims at filling this gap.

Understanding the effect of policy uncertainty on innovation is important for two reasons: first, innovation drives economic growth; second, policy uncertainty has been rising in the last decades and accelerated in recent years (Baker et al., 2016).[2] The focus on trade policy uncertainty, specifically on uncertainty about tariffs, is motivated by recent events such as the US-China trade war, Brexit, and the renegotiation of major trade agreements, such as the North American Free Trade Agreement (NAFTA), which contributed to making tariff uncertainty a key source of uncertainty for businesses. As the Wall Street Journal writes, "The trade war rollercoaster is the major cause of uncertainty among investors, businesses, and monetary policymakers, and has become the principal risk factor for a global recession. ... It can be argued that the uncertainty about tariffs has done more damage than the tariffs themselves."[3]

[1] Baker et al. (2016) find that higher policy uncertainty is associated with reduced investment and employment in sectors highly exposed to government spending such as defense, health care, finance, and infrastructure construction. Building on the approach of Baker et al. (2016), Gulen and Ion (2016) find a negative relationship between policy uncertainty and corporate investment. Handley and Limão (2015, 2017) find that trade policy uncertainty delays firm export entry. Koijen et al. (2016) find that government-induced uncertainty reduces medical R&D. Julio and Yook (2016) find that FDI flows fall before elections and increase after uncertainty is resolved.

[2] See for example the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016).

[3] Dr. Ira Kalish, chief global economist, Deloitte Touche Tohmatsu

I study the impact of resolving trade policy uncertainty on investment in innovation within Chinese industries during 1990-2007 by exploiting exogenous and heterogeneous exposure to trade policy uncertainty resolution arising from a major change in the US trade policy towards China: the conferral of Permanent Normal Trade Relations (PNTR) to China, which was passed by the US Congress in October 2000 and came into effect when China joined the the World Trade Organization (WTO) in December 2001.[4]

Since 1980, China's exports to the US were subject to Normal Trade Relations (NTR) tariffs, i.e. Most-Favored-Nation (MFN) tariffs reserved to WTO members. However, these preferential tariff rates required annual renewal by Congress. While practically automatic in the beginning, this process became highly politically contentious after the Tiananmen Square protests in 1989. Without Congress renewal, tariffs would have reverted to non-NTR tariff rates, also known as "column 2" tariffs, established in 1930 under the Smoot-Hawley Tariff Act and assigned to non-market economies.[5] The US conferral of Permanent Normal Trade Relations (PNTR) to China set tariffs permanently at their MFN level, and thus removed the uncertainty associated with the annual renewal of China's MFN status. The level of tariffs applied by the US to Chinese imported goods remained unchanged.

During this period, NTR tariffs were relatively low in all industries. Non-NTR tariffs, instead, were much higher, and exhibited substantial variation across industries. Exposure to trade policy uncertainty is measured as the log-difference between non-NTR and NTR tariffs across industries. Intuitively, while all firms faced the same probability of a

Limited - Wall Street Journal https://deloitte.wsj.com/cfo/2019/08/26/global-economic-brief-trade-war-uncertainty-vexes-business-fed/

[4]This shock has been used first by Pierce and Schott (2016) and Handley and Limão (2017) to explain the decline in employment in the US and entry into export by Chinese firms.

[5]The US threat of revoking China's MFN status was concrete. On average, 40% of Congressmen voted against the renewal between 1990 and 2001, and this percentage reached peaks of almost 60% in some years. In practice, China never lost the NTR status, but it came close on three occasions, when the US House voted in favor of revoking China's temporary MFN status, but the US Senate did not sustain the House votes. The US threat was also economically relevant. The US was a major export market for China even before China's export boom following admission into the WTO in 2001. Between 1995 and 2000, the US accounted for almost 25% of China's total export value, compared to 15% of Japan and less than 5% of all other top ten export markets.

trade policy regime change, firms in industries with larger gaps were more exposed to tariff spikes had the US reverted to non-NTR tariffs, and are expected to respond more strongly to a reduction in trade policy uncertainty.

I exploit the universe of patents filed in the period 1990-2007 to measure innovation. I observe nearly every firm worldwide that files a patent, when the patent was filed, the technical class of the patent, which I match to product codes, and in which country the firm and its inventors are located at the time of application. Using this rich set of information, I construct a panel of patenting activity in all technologies and countries worldwide.

The empirical strategy is based on a generalized triple difference-in-differences estimation: the source of variation is the difference between "column 2" and MFN tariffs across industries, and third countries' outcomes are used to remove industry specific trends in innovation. Then, I compare innovation in industries that are relatively more exposed to uncertainty to innovation in industries that are relatively less exposed to uncertainty (1st difference), before and after the transition to PNTR (2nd difference), across countries (3rd difference).

The main advantage of the triple difference-in-differences is that I can control for technology and industry trends in innovation. Furthermore, both the likelihood of patenting and the sunk research and development (R&D) costs vary by industry and/or product and potentially over time, and industry fixed effects eliminate only time-invariant industry differences.

I find a positive relationship between higher initial trade policy uncertainty exposure and subsequent innovation, which is consistent with the option value of waiting mechanism, statistically and economically significant. The baseline results show that a 1% increase in trade policy uncertainty exposure before the PNTR leads to a 0.7% increase in patented innovation after uncertainty is reduced. This implies that moving from the first to the third tercile of the observed trade policy uncertainty distribution increases patenting by 0.15 log points.

The results are robust to a number of potential concerns. First, controlling for contemporaneous policy changes in China associated with China's WTO accession–the elimination of foreign direct investment (FDI) restrictions and non-tariff barriers, the reduction of China's own import tariffs, and the phasing out of the Multi-Fiber arrangement (MFA)– does not change the main results. Second, results are robust to controlling for China's demand and other unobservable shocks. To control for the inflow of goods as a response to increased demand, and the inflow of both patented and unpatented innovations through trade, I include China's imports from the rest of the world in each sector. To capture demand and supply shocks as well as regulatory changes in China that may change the likelihood to patent in China, I construct an aggregate of all patent applications filed by foreign applicants to the Chinese State Intellectual Property Office (SIPO).

One may question whether the increase in patents represent more innovation. Patenting is typically found to be correlated with R&D and other measures of innovation in the literature (Griliches, 1990). However, the concern remains that patents are an imprecise measure of innovation and that the quality of patents is highly heterogeneous. I address this in several ways: first, the sample includes patents of invention that are successfully granted, and excludes utility models.[6] Second, I show that results are robust when using quality adjusted patents, using citations and other measures correlated with the economic value of a patent as weights.

A related concern is that the increase in patenting observed after the PNTR conferral might pick up technology transfers to China rather than innovation by Chinese industries. I address this in three ways. First, note that patents are dated by the earliest filing date, and patents filed in multiple countries are not double counted, so that subsequent

[6]Compared to patents of invention, utility models require compliance with less strict requirements (for example, lower level of inventive step), offer shorter intellectual property protection, generally between 7 and 10 years, and the costs to obtain and maintain them are lower. Requirements and procedures for obtaining protection and the duration of protection vary from one country to another. Utility models are often used to patent incremental innovations.

filings are irrelevant. Second, the regressions control specifically for patent applications filed by foreign applicants to the Chinese patent office. Third, I show that the baseline results are robust to excluding patents with one or more inventors based in the US, or, more conservatively, by restricting the sample to patents that have all domestic inventors.

I use additional information on patents and patent applicants to understand the mechanism behind this positive innovation response. I find that the effect is driven by an extensive margin response. This mechanism is consistent with a model of trade with heterogeneous firms and technology upgrading under uncertainty, where, within an industry, only the most productive firms find it optimal to incur the sunk cost to innovate. In this model, the productivity threshold above which firms find investment in innovation optimal drops when uncertainty is reduced, inducing more firms to innovate. Hence, in this model, firms in the middle range of the productivity distribution are expected to react, but not the already most productive firms.

The literature has emphasized the importance of market size for innovation. Even before the PNTR, the US was the most important market for China, but the possibility of sudden tariff spikes may have led firms to postpone incurring the sunk cost to both export to the US and to innovate. Handley and Limão (2017) show that transitioning to permanent MFN status led firms to incur the sunk cost and start exporting. One may therefore expect that exporting firms also started to patent in the US. I test this by checking whether the number of new patents filed to the US differentially increases in highly exposed industries. I find that the PNTR is associated with an increase in the number of patents filed to and granted at the United States Patent and Trademark Office (USPTO). Because patenting is costly, and firms tend to file patents abroad only if they intend to export there (Aghion et al., 2016; Coelli et al., 2020), this finding suggests that the increase in innovation is at least in part driven by exports to the US.

One limitation of this analysis is the transition from China's temporary to permanent MFN status changed not only the variance, but also the expected value of US tariffs on

Chinese imported goods. Even though one could decompose the PNTR effect into a mean-preserving compression of tariffs and a change in the expected value of tariffs in a model, empirically I cannot identify them separately. Therefore all results in this analysis should be interpreted as the combination of these two effects.

The paper builds on two extensive strands of literature. First, it was inspired by the key insight of the real option literature that uncertainty generates an option value of waiting which delays (partially) irreversible investment. Early theoretical contributions go back to (Bernanke, 1983; Dixit, 1989; Rodrik, 1991; Dixit and Pindyck, 1994),[7] while more recent analyses of the effect of uncertainty on investment behavior include Guiso and Parigi (1999); Bloom et al. (2007); Bloom (2007, 2009, 2014); Bloom et al. (2018).[8] Other studies have focused specifically on the implications of policy uncertainty for investment, both analytically and empirically (Fernández-Villaverde et al., 2015; Baker et al., 2016; Handley and Limão, 2015, 2017; Koijen et al., 2016; Julio and Yook, 2016; Gulen and Ion, 2016). This literature has traditionally focused on investment in physical capital, employment, and productivity, while the implications of uncertainty for R&D and innovation have been largely omitted from the analysis.[9] This article contributes to filling this gap by providing causal evidence that reducing trade policy uncertainty increases investment in innovation in a broad range of sectors.

The second building block is the recent literature on heterogeneous firms and trade, which has emphasized the complementarity between improved foreign market access and investment in productivity-enhancing activities in a deterministic framework (Costantini and Melitz, 2008; Aw et al., 2008; Atkeson and Burstein, 2010; Bustos, 2011; Lileeva and Trefler, 2010; Coelli et al., 2020).[10] The main departure from this literature is the in-

[7]Dixit and Pindyck (1994) provide a review of the early theoretical literature.

[8]Bloom (2014) provides a recent review of the literature.

[9]There are some exceptions: Bloom (2007) shows analytically that R&D is less responsive to changes in demand conditions under high uncertainty but provides no empirical evidence. Koijen et al. (2016) focus on the health care sector in the US and show that government-induced uncertainty generates a medical innovation premium and reduces medical R&D. Handley and Limão (2017) document some indirect evidence of technological upgrading which reduces the marginal export cost after the PNTR conferral.

[10]A related literature analyses the effect of export market participation on productivity (Clerides et al.,

troduction of uncertainty. Building on Handley and Limão (2017) and Bustos (2011), I introduce technology choice under uncertainty in a dynamic model of trade with heterogeneous firms, and use this model to guide empirical work. The model combines two mechanisms: the option value of waiting from the real option literature, and the market access from the trade literature (Bustos, 2011; Lileeva and Trefler, 2010). In the model, the innovation decision is endogenously driven by market size as in Bustos (2011), and paying the cost to innovate is profitable only for the most productive firms. But unlike in Bustos (2011), the cost to innovate is sunk, and, combined with uncertainty with respect to foreign trade policy, it generates a "band of inaction" where firms do not invest and keep a low technology. In this set up, firms need to be more productive to innovate in a policy uncertain scenario than in a deterministic scenario; a reduction in uncertainty reduces the option value of waiting, and induces more firms to innovate.

The empirical identification, through variation in the difference between "column 2" and MFN tariffs, follows a growing literature that examines the economic effects of the PNTR shock in the US and China. The first studies are by Pierce and Schott (2016), who analyze the role of the PNTR in explaining the drop in manufacturing jobs in the US, and Handley and Limão (2017), who focus on firms' dynamic export decisions.[11] Other recent papers look at the effect of the PNTR on investment in capital stock (Pierce and Schott, 2017), on the price index (Amiti et al., 2017), and on stock market returns (Bianconi et al., 2021). I look at a different outcome, namely investment in innovation as measured by patent data. In contemporaneous work, Liu and Ma (2020) look at the effect of the PNTR on firms' patent applications using Chinese firm level data in 1998-2007 and patent applications at the State Intellectual Property Office (SIPO). This paper differs in two key aspects. First, I rely on a different patent data source which has two main advan-

1998; Bernard and Bradford Jensen, 1999; Van Biesebroeck, 2005; De Loecker, 2007). Instead, the focus of this paper is on trade policy rather than on export status and on investment in innovation rather than in productivity.

[11] Feng et al. (2017) also look at Chinese firms' export market decision, but they use firm level data and document simultaneous entry into and exit from exporting within products.

tages: by observing the universe of patents filed over a long period of time, I construct and observe pre-trends over the entire uncertainty period, and I flexibly control for sector specific trends in innovation and changes in the propensity to patent. This is essential in a period which overlaps with the implementation of the WTO agreement and the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) that changed both patenting activity and incentives to patent. Second, this paper differs in that it explains the mechanisms through which reducing trade policy uncertainty induces more innovation. I derive predictions from the model, and show theoretically and empirically that the response happens on the extensive margin. I also show that innovation is driven by market size by showing that new innovations are patented in the export market.

The paper proceeds as follows: Section 2 presents the theoretical framework. Section 3 discusses the identification strategy and presents the empirical model. Section 4 describes the data and descriptives. Section 5 presents and discusses the main empirical results. Section 6 presents additional results and discusses the mechanisms. Section 7 concludes.

2 Economic framework

This section introduces the basic economic framework and the firm's decision to invest in new technologies, describes the economic mechanism, and provides the intuition for the empirical analysis. To derive the key insight, I introduce technology choice under uncertainty in a model of trade with heterogeneous firms. I build on Handley and Limão (2017), and focus on the firm's decision to invest in innovation. The economy consists of a single differentiated sector, characterized by monopolistic competition. Firms are heterogeneous in productivity, and can increase their productivity by paying a sunk investment cost. The technology choice is binary as in Bustos (2011).

2.1 Theoretical mechanism

2.1.1 Set up

Consider a model with two countries, home (China) and foreign (US). Let n denote the country, with $n = d$ for home and $n = x$ for foreign country respectively. Consider for simplicity a single differentiated sector j,[12] characterized by monopolistic competition, and in which each firm produces a variety i using only labor. Firms are heterogeneous in productivity, indexed by φ_i.

Initial productivity is exogenously given, but firms can increase their productivity by investing in new technology. There is a sunk cost I associated with R&D investment. This sunk investment cost captures start-up costs like purchasing specific assets, hiring or training specialized workers, acquiring information on new technologies, etc. that cannot be recovered.[13] The innovation choice is binary as in Bustos (2011): investment in R&D produces a high type technology,[14] which reduces the marginal cost of production from $\frac{1}{\varphi_{i0}}$ to $\frac{1}{\varphi_{i1}}$; if a firm does not invest, it keeps producing with a low type technology and initial productivity φ_{i0}.

A firm producing variety i faces an *ad valorem* tariff $T_x = \tau_x - 1$ to serve the foreign market. All firms in the differentiated industry face the same tariff. There is no sunk foreign market entry cost,[15] or per-period fixed cost, which implies that all firms active

[12] Since there is only one differentiated sector, I will omit the sector subscript.

[13] "Most expenditures on R&D are, by their very nature, sunk costs. The resources spent on a scientist to do research cannot be recovered. Once his time is spent, it is spent" (Stiglitz et al., 1987, p. 928).

[14] For simplicity, I ignore the fact that the outcome of the innovation process is uncertain.

[15] Including a sunk cost to enter the foreign market would generate an option value associated with entry. Empirical evidence suggests that this sunk cost is relevant. For example, Handley and Limão (2017) analyze the effect of a sunk cost of exporting on firms' foreign market entry decision, and find that policy uncertainty substantially reduces firms' entry. To simplify the exposition, I abstract from this and focus on the R&D investment decision only. Including a sunk export cost would enrich the model, but would not change the main mechanism.

To fix ideas, consider an economy in which firms face four choices: they can serve only the domestic market and keep the low type technology; they can pay a sunk cost to enter the export market; they can pay a sunk cost to invest in innovation and increase their productivity; or they can do both. Consider the case where the marginal entrant into export does not innovate such that in equilibrium firms sort into three groups, as in Bustos (2011): the least productive firms do not export and use the low type technology, the medium productivity firms export but keep using the low type technology, and the most productive firms in the domestic market also export to the foreign market.[16] Finally, in each period there is an exogenous probability of exit $1-\beta$, with $\beta \in (0,1)$, independent of firm's productivity.

Consumers have CES preferences across varieties, with constant elasticity of substitution $\sigma > 1$. This generates a home demand $q_{id} = A_d p_{id}^{-\sigma}$, and a foreign demand $q_{ix} = A_x p_{ix}^{-\sigma}$, where $A_d = E_d P_d^{\sigma-1}$ is a measure of domestic market size, and $A_x = E_x P_x^{\sigma-1}$ is a measure of foreign market size. E_n is the demand shifter, and $P_n^{\sigma-1}$ is the CES price index for the differentiated sector. p_{ix} is consumer price, inclusive of tariff;[17] hence, exporters receive p_{ix}/τ per unit sold abroad. Under monopolistic competition and CES preferences, the profit maximizing price is a constant markup over marginal cost, so a firm will charge: $p_{in} = \frac{\sigma}{\sigma-1}\frac{\tau_n}{\varphi_i}$, where n denotes the destination country and can be either domestic (d) or foreign (x), the wage is normalized to one for simplicity, $\varphi_i = \varphi_{i1}$ if the firm innovates, and $\varphi_i = \varphi_{i0}$ if the firm does not innovate.

Equilibrium per-period operating profits as a function of firm's technology investment choice are given by the sum of domestic and export profits. For a firm producing with the low type technology, profits are:

$$\pi(\varphi_{i0}) = \pi_d(\varphi_{i0}) + \pi_x(\varphi_{i0}) = B_d \varphi_{i0}^{\sigma-1} + B_x \tau_x^{-\sigma} \varphi_{i0}^{\sigma-1} \tag{1}$$

both export and innovate. Then, a reduction in trade policy uncertainty triggers innovation in two groups of firms. In the medium productivity group, some firms that are not productive enough to innovate under uncertainty will do so after a reduction in uncertainty. In the low productivity group, some firms will find it optimal to both start exporting and innovating if uncertainty decreases.

In the simpler version of the model I consider, the assumption of no sunk export cost implies that all firms active in the domestic market are also exporters, and the only relevant decision is whether to invest in innovation. Therefore, the response of firms serving only the domestic market is absent. However, the empirical application will take both decisions into account.

The sorting of firms in the three groups described above is true under some conditions. In particular, it requires the sunk innovation cost to be sufficiently high relative to the sunk cost to enter the export market. In my data, I cannot verify this assumption, but Bustos (2011) shows that it is plausible in the context of a developing country like Argentina, suggesting that this assumption is also plausible for China in the 1990s.

Finally, note that introducing a fix per-period export cost would not change the mechanism in the model because uncertainty is only relevant if the investment cost is irreversible.

[16] There is also no endogenous exit.

[17] $\tau_d = 1$ in the domestic market, and $\tau_x \geq 1$ abroad.

If a firm invests in R&D, profits are:

$$\pi(\varphi_{i1}) = \pi_d(\varphi_{i1}) + \pi_x(\varphi_{i1}) = B_d \varphi_{i1}^{\sigma-1} + B_x \tau_x^{-\sigma} \varphi_{i1}^{\sigma-1}, \tag{2}$$

where $B_n = (\sigma-1)^{\sigma-1}\sigma^{-\sigma}A_n$.

2.1.2 Uncertainty and innovation decision

Consider the problem of a firm, located in the home country, that has the option to invest in an R&D project to increase its productivity, but faces uncertainty with respect to future foreign market conditions. A larger market makes it more profitable to invest in R&D. However, foreign market access is uncertain, as it depends on the state of trade policy in future periods. Specifically, there is uncertainty with respect to foreign applied tariffs, $T = \tau - 1$.[18] At each period t, the firm faces a binary choice: pay a sunk cost I to invest in R&D, or wait until next period, when the same choice will be available again. The only source of uncertainty are τ and the exogenous probability of survival β.

The expected value from investing in R&D is given by the stream of domestic and export profits obtained using the productivity enhancing technology:

$$\Pi^I(\tau_s, \varphi_1) = \Pi_d^I(\varphi_1) + \Pi_x^I(\tau_s, \varphi_1), \tag{3}$$

where expected domestic profits, $\Pi_d^I(\varphi_1)$, without time discounting, are given by

$$\Pi_d^I(\varphi_1) = \pi_d(\varphi_1) + \sum_{t=1}^{\infty} \beta^t \pi_d(\varphi_1) = \frac{\pi_d(\varphi_1)}{1-\beta}, \tag{4}$$

[18] Since $\tau_d = 1$ in the domestic market, and $\tau_x \geq 1$ abroad, I omit the x subscript, and use τ to denote τ_x to avoid redundant notation.

and expected export profits, $\Pi_x^I(\tau_s, \varphi_1)$, are given by

$$\Pi_x^I(\tau_s, \varphi_1) = \pi_x(\tau_s, \varphi_1) + \mathbb{E}_s \sum_{t=1}^{\infty} \beta^t \pi_x(\tau_s', \varphi_1). \tag{5}$$

$\mathbb{E}_s$ denotes the expectation over future values of τ conditional on the information available in the current state of trade policy, s, and φ_1 is firm's productivity when using the high type technology. The variety subscript i is omitted.

The expected value of the firm without upgrading is given by the stream of domestic and export profits obtained by using the low type technology:

$$\Pi(\tau_s, \varphi_0) = \Pi_d(\varphi_0) + \Pi_x(\tau_s, \varphi_0), \tag{6}$$

where expected domestic profits, $\Pi_d(\varphi_0)$, are given by

$$\Pi_d(\varphi_0) = \pi_d(\varphi_0) + \sum_{t=1}^{\infty} \beta^t \pi_d(\varphi_0) = \frac{\pi_d(\varphi_0)}{1-\beta}, \tag{7}$$

and expected export profits, $\Pi_x(\tau_s, \varphi_0)$, are given by

$$\Pi_x(\tau_s, \varphi_0) = \pi_x(\tau_s, \varphi_0) + \mathbb{E}_s \sum_{t=1}^{\infty} \beta^t \pi_x(\tau_s', \varphi_0). \tag{8}$$

where φ_0 is firm's productivity when using the low type technology.

Consider the case without uncertainty first. If there is no uncertainty over future market access conditions, summarized by τ_s, the optimal investment decision is to invest whenever the expected value from investing net of the sunk investment cost is higher than the expected value of producing with the low type technology; and there is no option value of waiting. The investment indifference condition is:

$$[\pi_d(\varphi_1) - \pi_d(\varphi_0)] + \left[\pi_x(\tau_s^D, \varphi_1) - \pi_x(\tau_s^D, \varphi_0)\right] = I(1-\beta), \tag{9}$$

where τ_s^D denotes the value of τ_s that satisfies this condition in the deterministic case.

If future foreign market access is uncertain, instead, the firm must decide whether to invest today, or to keep producing with the low type technology and wait until conditions improve. This dynamic investment decision takes the form of an optimal stopping problem, where stopping corresponds to investing, and continuation corresponds to waiting. The Bellman equation for the firm's decision problem is given by

$$F(\tau_s, \varphi) = \max\left\{\Pi_d^I(\varphi_1) - \Pi_d(\varphi_0) + \Pi_x^I(\tau_s, \varphi_1) - \Pi_x(\tau_s, \varphi_0) - I, \beta \mathbb{E}_s F(\tau_s', \varphi)\right\}. \tag{10}$$

The solution to this optimal stopping problem is characterized by a division of the range of τ_s into 'continuation regions' and 'stopping regions'. In general, intervals where termination is optimal can alternate with ones where continuation is optimal. However it is possible to show that, under reasonable assumptions,[19] there is a unique threshold value of τ_s, $\tau_s^U(\varphi_i)$, which generates a clean division of the range of τ_s into a 'continuation region' and a 'stopping region': if $\tau_s > \tau_s^U(\varphi_i)$ it is optimal to wait; if $\tau_s < \tau_s^U(\varphi_i)$ if is optimal to invest. The cutoff $\tau_s^U(\varphi_i)$ must satisfy

$$\Pi_d^I(\varphi_1) - \Pi_d(\varphi_0) + \Pi_x^I(\tau_s^U, \varphi_1) - \Pi_x(\tau_s^U, \varphi_0) - I = \beta \mathbb{E}_s F(\tau_s'^U, \varphi). \tag{11}$$

Thus, under uncertainty, the investment indifferent condition becomes:

$$F(\tau_s^U, \varphi) = \Pi_d^I(\varphi_1) - \Pi_d(\varphi_0) + \Pi_x^I(\tau_s^U, \varphi_1) - \Pi_x(\tau_s^U, \varphi_0) - I. \tag{12}$$

To understand the role of uncertainty, it is useful to rearrange (10) by subtracting

[19]See Appendix B.2

$\Pi^I_d(\varphi_1) - \Pi_d(\varphi_0) + \Pi^I_x(\tau_s, \varphi_1) - \Pi_x(\tau_s, \varphi_0) - I$ from both sides of the equal sign to obtain [20]

$$
\begin{aligned}
V_s \quad &= \max\{0, \beta \mathbb{E}_s V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_s, \varphi_1) - \pi_x(\tau_s, \varphi_0)] \\
&\quad + (1-\beta)I\} \qquad (13)
\end{aligned}
$$

where $V_s \equiv F(\tau_s, \varphi) - \Pi^I_d(\varphi_1) + \Pi_d(\varphi_0) - \Pi^I_x(\tau_s, \varphi_1) + \Pi_x(\tau_s, \varphi_0) + I$ is the option value of waiting. $\pi_d(\varphi_1) - \pi_d(\varphi_0)$ and $\pi_x(\tau_s, \varphi_1) - \pi_x(\tau_s, \varphi_0)$ are the one-period difference in domestic and export profits by using the high *versus* low type technology, which are given up by waiting, and I is the saved sunk investment cost from postponing the decision to invest in R&D. When $\tau_s = \tau^D_s(\varphi_i)$ the option value of waiting is zero, and postponing is worthless. Compared to a situation without uncertainty, the existence of an option value of waiting requires the expected return of investing in R&D to be higher, and thus investment in R&D is lower.

This simple economic framework is helpful to understand how incentives to conduct R&D activities for Chinese firms change after 2001. When China enters the WTO, the possibility of sudden increases in applied tariffs by the US disappears: an important source of foreign market access uncertainty is resolved and thus the option value of waiting becomes zero. The firm decision problem becomes a static one, and the firm invests whenever the expected value of export and domestic profits using the high technology, net of the sunk investment cost, exceeds the expected value of export and domestic profits with the low technology, as described in (9).

2.2 Trade policy regime

The trade policy regime is modelled as in Handley and Limão (2017). It is characterized by an exogenous Markov process, $\Lambda(\tau_s, \gamma)$, with 3 possible trade policy states, $s = 0, 1, 2$: a high protection state, $s = 2$, with tariffs $\tau_2 > \tau_0$, a low protection state (e.g. a credible

[20] I use the fact the (5) can be rewritten recursively as $\Pi^I_x(\tau_s, \varphi_1) = \pi_x(\tau_s, \varphi_1) + \beta \mathbb{E}_s \Pi^I_x(\tau_s', \varphi_1)$. (4), (7), and (8) can be rearranged in the same way.

trade agreement), $s = 0$, with tariffs τ_0, and an intermediate protection state, $s = 1$, with a temporary tariff, $\tau_1 \in [\tau_0, \tau_2]$ and a positive probability $\gamma > 0$ of a trade policy (tariff) change. I consider a case where there is trade policy uncertainty only in the intermediate state ($\gamma > 0$), and extreme states ($s = 2$ and $s = 0$) are assumed to be absorbing.[21]

In the empirical application, the intermediate state captures China's status in the 1990s, before obtaining permanent MFN status. In this period, China's temporary MFN status in the US could change with probability $\gamma > 0$ and give rise to either high protection, where "column 2" tariffs apply, with probability λ, or low protection with probability $1 - \lambda$. Let $\lambda_{ss'}$ denote the transition probability from state s to s'. The policy transition matrix S summarizes the transition probabilities for all possible states:

$$S = \begin{bmatrix} \lambda_{00} & 0 & 0 \\ \lambda_{10} & \lambda_{11} & \lambda_{12} \\ 0 & 0 & \lambda_{22} \end{bmatrix}, \tag{14}$$

where $\lambda_{11} = (1 - \gamma)$, $\lambda_{12} = \gamma\lambda$, and $\lambda_{10} = \gamma(1 - \lambda)$.

All firms have the same beliefs about γ and λ, and are exposed to the same possibility of a trade policy shock.

2.3 Partial equilibrium

To understand the effect of trade policy uncertainty on firms' R&D investment, it useful to derive and compare the productivity threshold above which firms find innovation optimal under a deterministic scenario and under uncertainty.

Applied tariffs τ_s are the only source of uncertainty, and, for simplicity, I focus on a small country so changes in firms' investment behavior have a negligible effect on the aggregate variables E_n and P_n. However, in the empirical application I control for general

[21] The same qualitative predictions can be obtained if the probability of a low protection state were ignored. In the presence of uncertainty, only the possibility of a worst case scenario matters, while the possibility of good news doesn't affect the investment decision (See Bernanke, 1983).

equilibrium effects. Define, as in Bustos (2011), $\varphi_0 \equiv \varphi$ and $\varphi_1 = \eta\varphi_0 \equiv \eta\varphi$, with $\eta > 1$, so that investment increases firm specific productivity by a fraction $\eta > 1$.

Consider the deterministic case first, where trade policy is in one of the three possible states $s = \{0, 1, 2\}$ and is not expected to change. For each firm i in the differentiated sector, there is one value of $\tau_s^D(\varphi_i)$ that satisfies the innovation indifference condition (9). If τ_s is below the firm's specific threshold, then the firm finds it optimal to invest in R&D. Since all firms in the differentiated sector only differ according to their productivity, there is a threshold productivity level for the industry, $\varphi_s^D(\tau_s)$, such that all firms with productivity at or above this threshold will invest in R&D. For any given τ_s, the cutoff productivity level in the benchmark deterministic case is obtained from the investment indifference condition in (9) (for the marginal firm):

$$\frac{\left[\pi_d(\eta\varphi_s^D) - \pi_d(\varphi_s^D)\right] + \left[\pi_x(\tau_s, \eta\varphi_s^D) - \pi_x(\tau_s, \varphi_s^D)\right]}{(1-\beta)} = I \iff$$

$$\varphi_s^D = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1} - 1)(B_d + B_x\tau_s^{-\sigma})}\right)^{\frac{1}{\sigma-1}} \tag{15}$$

where the second line uses the expressions for per-period domestic (π_d) and export profits (π_x) in (1) and (2).

Consider now the case when trade policy is uncertain. The optimal investment decision for a firm i in state s is given by the solution to the Bellman equation in (10). It is possible to show that, under reasonable assumptions (see Appendix B.2), there is a unique threshold value $\tau_s^U(\varphi_i, \gamma)$ such that a firm will find it optimal to invest in R&D if current tariffs are below the firm specific tariff cutoff. Firms in the differentiated sector face the same τ_s and γ, but differ in productivity. Thus, for any given τ_s, there exists a marginal firm i with productivity equal to the cutoff $\varphi_s^U(\tau_s, \gamma)$, which satisfies the indifference condition in (12):

$$F(\tau_s, \varphi_s^U, \gamma) = \Pi_d^I(\eta\varphi_s^U) - \Pi_d(\varphi_s^U) + \Pi_x^I(\tau_s, \eta\varphi_s^U, \gamma) - \Pi_x(\tau_s, \varphi_s^U, \gamma) - I. \tag{16}$$

By rewriting the Bellman as in (13), the marginal firm has an option value of waiting equal to zero, that is:

$$
\begin{aligned}
V_s\left(\varphi_s^U\right) &= 0 \\
&= \max\{0, \beta \mathbb{E}_s V_s'\left(\varphi_s^U\right) - \left[\pi_d(\eta\varphi_s^U) - \pi_d(\varphi_s^U)\right] - \left[\pi_x(\tau_s, \eta\varphi_s^U) - \pi_x(\tau_s, \varphi_s^U)\right] \\
&\quad + (1-\beta)I\}, \qquad (17)
\end{aligned}
$$

and the cutoff productivity level φ_s^U is found by equating the second element in the curly bracket to zero. Consider a firm in the intermediate state , $s = 1$, when MFN tariffs are subject to annual renewal. Replace π_x and π_d with the equations (1) and (2). Then, the productivity cutoff in the intermediate state is given by

$$
\varphi_1^U = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)\left(B_d + B_x \tau_1^{-\sigma} U(\gamma,\omega)\right)} \right)^{\frac{1}{\sigma-1}} \qquad (18)
$$

$$
U(\gamma,\omega) \equiv \frac{1+u(\gamma)\omega}{1+u(\gamma)}. \qquad (19)
$$

$U(\gamma,\omega)$ is an uncertainty factor, and if $U(\gamma,\omega) < 1$, then $\varphi_1^U > \varphi_1^D$, and investment in R&D is reduced under uncertainty. $\omega \equiv \left(\frac{\tau_2}{\tau_1}\right)^{-\sigma} < 1$ is the ratio of export profits under "column 2" tariffs, relative to the temporary MFN state. $u(\gamma) \equiv \frac{\beta\gamma\lambda}{1-\beta}$ uses $\gamma \equiv 1 - \lambda_{11}$, and $\gamma\lambda = \lambda_{12}$.

To understand the effect of uncertainty in R&D investment, consider under which conditions $U(\gamma,\omega) < 1$. First, firms must face higher tariffs under the worst case scenario compared to the temporary MFN status: $\tau_2 > \tau_1$, as if $\tau_2 = \tau_1$, then $\omega = 1$ and $\varphi_1^U = \varphi_1^D$. Second, $u(\gamma) > 0$, which implies $\gamma > 0$ and $\lambda > 0$: if $\gamma = 0$, then policy is fixed in all states and there is no policy uncertainty, and $\varphi_1^U = \varphi_1^D$; if $\lambda = 0$, then tariff increases are not possible, and uncertainty has no impact on R&D investment.

To understand the model implication, and to build a bridge between the theory and the empirical application, let M be the mass of active firms (producing both for the domestic and the export market), and $G(\varphi)$ the productivity cumulative distribution function. The model highlights an extensive margin effect of trade policy uncertainty, whereby more firms find it profitable to innovate when trade policy uncertainty is low or absent: when $U(\gamma, \omega) < 1$, the number of firms that engage in innovative activity increases from $M_1^U = M(1 - G(\varphi_1^U))$, when trade policy is uncertain, to $M_1^D = M(1 - G(\varphi_1^D))$, when trade policy uncertainty is resolved. This should translate in an increase in innovative activity observed in the data after 2001, and is the focus of the empirical analysis.

The effect of eliminating trade policy uncertainty can be decomposed in two parts: a change in variance and, potentially, a change in expected value of tariffs. If τ_1 is at the expected value of tariffs under uncertainty, then a reduction in uncertainty captures exactly a mean-preserving compression of tariffs. However, in the empirical application τ_1 is below the expected value under uncertainty, because $\tau_1 = \tau_0$. Therefore, the reduction in uncertainty that followed the transition to permanent MFN status to China captures the combined effect of a change in the variance and a change in the expected mean of tariffs.

3 Estimation and identification

Based on the intuition provided by the theoretical framework presented in Section 2, this section develops the empirical model and discusses the identification strategy.

The model predicts that the innovation productivity threshold drops from φ_1^U to φ_1^D when tariff uncertainty is resolved, inducing firms with productivity between φ_1^D and φ_1^U to incur the sunk cost to innovate. The model provides the intuition for one sector. The empirical strategy uses all sectors. It exploits the fact that sectors are heterogeneous in the exposure to uncertainty, measured as the log difference between "column 2" and MFN tariffs. All firms face the same probability of a policy reversal, but the productivity threshold reduction is larger in sectors with larger tariff gaps. Therefore, we should expect a larger innovation response in more exposed sectors. This innovation response is measured using patent data.

The theoretical framework highlights an extensive margin response. The baseline empirical application is more general and focuses on the overall effect on innovation. However, in Section 5 I study the mechanism behind the innovation response more closely and test the extensive margin prediction by looking at patents by new inventors and entry of new inventors.

3.1 Identification

The empirical strategy is based on a generalized triple difference-in-differences, and it exploits time-sector-country variation. Identification relies on the assumption that, in the absence of PNTR, firms in sectors relatively more exposed to trade policy uncertainty would have experienced the same trend in patenting/innovation as firms in sectors relatively less exposed to trade policy uncertainty. If this assumption holds, then a difference-in-differences strategy identifies the causal effect of trade policy uncertainty on innovation.

Identifying the effect of interest may be challenging. The first challenge is that tariffs may be endogenous. The common trend assumption may be violated if firms in expanding sectors are more likely to start innovating, and are also more likely to face higher exposure to trade policy uncertainty, for example because "column 2" and MFN tariffs are set by the US to protect industries with declining innovation, and/or industries in which innovation growth and competition are expected from China. Reassuringly, most of the variation in the uncertainty exposure measure is explained by variation in the "column 2" tariffs, which were established in 1930 under the Smoot-Hawley Tariff Act and assigned to all non-market economies. MFN tariffs remained largely unchanged during this period, were on average very low (mean is 3 percent) and exhibited little variations across industries (standard deviation is 3 percent) (See Table 1). Furthermore, US MFN tariffs apply to all WTO member countries, and thus are unlikely to be set to target specific industries in China. If the US set MFN strategically high in some industries, this would bias the results against finding an effect because it would reduce the gap between non-NTR and MNF tariffs. In section 5, I show a robustness where the tariff difference is instrumented with non-NTR tariff; results are nearly identical.

A second challenge is that technology and/or industry specific trends may confound the results. For example, being more exposed to a trade policy uncertainty may be correlated with innovation simply because an industry is growing fast. Furthermore, the incentives to patent/likelihood of patenting as well as the sunk costs associated with investing in R&D depend on a host of technological and other characteristics of a sector. To the extent that these characteristics are time-varying, industry fixed effects do not help. To address this concern, I exploit the richness of the patent data, available for other countries than China, and use time-sector-country variation in a triple difference-in-differences. Precisely, I construct a panel of patenting activity for each country and technology available in the data. The simple difference-in-differences removes time varying trends that are common across sectors within the same country. Adding a third difference removes sector-specific trends that are common across countries. Then, I compare innovation in industries relatively more exposed to trade policy uncertainty (1^{st} difference), before and after PNTR conferral (2^{nd} difference), across countries (3^{rd} difference). An alternative strategy would be to include an industry-specific linear trend in a difference-in-differences estimation and identify the effect of reduced trade policy uncertainty as deviation from this linear trend. But linearity is a very strong assumption in a period in which the implementation of the WTO and TRIPS agreements changed patenting activity and incentives to patent worldwide.

A third concern is that contemporaneous policy changes in China may be correlated with the PNTR, even after controlling for country and sector-specific trends in innovation, invalidating the common trend assumption. For example, as part of WTO accession, China committed to implement several reforms to liberalize its economy. These include the reduction of its import tariff rates, which are bound at an average of 9 percent, the removal of restriction on exporting, importing, and barriers to foreign investment. Finally, China's WTO accession coincides with the elimination of quotas for textiles exports under the MFA in 2002 and 2005. If these reforms are disproportionately targeted at sectors that are both more exposed to trade policy uncertainty and that face higher export and innovation opportunities, for example globally expanding sectors, then sector-specific trends in patenting may arise. I explicitly control for the policy changes associated with China's WTO accession to eliminate remaining sectoral trends that are specific to China. I include indicators for all Chinese sectors that faced FDI restrictions and non-tariff barriers before 2001,[22] and the log of China's import tariffs in 1995. These controls are measured in the pre-period, and interacted with an indicator for the post-PNTR period and China.[23] I also include a measure of exposure to MFA quotas reduction, measured as the share of products within a sector that were subject to an export quota until year $t-1$.[24]

A last remaining concern is that there may be unobserved demand shocks and other unobservable shocks in China, that are correlated with the PNTR conferral. I address this concern in two ways. First, I include China imports from the rest of the world for each sector.[25] This controls for both the inflow of goods as a response to increased demand, and the inflow of both patented and unpatented innovations through trade. Second, for each sector, I construct an aggregate of all patent applications filed by foreign applicants to the Chinese patent office. This captures both unobserved demand shocks and regulatory changes in China that may change the likelihood to patent. For example, one may worry that after China joins the WTO foreign firms start patenting existing technologies

[22] Data are from Brandt et al. (2017), as well as the concordance between Chinese CIC industries and HS product codes.

[23] The product level information is available at the HS 6-digit level, and mapped to IPC patent classes. I use the same system of weights as described in (21) and construct a weighted average for each IPC patent class.

[24] The product level information is available at the HS 6-digit level, and mapped to IPC patent classes. I use the same system of weights as described in (21) and construct a probability weighted number of products for each IPC patent class.

[25] I exclude imports from the US, as the US are themselves affected by the PNTR.

at the Chinese patent office, either because they move production to China, or because they face competition from Chinese firms. Controlling for foreign filings captures this. Note that this control is constructed using all granted and not granted patents, all types of patents, i.e.both invention patents and utility models, and the exact date of filing at the Chinese patent office. Thus, it covers the population of foreign filings to China.

3.2 Empirical model

I estimate the following generalized triple difference-in-differences model:

$$\ln(p_{jnt}) = \alpha + \delta_{nt} + \delta_{jn} + \delta_{jt} + \beta PostPNTR_t \times \ln(TPU_j) \times \mathbb{1}\{n = CN\} + \epsilon_{jnt}. \tag{20}$$

The dependent variable, $\ln(p_{jnt})$, is the log number[26] of unique granted invention patents filed in technology j and year t by all applicants resident in country n. The technology j is identified empirically using the 4-digit technology code (IPC)[27] of the patent.[28] Note that n denotes the residence country of the applicant (patentee), not the patent office where the patent is filed. δ_{nt}, δ_{jn}, and δ_{jt} are country-time, country-technology, and technology-time dummies respectively. The fourth term on the right-hand side is the term of interest, and it is composed by the interaction of a post-PNTR dummy ($PostPNTR_t$), the trade policy uncertainty exposure ($\ln(TPU_j)$), and an indicator variable equal to one for China, and zero otherwise ($\mathbb{1}\{n = CN\}$). ϵ_{jnt} is the error term.

The uncertainty exposure measure of a sector/technology j, $\ln(TPU_j)$, is a weighted average of the log difference between "column 2" and MFN tariffs, and is constructed as follows:

$$\ln(TPU_j) = \sum_h \omega_{jh} ln\left(\frac{\tau_{h2}}{\tau_{h1}}\right), \tag{21}$$

[26]In the empirical application, I use the inverse hyperbolic sine of the number of patents instead of the logarithm, to avoid dropping zeros. The inverse hyperbolic sine transformation is similar to the logarithm, but has the advantage of being defined at zero.

[27]The IPC is the International Patent Classification.

[28]Patents with multiple IPC codes, are assigned fractionally to each IPC code.

where $\tau_{h2} = 1 + T_{h2}$, and $\tau_{h1} = 1 + T_{h1}$,[29] are the iceberg-equivalent "column 2" and MFN tariffs respectively, at the 6-digit Harmonized System (HS) level. I use the τ_{h2} and τ_{h1} levels of 1999,[30] but both MFN and "column 2" tariffs for China are stable over the period.[31] ω_{jh} is a weight equal to the probability that technology j is mapped into HS product h. This weight can be interpreted as the relative importance of each HS product h that can be produced using technology j, or alternatively as the researcher's uncertainty when mapping a patented technology into a specific product. The concordance between patent technologies (IPC) and product (HS) codes is provided by Lybbert and Zolas (2014).

The sample includes annual data from 1990 to 2007. I define 1990-2000 as the pre-period, and 2001-2007 as the post period. More than one event is likely to have played a role in reducing policy uncertainty: in November 1999, the US and China signed an agreement governing China's entry into the WTO; in October 2000, the US Congress passed the bill granting PNTR status to China; in December 2001, when China joined the WTO, the PNTR came into effect, and in January 2002 it was implemented. I follow the literature Pierce and Schott (2016) and treat the years from 2001 (included) to 2007 as post-PNTR.

4 Data

4.1 Patents

Innovation is measured empirically using patent data. The data source is the European Patent Office's (EPO) Worldwide Patent Statistical Database (PATSTAT).[32] PATSTAT contains the population of all patents filed globally since the mid 1960s, approximately 100 million patent applications from 90 patent authorities, and collects a wide range of in-

[29] T_{h2} and T_{h1} are *ad-valorem* "column 2" and MFN tariff lines respectively at the HS 6-digit level.

[30] Using other pre-period years or the pre-period average gives similar results.

[31] Note that this uncertainty exposure measure is by definition zero for countries considered by the US as market economies.

[32] October 2016 version.

formation, including bibliographic information, family links, citations, etc. I have information on the name and the address of patent applicants, and use it to identify the population of all applicants resident in a country in the period of analysis. For each patent application, I observe where it was filed, the filing date, publication date, and whether and when the patent was granted. I have this information for all patent offices where the patent is filed. This allows dating patents by the earliest filing date observed in the data[33] rather than the filing date at a specific patent office. I have information on the technology areas of patents (IPC codes), citations, the research team behind the invention and the location of inventors at the time of filing.

Using this data, I construct a panel of patenting activity by all technologies and countries worldwide. To measure the innovative activity in a technology area j in country n in year t (p_{jnt}), I count granted patents filed by applicants resident in country n and dated by earliest filing year t. n is the residence country of the applicant (not the patent office), and t is the earliest filing year of the patent. Dating patents by application filing date is the conventional approach in the empirical literature because the application date is more closely timed with when the R&D process takes place than the publication and grant date. I use patent families[34] to identify unique inventions, that is identical inventions filed in multiple patent offices (countries) are not double counted.

Griliches (1990) documents extensively that patents are highly correlated with innovation and R&D, and in Appendix C I show that there is a close relationship between R&D expenditure and patenting for a sample of Chinese firms. The literature has discussed extensively the advantages and disadvantages of using patent data.[35] For the purpose of this analysis, there are two main advantages of using patent data: first, it is the only source of data that makes it possible to check pre-trends because one can construct a long pre-period that covers the entire period of uncertainty, from 1990 to 2000.

[33]The earliest application date of a patent is known as priority date.

[34]I use DOCDB patent family.

[35]See e.g. OECD (2009); Griliches (1990); Nagaoka et al. (2010) for reviews and discussion of patent data as innovation indicators.

Second, one can construct a triple difference by using patents in the same technologies in other countries to control for technology trends in innovation. To ensure that patents by Chinese applicants are comparable in terms of quality, validation procedure, and duration of intellectual property (IP) protection to patents in other countries, I restrict the sample to granted[36] patents of invention, and exclude utility models. Compared to patents of invention, utility models require compliance with less strict requirements (for example, lower level of inventive step), offer shorter IP protection, generally between 7 and 10 years, and the costs to obtain and maintain them are lower. Requirements and procedures for obtaining protection and the duration of protection vary from one country to another. Utility models are often used to patent incremental innovations. I also use different proxies for patent quality, such as citations, family size, and number of inventors, to take into account the fact that patent quality is highly heterogeneous.

Finally, an advantage of using information from all patent offices is that one can observe patents by Chinese firms that are filed abroad but not in China. One would not observe these patents by relying on data from the Chinese patent office alone.

Patents are organized according to their technical features by the International Patent Classification (IPC),[37] while tariffs are levied on products available in the HS classification. I map IPC technical classes to HS product codes using the concordance provided by Lybbert and Zolas (2014). This concordance links patent technologies to products probabilistically.[38] For each IPC-HS match, a weight ω_{jh} is provided. For example, a patent on Hats; Head Coverings, (IPC A42B)[39] is linked to Safety headgear (HS 650610) with weight 0.89, Hats and other headgear, plaited or made by assembling strips of any material, whether or not lined or trimmed (HS 650400) with weight 0.06 and Other headgear,

[36] To be granted a patent, an innovation must satisfy three key criteria: it must be novel or new, it must involve an inventive step, and it must be industrially applicable.

[37] IPC technical codes are organized in classes (3-digit), subclasses (4-digit), and groups (5-7 digit).

[38] Precisely, the approach combs through titles and abstracts of patents in PATSTAT for keywords specifically developed to describe the HS classification, and computes the frequency of the match.

[39] Hats; Head Coverings, (IPC A42B) include technologies such as Hats; Caps; Hoods (IPC A42B 1/00), Helmets; Helmet covers (IPC A42B 3/00), Veils; Holders for veil (IPC A42B 5/00) and Fastening means for head coverings; Elastic cords; Ladies' hat fasteners (IPC A42B 7/00).

whether or not lined or trimmed of Other materials (HS 650699) with weight 0.05. I use these weights to construct the uncertainty exposure measure in (21).

4.2 Tariffs

The source of tariff data is the UNCTAD Trade Analysis Information System (TRAINS). I extract average applied MFN and "column 2"[40] tariff lines disaggregated at 6-digits level of the Harmonized System (HS) for the US. All tariff lines are converted to their iceberg form, $\tau_h = 1 + T_h$, where T_h is the *ad-valorem* tariff.

There are 4223 HS 6-digit industries in the 2002 classification for which both "column 2" and MFN tariffs are available. 3980 of these HS products are matched to 634 patent technical classes.

4.3 Descriptives

Table 1 shows mean and standard deviation of $ln(TPU_j)$, which proxies for industries' differential exposure to uncertainty and provides the source of variation in the empirical analysis, "column 2", and MFN tariffs in 1999. The tariff threat faced by Chinese inventors willing to export to the US market was high on average, but there was considerable variation across industries: the average $ln(TPU_j)$ was 0.25, with a standard deviation of 0.10. Instead, the level of protection was relatively low for all industries, averaging around 0.03, with a standard deviation of 0.03. Similar to $ln(TPU_j)$, "column 2" tariff lines were high on average and varied significantly across industries. The average (0.28) and the standard deviation (0.11) were very close to the ones of the $ln(TPU_j)$, confirming that the source of variation used in the empirical analysis comes primarily from the "column 2" tariffs.

Figure 1 plots the average patent growth within a 2-digit technology sector against the

[40] Column 2 tariffs are extracted at 8-digit level and converted to 6-digit by taking the simple average of HS 8-digit tariffs within each HS 6-digit product category.

(log) difference between "column 2" and MFN tariffs. On average, sectors relatively more exposed to uncertainty before the PNTR conferral experienced higher patent growth in the period 2001-2007.

Table 2 provides summary statistics for the change in log average patents between the pre- and post-period by terciles of $ln(TPU_j)$, along with the average uncertainty exposure within each tercile. Firms investing in technologies in the bottom tercile of $ln(TPU_j)$ faced relatively lower exposure to trade policy uncertainty in the pre WTO phase than firms investing in technologies in the top tercile of $ln(TPU_j)$. The table shows that patent growth is higher in technology areas initially more exposed to uncertainty, and the difference relative to the lowest tercile is statistically significant.

Table 1: Summary statistics of trade policy uncertainty exposure, "column 2" and MFN tariffs in 1999.

	$ln(\tau_2/\tau_1)$	$ln\tau_2$	$ln\tau_1$
Mean	0.252	0.279	0.028
St. deviation	0.101	0.114	0.028

Notes: The table reports mean and standard deviation of the trade policy uncertainty measure, the MFN and the "column 2" tariffs in 1999. Tariffs are converted to their iceberg equivalent: $\tau = 1+T$, where$T$ is the *ad-valorem* tariff. τ_1 denotes MFN tariffs, τ_2 denotes "column 2" tariffs. $ln(\tau_2/\tau_1)$, $ln\tau_2$, and $ln\tau_1$ are weighted averages constructed as in (21).

5 Results

This section estimates the model presented in equation (20) and discusses the results.

I proceed by estimating the model presented in equation (20). As described in Section 3.2, the model includes country-time, country-sector, and sector-time dummies, and standard errors are clustered at the country-sector level. I estimate the model using all countries and sectors available in PATSTAT, and exclude the US.

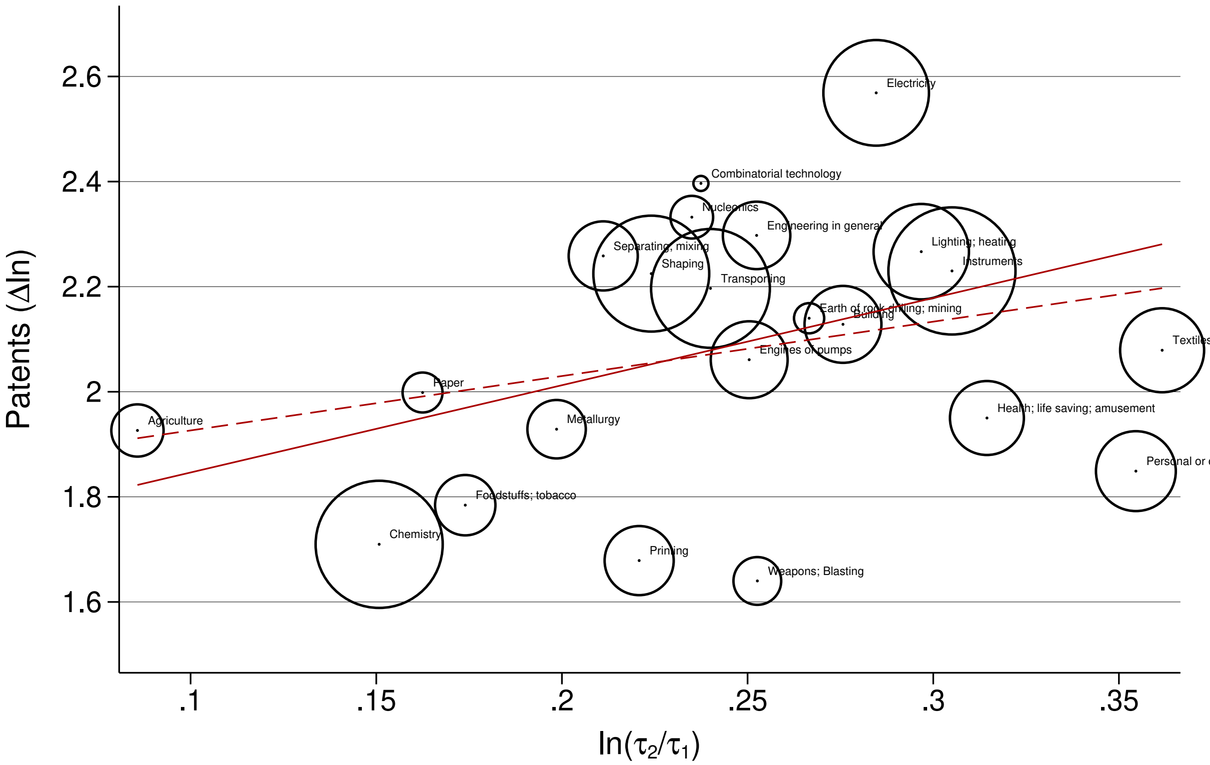

Figure 1: Industry-level patent growth *vs* initial uncertainty exposure.

Notes: The figure shows average patent growth (Δln) within (2-digit) IPC technology sector *vs* average initial uncertainty exposure measured as (log) difference between "column 2" and MFN tariffs in 1999. The dashed line represents an unweighted linear fit and the solid line represent a weighted linear fit weighted by the number of 4-digit technologies within a 2-digit technology sector. Circles are proportional to the weights in the linear regression fit.

Table 3 reports the results. Column 1 shows the estimates of the difference-in-differences specification estimated using only China, and includes the DID term along with time and sector fixed effects. It shows the results obtained by comparing high *vs* low policy uncertainty exposure sectors, before and after the PNTR.

Columns 2-5 report the triple difference-in-differences estimation. Column 2 includes the DDD term and the required fixed effects: country-time, country-sector, and sector-time. Column 3 includes controls for contemporaneous policy changes implemented as part of China's WTO accession: indicators of pre-period FDI restrictions, non-tariff barriers, and China import tariffs in 1995, interacted with the post-PNTR indicator, and

Table 2: Summary statistics of patents by pre-PNTR trade policy uncertainty.

		Terciles of $ln(TPU_j)$			
		Lowest	Middle	Highest	All
Uncertainty exposure	Mean	0.141	0.263	0.351	0.252
($lnTPU_j$)	St. dev.	0.067	0.020	0.059	0.101
Patent growth	Mean	1.920	2.238	2.134	2.099
($\Delta ln\bar{p}$)	St. dev.	0.761	0.707	0.735	0.746
Total patents					
(1990-2000)		24931.03	10905.70	12170.38	48007.11
(2001-2007)		105717.20	76824.56	97124.02	279665.78

Notes: The table reports mean and standard deviation of trade policy uncertainty exposure $ln(TPU_j)$ and patent growth by terciles of trade policy uncertainty exposure in 1999. Patent growth $\Delta ln\bar{p}$ is calculated as the difference in the log average patents between the pre- and post-period.

exposure to MFA quota elimination. Columns 4 and 5 include controls for demand and other unobserved shocks: China's sector imports from the rest of the world, and aggregate patenting by foreign applicants in China for each sector. As import data are not available before 1995, column 5 is estimated using the period 1995-2007. As predicted by the theory, the coefficient on the $PostPNTR_t \times ln(TPU_j) \times CN$ is positive and statistically significant, indicating that being *ex-ante* exposed to higher policy uncertainty is associated with more innovation after uncertainty over US trade policy is eliminated.

The estimated coefficient in the baseline specification in column 2 indicates that a 1% increase in exposure to trade policy uncertainty in the pre-WTO period leads to a 0.7% more patenting in the post 2001 period. The estimated effect of uncertainty is also economically significant. The average $\ln(TPU_j)$ in the lowest tercile of the observed trade policy uncertainty distribution is 0.14, while the average $\ln(TPU_j)$ in the highest tercile in 0.35. This indicates that moving from the first to the third tercile of the observed distribution increases patenting by $0.7 \times (0.35 - 0.14) = 0.15$ log points.

5.1 Robustness

This section presents robustness tests that assess the validity of the empirical strategy with respect to the timing of the innovation response, the exogeneity of the uncertainty exposure measure ($\ln(TPU_j)$), and the sensitivity to the group of countries used as control group.

Event timing: Innovation should be correlated with exposure to trade policy uncertainty after the PNTR conferral in 2001, but not before. To assess this, I perform a timing of events analysis, in which I replace the $PostPNTR$ dummy in equation (20) with a full set of year dummies:

$$\ln(p_{jnt}) = \alpha + \delta_{nt} + \delta_{jn} + \delta_{jt} + \sum_{y \neq 2000} \beta_y \mathbb{1}\{y = t\} \times \ln(TPU_j) \times \mathbb{1}\{n = CN\} + \epsilon_{jnt}. \quad (22)$$

Figure 2 shows the estimated β_y coefficients relative to the year prior to the reform.[41] Consistently with the parallel trend assumption, the point estimates are insignificant at conventional levels before 2001, and become positive and statistically significant after 2001.

Exogeneity: In Section 3 I argued that the uncertainty exposure measure, $lnTPU_j$, is plausibly exogenous as almost the entire variation comes from the "column 2" tariffs established in 1930 under the Smoot-Hawley Act. Furthermore, if MFN tariffs were set strategically by the US, this would lead to smaller log differences between "column 2" and MFN tariffs, biasing the result against finding any effect of uncertainty on innovation. Nevertheless, it is possible to instrument the baseline uncertainty exposure measure with the "column 2" tariffs established under the Smoot-Hawley Act. Table 4 shows the two-stage least squares estimation which uses $PostPNTR \times ln\tau_2 \times CN$ as instrument for $PostPNTR \times lnTPU_j \times CN$, and shows that the estimated effect remains statistically significant and similar in magnitude to the baseline estimation.

[41] Table 7 in Appendix D reports the event timing estimation with and without controls.

Control group: The baseline estimation uses all available countries with patenting activity in the same patent classes as China in the period of analysis, excluding the US. As a robustness, I use alternative groups of countries to construct the triple difference: the EU 15 member countries,[42] the Asean economies,[43] the Brics,[44] the Eagle,[45] and an additional group of emerging economies which includes the Brics, Mexico, and Turkey. Figure 3 shows graphically how the baseline result is sensitive to the choice of the control group of countries.

5.2 Does more patenting mean more innovation?

Estimation of model (20) indicates that higher ex-ante exposure to trade policy uncertainty is associated with increased patenting activity after uncertainty is eliminated. However, one may question whether the increase in patents represent more innovation.

Patenting is typically found to be correlated with R&D and other measures of innovation in the literature Griliches (1990). In Appendix C, I show that for a subsample of Chinese firms for which both patenting and R&D are available, patents are highly correlated with R&D expenditures, both on the intensive and on the extensive margin. Nevertheless, one may argue that patents remain an imprecise measure of innovation, and that the quality of patents is highly heterogeneous. I address this concern in two ways. First, all specifications use only patents of invention that are successfully granted, and exclude utility models, which are easier and cheaper to obtain and maintain, and less comparable across countries. Note also the triple difference-in-differences accounts for differences in the propensity to patent across sectors.

Second, I show that results are robust when using quality adjusted patents in the

[42]Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom.

[43]Indonesia, Malaysia, the Philippines, Singapore, Thailand, Brunei, Cambodia, Laos, Myanmar and Vietnam.

[44]Brazil, Russia, India, China, and South Africa.

[45]Brazil, China, India, Indonesia, Mexico, Russia, and Turkey.

Table 3: Baseline results, DDD

	(1)	(2)	(3)	(4)	(5)
Post × $\ln\text{TPU}_j$ × CN	0.756^a	0.660^a	0.927^a	0.700^a	0.952^a
	(0.285)	(0.256)	(0.271)	(0.231)	(0.227)
Post × CN × NTB_{CNj}			0.253^a	0.217^a	0.173^b
			(0.088)	(0.076)	(0.071)
Post × CN × FDI_{CNj}			0.062	0.078	0.055
			(0.085)	(0.074)	(0.069)
Post × CN × import $\text{tariff}_{CNj1995}$			-0.566^a	-0.531^a	-0.561^a
			(0.202)	(0.168)	(0.163)
MFA exposure_{CNjt} × CN			−0.158	−0.041	−0.022
			(0.143)	(0.136)	(0.133)
Foreign patents_{CNjt} × CN				0.308^a	0.249^a
				(0.021)	(0.027)
CN imports_{CNjt} × CN					0.047^c
					(0.027)
Observations	11196	873270	864396	864396	622739
Adj. R^2	0.87	0.91	0.91	0.91	0.92
Fixed effects	t, j	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn
Estimation	*DID*	*DDD*	*DDD*	*DDD*	*DDD*

Notes: The table reports generalized difference-in-differences estimates (column 1), and generalized triple difference-in-differences estimates using all countries except the US (column 2-5). The dependent variable is the inverse hyperbolic sine of sector-year-country patents. The independent variable is the interaction of the post-PNTR dummy, the TPU exposure, and the China indicator. Constant, time and sector fixed effects in column 1; constant and country-time, country-sector, and sector-time fixed effects in columns 2-5 are included but not reported. Additional controls include time-varying variables–China's MFA exposure, China's imports from the rest of the world, and foreign patent filings at the SIPO in each sector–and interactions of the post-PNTR indicator, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Data span 1990 to 2007. Total sample in columns 5 is reduced because import data are not available before 1995. Robust standard errors are clustered at the 4-digit IPC sector-country level and displayed in parentheses. [a] significant at the 1 percent level, [b] significant at the 5 percent level, [c] significant at the 10 percent level.

Table 4: IV

	(1) OLS	(2) FS	(3) 2SLS	(4) RF
Post × $\ln\text{TPU}_j$ × CN	0.700^a		0.648^a	
	(0.231)		(0.227)	
Post × CN × NTB_{CNj}	0.217^a	-0.012^a	0.214^a	0.206^a
	(0.076)	(0.003)	(0.076)	(0.075)
Post × CN × FDI_{CNj}	0.078	0.002	0.077	0.079
	(0.074)	(0.003)	(0.074)	(0.075)
Post × CN × import $\text{tariff}_{CNj1995}$	-0.531^a	-0.038^a	-0.523^a	-0.548^a
	(0.168)	(0.006)	(0.169)	(0.170)
MFA exposure_{CNjt} × CN	−0.041	-0.033^a	−0.035	−0.056
	(0.136)	(0.004)	(0.135)	(0.135)
Foreign patents_{CNjt} × CN	0.308^a	0.002^a	0.308^a	0.309^a
	(0.021)	(0.000)	(0.021)	(0.021)
Post × CN × $\ln\tau_{col2}$		0.878^a		0.569^a
		(0.010)		(0.199)
Observations	864396	864396	864396	864396
Adj. R^2	0.91	1.00	−0.01	0.91
Fixed effects	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn

Notes: The table reports 2SLS generalized triple difference-in-differences estimates of the inverse hyperbolic sine of patents on the interaction of the post-PNTR dummy, the TPU exposure, and the China indicator. TPU exposure measure is instrumented with "column 2" tariffs. Columns 1-4 report OLS, first stage, 2SLS and reduced form estimates respectively. Constant and country-time, country-sector, and sector-time fixed effects are included but not reported. Additional controls include time-varying variables–China's MFA exposure, and foreign patent filings at the SIPO in each sector–and interactions of the post-PNTR indicator, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Data span 1990 to 2007. Robust standard errors are clustered at the 4-digit IPC sector-country level and displayed in parentheses. [a] significant at the 1 percent level, [b] significant at the 5 percent level, [c] significant at the 10 percent level.

outcome variable. I use three proxies for quality that are correlated with the economic value of a patent and that are generally used in the literature: the number of citations,[46] the size of the research team behind a patent,[47] and the patent family size,[48] and weigh patents accordingly. In this way, higher value inventions receive more weight. The results for these quality adjusted measures confirm the findings in the baseline estimation and are reported in columns 3-5 of Table 5.

A related concern is that the increase in patenting observed after the PNTR conferral might pick up technology transfers to China rather than innovation by Chinese industries. To rule this out, note first that all patents in the analysis are dated by the earliest filing date. This date, known as priority date, is the closest to when the R&D process took place. Any subsequent filings at home or abroad are irrelevant in dating the patent. To fix ideas, suppose a US-based firm patents a new invention in 1995 (priority date) in the US, and subsequently files the same patent to the Chinese patent office in 2001 or later. If the US firm is the only applicant at the Chinese patent office, then this patent would not be counted as Chinese innovation because the applicant is based in the US. But the patent would be captured by the foreign filings control in Column 4 and Column 5 in Table 3. If the US-based firm files the patent to the Chinese patent office through a Chinese applicant, for example a subsidiary, then the patent would be assigned to both countries, but the date would be 1995, the priority date, and not 2001, the date of filing at the Chinese patent office. Thus, the patent would not be counted as innovation resulting from reduced uncertainty after the PNTR conferral.

Second, the regressions in Column 4 and Column 5 of Table 3 control specifically for patent applications filed by foreign applicants to the Chinese patent office, and this control is built using the filing date at the SIPO rather than the priority date of the patents.

[46] High value inventions are more extensively cited than low value patents (Harhoff et al., 1999). I calculate citations over a fixed 3-year window to account for the fact that older patents have a higher chance of being cited than more recent patents.

[47] A set of studies have associated the number of inventors listed on a patent with the economical and technological value of the patent (OECD, 2009).

[48] The number of patent applications in the same patent family.

Table 5: Innovation quality, DDD

	Exclude foreign inventors		Quality adjusted		
	(1) No US inventors	(2) All domestic inventors	(3) Citations	(4) Team size	(5) Family size
Post × $\ln TPU_j$ × CN	0.694^a	0.560^b	0.665^b	0.751^a	0.951^a
	(0.237)	(0.247)	(0.328)	(0.247)	(0.218)
Post × CN × NTB_{CNj}	0.241^a	0.247^a	0.367^a	0.175^b	0.168^b
	(0.080)	(0.083)	(0.111)	(0.077)	(0.070)
Post × CN × FDI_{CNj}	0.040	0.041	0.215^c	0.099	0.034
	(0.078)	(0.081)	(0.113)	(0.075)	(0.071)
Post × CN × import $tariff_{CNj1995}$	-0.354^b	-0.402^b	-0.741^a	-0.724^a	-0.388^b
	(0.175)	(0.182)	(0.238)	(0.181)	(0.164)
MFA $exposure_{CNjt}$ × CN	−0.086	−0.061	−0.102	0.045	−0.168
	(0.140)	(0.144)	(0.208)	(0.168)	(0.146)
Foreign $patents_{CNjt}$ × CN	0.298^a	0.302^a	0.425^a	0.310^a	0.314^a
	(0.021)	(0.021)	(0.026)	(0.023)	(0.021)
Observations	864396	864396	864396	864396	864396
Adj. R^2	0.90	0.90	0.86	0.88	0.87
Fixed effects	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn

Notes: The table reports generalized triple difference-in-differences estimates of variations of the inverse hyperbolic sine of patents on the interaction of the post-PNTR dummy, the TPU exposure, and the China indicator. Column 1 and 2 exclude patents with foreign inventors: inventors in the US in column 1 and all foreign inventors in column 2. Column 3-5 use patents weighted by citations (column 3), team size (column 4), and family size (column 5). Constant and country-time, country-sector, and sector-time fixed effects are included but not reported. Additional controls include time-varying variables–China's MFA exposure, and foreign patent filings at the SIPO in each sector– and interactions of the post-PNTR indicator, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Data span 1990 to 2007. Robust standard errors are clustered at the 4-digit IPC sector-country level and displayed in parentheses. [a] significant at the 1 percent level, [b] significant at the 5 percent level, [c] significant at the 10 percent level.

Third, I observe the address of all inventors registered on the patent and proceed by excluding all patents with one or more inventors based in the US or, more conservatively, by restricting the sample to patents with all domestic inventors.[49] The results are shown in Column 1 and Column 2 of Table 5. The effect of reducing trade policy uncertainty remains strong and significant.

6 The Mechanism

In this section I use additional information on patent applicants and the geography of patents to examine the mechanism through which reducing trade policy uncertainty induces more innovation. I look at the margins of the innovation response as predicted by

[49]I do this for all patents assigned to China; in the control group of countries, I use all patents as in the baseline.

the model and at whether innovation is directed towards the export market.

The model presented in Session 2 highlights the extensive margin response to reduced trade policy uncertainty. It predicts that the productivity level required to invest in R&D is higher in the presence of uncertainty, and thus more firms are expected to find R&D investment profitable when trade policy uncertainty is reduced. Furthermore, within a sector, this response is driven by firms in the middle of the productivity distribution, as the most productive firms are already sufficiently productive to innovate under uncertainty. To better understand this mechanism, and if it is supported by the data, I exploit information on patent applicants and their innovation behaviour over time. In the data, I observe the first time an applicant files for a patent,[50] and I can follow applicants over time. Using this data, I estimate two additional regressions: *i.* For every year-sector-country, I count the number of applicants that patent for the first time.[51] Then, I run a regression using the log-number of new applicants as outcome variable.[52] In this regression, the triple difference accounts for sector-specific entry trends. *ii.* In the post-period, I separate patents by firms that file a patent for the first time after 2000 (extensive margin) and innovation by incumbent firms (intensive margin). I do this for all patents assigned to China; in the control group of countries, I use all patents as in the baseline to capture technology trends. The pre-period is unchanged. Then, I estimate the baseline specification on this modified sample.

The results are reported in Table 6. Column 1 shows a positive and significant increase in the number of applicants that patent for the first time after the transition to permanent MFN status, consistently with the model prediction. The second column shows the innovation response accounted for by applicants that start to innovate after the PNTR. This response is positive and significant. The coefficient is similar in magnitude to the specifi-

[50] For most countries, the first year available is 1965.

[51] I assign the applicant to the sector the first patent belongs to. The firm is assigned fractionally if the patent belongs to more than one IPC code. If an applicant files more than one patent in its first year of activity, I retain all technology codes and assign the applicant fractionally to each sector.

[52] As with the regression that use patents in the outcome variable, I use the inverse hyperbolic sine instead of the logarithm of the number of new applicants to avoid dropping zeros.

cation in Column 4 of Table 3 and indicates that a 1% increase in exposure to trade policy uncertainty in the pre-PNTR period leads to a 0.6% more patenting by new applicants in the post-period. New applicants account for 86% of the innovation response.

Next, I examine to which extent the increase in innovation is driven by increased exports to the US. The literature has emphasized the importance of market size for innovation. The US was the most important market for China, accounting for almost 25% of China's total export value between 1995 and 2000, compared to 15% of Japan and less than 5% of all other top 10 export markets.[53][54] However, the possibility of sudden tariff spikes may have led firms to postpone incurring the sunk cost to both export to the US and to innovate. Handley and Limão (2017) show that the transitioning to PNTR led to firms to incur the sunk cost and start exporting. One may therefore expect that exporting firms also started to innovate and patent their innovation at the USPTO. I test this by checking whether the number of new patents filed to and granted at the USPTO differentially increases in highly exposed industries.

I observe all patent offices where patents are filed and using this information I modify the outcome variable: patents are always dated using the priority date,[55] but I only retain patents that are filed and granted at the USPTO. Results of this specification are reported in Column 3 of Table 6 and show that the PNTR is associated with an increase in the number of patents filed to and granted at the USPTO. Because patenting is costly, and firms tend to file patents abroad only if they intend to export there Aghion et al. (2016); Coelli et al. (2020), these findings suggest that the increase in innovation is at least in part driven by exports to the US. With the data at hand, however, I cannot say if firms start investing in R&D before they start exporting, or vice versa, as this would require firm level data where one observes both export and investment behaviour of the firm.

[53]The only exception is Hong Kong, with an import share of 24%.

[54]Figure 7 in Appendix D shows China's export value shares to its main export markets before and after 2001.

[55]This ensures that innovations undertaken before the PNTR are not counted as innovations patented at the USPTO as a result of transitioning to PNTR.

Table 6: Mechanism, DDD

	Entry		US filings only
	(1) No. new applicants	(2) Patents by new applicants	(3) USPTO granted
Post × $\ln\text{TPU}_j$ × CN	0.457^{b}	0.592^{a}	0.919^{a}
	(0.205)	(0.210)	(0.247)
Post × CN × NTB_{CNj}	0.120^{c}	0.107	0.162^{b}
	(0.067)	(0.069)	(0.083)
Post × CN × FDI_{CNj}	0.030	−0.027	0.191^{b}
	(0.067)	(0.066)	(0.085)
Post × CN × import $\text{tariff}_{CNj1995}$	−0.228	−0.064	-0.424^{b}
	(0.147)	(0.158)	(0.169)
MFA exposure_{CNjt} × CN	−0.089	0.075	-0.206^{b}
	(0.115)	(0.132)	(0.099)
Foreign patents_{CNjt} × CN	0.228^{a}	0.266^{a}	0.248^{a}
	(0.018)	(0.019)	(0.019)
Observations	864396	864396	864396
Adj. R^2	0.83	0.91	0.89
Fixed effects	nt, jt, jn	nt, jt, jn	nt, jt, jn

Notes: Columns 1 and 2 report generalized triple difference-in-differences estimates of the inverse hyperbolic sine of the number of new applicants (column 1) and patents by new applicants (column 2) on the interaction of the post-PNTR dummy, the TPU exposure, and the China indicator. The dependent variable in column 3 is the inverse hyperbolic sine of the number of patents filed to and granted at the USPTO. Constant and country-time, country-sector, and sector-time fixed effects are included but not reported. Additional controls include time-varying variables–China's MFA exposure, and foreign patent filings at the SIPO in each sector– and interactions of the post-PNTR indicator, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Data span 1990 to 2007. Robust standard errors are clustered at the 4-digit IPC sector-country level and displayed in parentheses. [a] significant at the 1 percent level, [b] significant at the 5 percent level, [c] significant at the 10 percent level.

7 Conclusion

This paper sets out to analyze the impact of resolving trade policy uncertainty on investment in innovation within Chinese industries during 1990-2007. To do so, it exploits exogenous and heterogeneous exposure to trade policy uncertainty and it's resolution when China's status in the US changed from temporary to Permanent Normal Trade Relations (PNTR), along with detailed data on innovation from all sectors and countries worldwide.

The PNTR did not change the level of tariffs, but by eliminating the uncertainty on tariffs and securing the level of tariffs at their MFN level through a credible trade agreement, it had a large effect on innovation. Using a generalized triple difference-in-differences that flexibly controls for sectoral trends in innovation and changes in the incentives to patents, I find that reducing tariff uncertainty has an economically and statistically significant effect on innovation and that this effect represents actual innovation, rather than just more patent filings. Additional analysis on the mechanisms highlighted in the theoretical framework reveals that the positive innovation response is mostly driven by firms that start innovating (extensive margin) and at least in part driven by exports to the US.

I show that these results are robust to controlling for contemporaneous policy changes and the inflow of foreign technologies in China.

These results point at the important role of trade agreement in reducing tariff uncertainty and generating economic growth, and are relevant in light of recent events such as the US-China trade war, Brexit, and the renegotiation of major trade agreements, such as the NAFTA, which contributed to making tariff uncertainty a key source of uncertainty for businesses.

The focus of this paper has been on identifying the effect of trade policy uncertainty on innovation by exploiting exogenous exposure to trade policy uncertainty and by controlling for potential confounders. Eliminating the possibility of sudden tariff spikes on Chinese imports may have affected other outcomes in addition to innovation, such as imitation, adoption, and technology transfers. These outcomes are consistent with the theoretical mechanism highlighted by the real option literature and are an interesting area of future research.

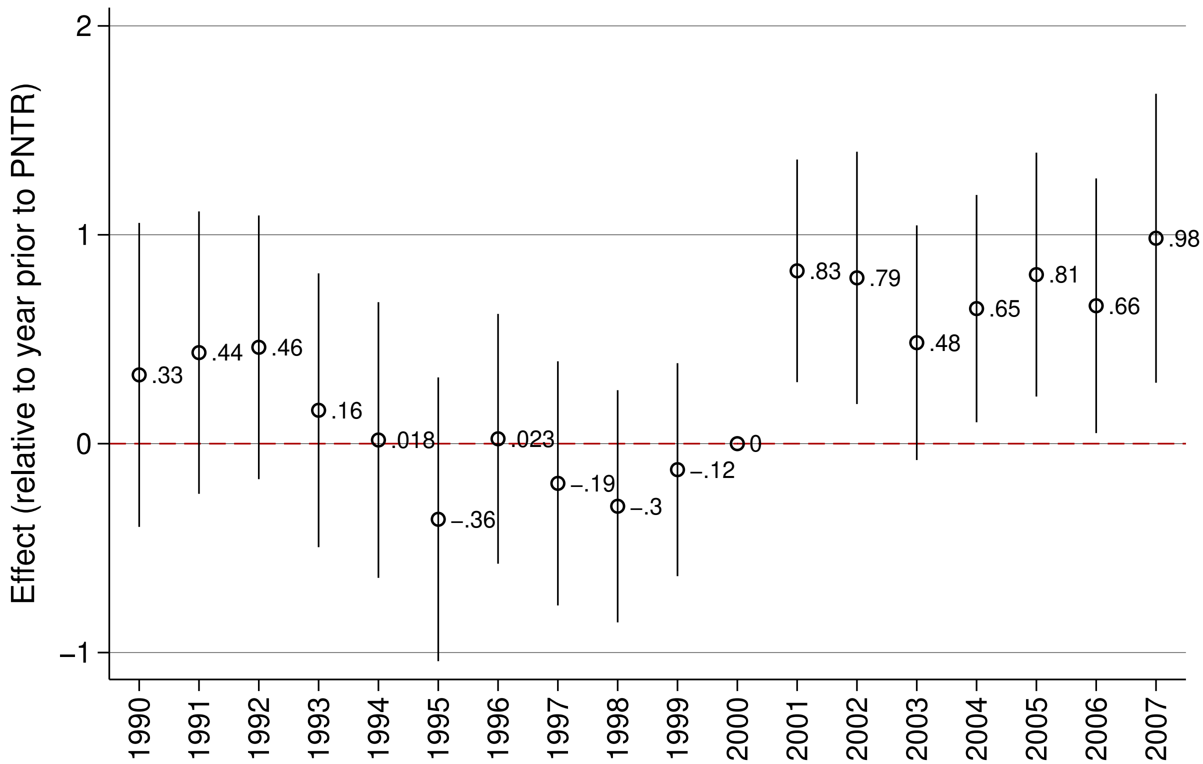

Figure 2: Event timing relative to year prior to PNTR

Notes: The figure displays the event timing plot of a regression of the inverse hyperbolic sine of patents on the interaction of the TPU exposure, the China indicator, and year dummies. Coefficients represent the TPU effect relative to the omitted year, 2000. Bars represent 95 percent confidence level intervals. Controls include fixed effects, time-varying variables–China's MFA exposure, and foreign patent filings at the SIPO in each sector–and interactions of year dummies, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Data span 1990 to 2007. Robust standard errors are clustered at the 4-digit IPC sector-country.

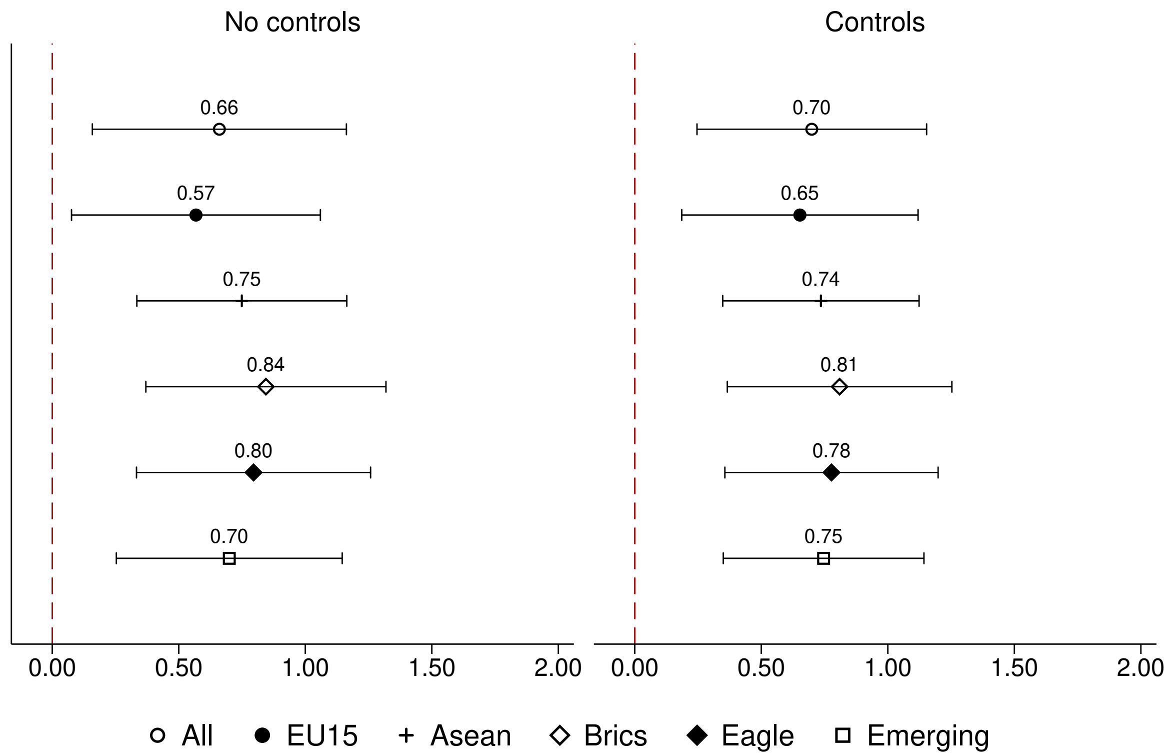

Figure 3: Changing control group

Notes: The figure displays generalized triple difference-in-differences estimates of the inverse hyperbolic sine of patents on the interaction of the post-PNTR dummy, the TPU exposure, and the China indicator using various control groups of countries. Bars represent 95 percent confidence level intervals. The left side includes the DDD coefficient and the fixed effects. The right side includes additional controls: time-varying variables–China's MFA exposure and foreign patent filings at the SIPO in each sector–and interactions of the post-PNTR indicator, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Data span 1990 to 2007. Robust standard errors are clustered at the 4-digit IPC sector-country. EU 15: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom. Asean: Indonesia, Malaysia, the Philippines, Singapore, Thailand, Brunei, Cambodia, Laos, Myanmar and Vietnam. Brics: Brazil, Russia, India, China, and South Africa. Eagle: Brazil, China, India, Indonesia, Mexico, Russia, and Turkey. Emerging: Brics, Mexico, and Turkey.

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Appendices

A Policy Background

Chinese exports to the US used to be subject to high tariffs that the US reserves to non-market economies until 1980. These tariffs, called ''“non-NTR” or “column 2” tariffs, were set in 1930 under the Smoot-Hawley Tariff Act, and are higher than the tariffs US applies to all other countries. In 1980, the President of the United State granted temporary MFN status to China, [56] and from this moment, annual renewal of China's MFN status kept US effective applied tariffs low. In 2001, as a result of China's WTO accession, US applied tariffs on Chinese imports were permanently set to MFN levels.

Renewal of China's MFN status occurred nearly automatically in the first decade. However, after the Tienanmen Square protests in 1989, US Congress introduced and voted on a joint resolution to revoke China's MFN status every year from 1990 to 2001. The need of annual renewal introduced uncertainty over US trade policy. Had the US revoked China's MFN status, US import tariffs would have jumped to the much higher ‘non-NTR’ rates. The average ‘non-NTR’ tariff was 32%, while the average applied MFN tariff was 3%. Figure 4 shows House of Representatives votes against renewing China's temporary NTR status. For three times, in 1990, 1991, and 1992, the House voted against renewal, but China didn't lose MFN status because of the lack of support by the US Senate.

With accession to WTO in 2001, China obtained Permanent Normal Trade Relation (PNTR) status. This set US import tariffs to MFN levels permanently, and thus ended the threat of potential tariff increases and uncertainty on US trade policy.

B Mathematical derivations

B.1 Productivity cutoff in deterministic scenario

Using the expressions for domestic and export profits, the innovation indifference condition (9) gives the productivity cutoff for any given τ_s in the benchmark deterministic case:

$$\frac{\left[\pi_d(\eta\varphi_s^D) - \pi_d(\varphi_s^D)\right] + \left[\pi_x(\tau_s, \eta\varphi_s^D) - \pi_x(\tau_s, \varphi_s^D)\right]}{(1-\beta)} = I$$

$$\frac{B_d(\eta\varphi_s^D)^{\sigma-1} - B_d(\varphi_s^D)^{\sigma-1} + B_x\tau_s^{-\sigma}(\eta\varphi_s^D)^{\sigma-1} - B_x\tau_s^{-\sigma}(\varphi_s^D)^{\sigma-1}}{(1-\beta)} = I$$

$$\Longleftrightarrow \varphi_s^D = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)(B_d + B_x\tau_s^{-\sigma})}\right)^{\frac{1}{\sigma-1}} \tag{23}$$

[56]Under the US Trade Act of 1974, the President of the United States has the right to grant temporary MFN status to non-market economies.

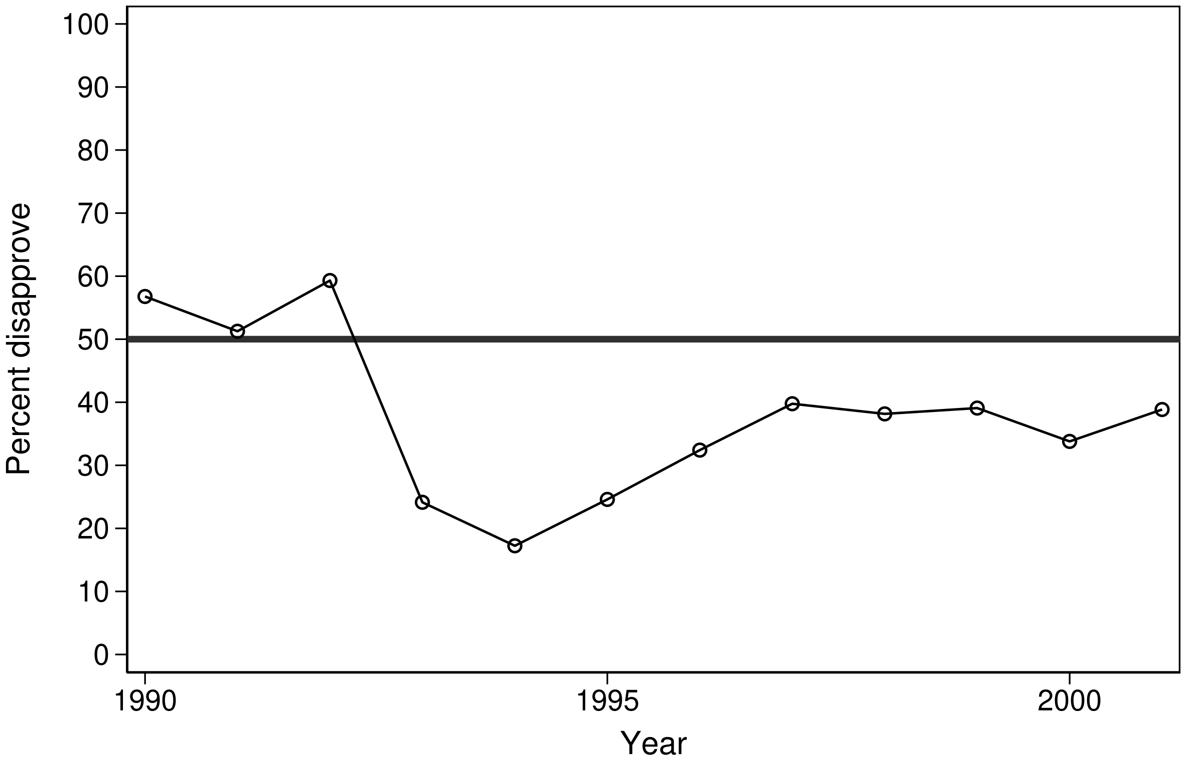

Figure 4: House votes to renew China's temporary MFN status (1990-2001).

Source: Own calculation using Pierce and Schott (2016) data.

B.2 Productivity cutoff under uncertainty

B.2.1 Proof that innovation cutoff is unique

Proposition: For any policy regime $\Lambda(\tau_s, \gamma)$ that exhibits policy persistence, and for each firm in a small country, there is a unique threshold tariff per state, $\tau_s^U(\gamma, \varphi)$, below which the firm innovates, and above which it waits.
Proof: Start from equation (13), which I rewrite for reference:

$$V_s = \max\{0, \beta \mathbb{E}_s V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_s, \varphi_1) - \pi_x(\tau_s, \varphi_0)] + (1-\beta)I\}, \qquad (24)$$

where $V_s \equiv F(\tau_s, \varphi, \gamma) - \Pi_d^I(\varphi_1) + \Pi_d(\varphi_0) - \Pi_x^I(\tau_s, \varphi_1, \gamma) + \Pi_x(\tau_s, \varphi_0, \gamma) + I$ is the option value of waiting. Two conditions are sufficient to establish the uniqueness of the cutoff:

1. $-[\pi_x(\tau_s, \varphi_1) - \pi_x(\tau_s, \varphi_0)]$ is a monotonic function, and since it is increasing in τ, waiting is more attractive than innovating for high τ. This condition is verified.

2. There is positive persistence of uncertainty. This condition is verified since the trade policy regime, $\Lambda(\tau_s, \gamma)$, is a Markov process with transition matrix as in (14), and thus $\Lambda(\tau_{s+1}, \gamma)$ first order stochastically dominates $\Lambda(\tau_s, \gamma)$.

Because of these two conditions, the second part of the max operator in equation (24) is increasing in τ. Thus, if we start with an increasing function, V_s, the right-hand side of (24) gives another increasing function. Therefore, the fixed point of the iteration is an increasing function. Because the solution function of (24) is increasing in τ, there is a unique $\tau_s^U(\gamma,\varphi)$ below which the firm invests in innovation, and above which it waits.

Each firm i has a unique tariff innovation cutoff $\tau_s^U(\gamma,\varphi_i)$. Firms in the differentiated sector differ according to their productivity, φ_i, but face the same τ_s and γ. Thus, for any given τ_s, there is a unique innovation productivity cutoff $\varphi_s^U(\tau_s,\gamma)$, and only firms with productivity higher than $\varphi_s^U(\tau_s,\gamma)$ innovate.

B.2.2 Uncertainty cutoff

Consider now a firm in the intermediate state, $s=1$, with MFN tariffs subject to annual renewal. The productivity threshold with uncertainty is given by the solution to the Bellman equation in (10). By rewriting the Bellman as in (13), the marginal firm has

$$
\begin{aligned}
V_s\left(\varphi_s^U\right) &= 0 && (25)\\
&= \max\{0, \beta\mathbb{E}_s V_s'\left(\varphi_s^U\right) - \left[\pi_d(\eta\varphi_s^U) - \pi_d(\varphi_s^U)\right] - \left[\pi_x(\tau_s,\eta\varphi_s^U) - \pi_x(\tau_s,\varphi_s^U)\right] \\
&\qquad + (1-\beta)I\}, && (26)
\end{aligned}
$$

and the cutoff productivity level φ_s^U is found by equating the second element in the curly bracket to zero. In order to solve for φ_s^U, it is necessary to know the expected option value of waiting for the marginal firm $\mathbb{E}_s V_s'\left(\varphi_s^U\right)$. This can be found by starting with (13) as follows:

Finding $\mathbb{E}_s V_s'$:

Starting with (13)

$$
\begin{aligned}
\mathbb{E}_s V_s' &= \lambda_{s,s+1}\Bigg[\beta\mathbb{E}_{s+1} V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1},\varphi_1) - \pi_x(\tau_{s+1},\varphi_0)] \\
&\qquad + (1-\beta)I\Bigg] \qquad \text{if } \varphi_s^U \le \varphi < \varphi_{s+1}^U \\
&= \lambda_{s,s+1}\Bigg[\beta\left(\frac{\lambda_{s+1,s+1}}{1-\beta\lambda_{s+1,s+1}}\Big[I(1-\beta) - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1},\varphi_1) - \pi_x(\tau_{s+1},\varphi_0)]\Big]\right) \\
&\qquad - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1},\varphi_1) - \pi_x(\tau_{s+1},\varphi_0)] + (1-\beta)I\Bigg] \\
&= \frac{\lambda_{s,s+1}}{1-\beta\lambda_{s+1,s+1}}\Big[I(1-\beta) - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1},\varphi_1) - \pi_x(\tau_{s+1},\varphi_0)]\Big], && (27)
\end{aligned}
$$

where $\beta\mathbb{E}_{s+1} V_s'$ is the conditional expectation starting at $s+1$:

$$
\begin{aligned}
\mathbb{E}_{s+1} V_s' = \lambda_{s+1,s+1}\Big[&\beta\mathbb{E}_{s+1} V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1},\varphi_1) - \pi_x(\tau_{s+1},\varphi_0)] \\
&+ (1-\beta)I\Big] \qquad \text{if } \varphi_s^U \le \varphi < \varphi_{s+1}^U \\
= &\frac{\lambda_{s+1,s+1}}{1-\beta\lambda_{s+1,s+1}}\Big[I(1-\beta) - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1},\varphi_1) - \pi_x(\tau_{s+1},\varphi_0)]\Big] \qquad (28)
\end{aligned}
$$

Using (27) in (25) gives:

$$
\begin{aligned}
&\left(1 + \frac{\beta\lambda_{s,s+1}}{1-\beta\lambda_{s+1,s+1}}\right)\Big[\pi_d(\eta\varphi_s^U) - \pi_d(\varphi_s^U)\Big] + \Big[\pi_x(\tau_s,\eta\varphi_s^U) - \pi_x(\tau_s,\varphi_s^U)\Big] \\
&\quad + \left(\frac{\beta\lambda_{s,s+1}}{1-\beta\lambda_{s+1,s+1}}\right)\Big[\pi_x(\tau_{s+1},\eta\varphi_s^U) - \pi_x(\tau_{s+1},\varphi_s^U)\Big] = (1-\beta)I\left(1 + \frac{\beta\lambda_{s,s+1}}{1-\beta\lambda_{s+1,s+1}}\right)
\end{aligned}
$$

This equation shows that, whenever trade policy in either of the absorbing states, the equation reduces to the investment indifferent condition in the deterministic case. Starting at the intermediate policy state,$s = 1$, instead, and replacing π_x and π_d with the equations (1) and (2) in 2, the productivity cutoff in the intermediate state is given by:

$$
\begin{aligned}
&\left(\varphi_1^U\right)^{\sigma-1}\left[\left(1 + \frac{\beta\lambda_{12}}{1-\beta\lambda_{22}}\right)B_d(\eta^{\sigma-1}-1) + \frac{\beta\lambda_{12}}{1-\beta\lambda_{22}}B_x\tau_2^{-\sigma}(\eta^{\sigma-1}-1) + B_x\tau_1^{-\sigma}(\eta^{\sigma-1}-1)\right] \\
&\qquad = (1-\beta)I\left(1 + \frac{\beta\lambda_{12}}{1-\beta\lambda_{22}}\right) \\
&\left(\varphi_1^U\right)^{\sigma-1}\Big[(1+u(\gamma))B_d(\eta^{\sigma-1}-1) + u(\gamma)B_x\tau_2^{-\sigma}(\eta^{\sigma-1}-1) + B_x\tau_1^{-\sigma}(\eta^{\sigma-1}-1)\Big] \\
&\qquad = (1-\beta)I\,(1+u(\gamma)) \\
&\left(\varphi_1^U\right)^{\sigma-1}\left[(1+u(\gamma))B_d(\eta^{\sigma-1}-1) + (\eta^{\sigma-1}-1)B_x\tau_1^{-\sigma}\left(u(\gamma)\left(\frac{\tau_2}{\tau_1}\right)^{-\sigma} + 1\right)\right] \\
&\qquad = (1-\beta)I\,(1+u(\gamma)) \\
&\qquad \varphi_1^U = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)\left(B_d + B_x\tau_1^{-\sigma}\frac{1+u(\gamma)\omega}{1+u(\gamma)}\right)}\right)^{\frac{1}{\sigma-1}} \qquad (29) \\
&\qquad\quad = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)\left(B_d + B_x\tau_1^{-\sigma}U(\gamma,\omega)\right)}\right)^{\frac{1}{\sigma-1}}
\end{aligned}
$$

$U(\gamma,\omega) \equiv \frac{1+u(\gamma)\omega}{1+u(\gamma)}$ is an uncertainty factor, $\omega \equiv \left(\frac{\tau_2}{\tau_1}\right)^{-\sigma}$ is the ratio of export profits under "column 2" tariffs, relative to the temporary MFN state. $\gamma \equiv 1-\lambda_{11}$, and $\gamma\lambda = \lambda_{12}$, $u(\gamma) \equiv \frac{\beta\gamma\lambda}{1-\beta}$.

C Patents as a measure of innovation

In this session, I examine whether patents can be used as a measure of innovation. In particular, I provide descriptive evidence suggesting that the output of the innovation process, namely patents, is correlated with one of the main inputs of the innovation process, namely R&D expenditures, both on the extensive and on the intensive margin. I use firm level R&D expenditures data from China's National Bureau of Statistics (NBS), and patent data from the China's State Intellectual Property Office (SIPO). [57] Patents are linked to Chinese firms using the concordance provided by He et al. (2018). I keep all firms that are active [58] in the period.

On the intensive margin, I find that firms that spend more on R&D also apply for more patents. Figure 5 shows a kernel-weighted local polynomial regression of firm's R&D expenditures on the number of patent applications. The relationship is strong and positive. The corresponding coefficient on a linear regression slope is 0.76 (s.e. 0.03).

On the extensive margin, the data show that firms with at least one patent application on average tend to spend more on R&D. I divide firms in two groups, firms that applied for at least on patent in the period 2005-2007 [59], and firms that did not, and look at the distribution of their R&D expenditures. Figure 6 shows a histogram of average R&D spending for firms with (white) and without (gray) patents. While the shapes of the distributions are very similar, the distribution of the group of firms with at least one patent application is shifted to the right, suggesting a positive correlation between firm's R&D expenditures and patent filing.

D Additional tables and figures

[57] I have access to R&D expenditures for the period 2005-2007, and patent data for the period 1998-2007. For consistency, I use both R&D expenditures and patent data for the years 2005-2007.

[58] A firm is considered active if it has both positive output and positive employment in the reference period.

[59] I have access to firm level R&D expenditures only for the period 2005-2007.

Table 7: Event timing

	(1)	(2)	(3)	(4)
$1990 \times \ln\text{TPU}_j \times$ CN	0.119	0.216	0.329	0.000
	(0.394)	(0.374)	(0.371)	(.)
$1991 \times \ln\text{TPU}_j \times$ CN	0.007	0.143	0.436	0.000
	(0.383)	(0.360)	(0.345)	(.)
$1992 \times \ln\text{TPU}_j \times$ CN	0.077	0.195	0.461	0.000
	(0.325)	(0.312)	(0.322)	(.)
$1993 \times \ln\text{TPU}_j \times$ CN	−0.284	−0.166	0.160	0.000
	(0.330)	(0.317)	(0.334)	(.)
$1994 \times \ln\text{TPU}_j \times$ CN	−0.251	−0.173	0.018	0.000
	(0.336)	(0.322)	(0.337)	(.)
$1995 \times \ln\text{TPU}_j \times$ CN	−0.534	−0.473	−0.362	−0.411
	(0.345)	(0.333)	(0.347)	(0.348)
$1996 \times \ln\text{TPU}_j \times$ CN	−0.027	0.001	0.023	−0.013
	(0.289)	(0.283)	(0.305)	(0.303)
$1997 \times \ln\text{TPU}_j \times$ CN	−0.312	−0.289	−0.190	−0.228
	(0.293)	(0.285)	(0.298)	(0.300)
$1998 \times \ln\text{TPU}_j \times$ CN	−0.306	−0.277	−0.300	−0.327
	(0.275)	(0.270)	(0.284)	(0.284)
$1999 \times \ln\text{TPU}_j \times$ CN	−0.168	−0.167	−0.124	−0.158
	(0.251)	(0.250)	(0.260)	(0.260)
$2000 \times \ln\text{TPU}_j \times$ CN	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
$2001 \times \ln\text{TPU}_j \times$ CN	0.700^a	0.708^a	0.827^a	0.843^a
	(0.255)	(0.252)	(0.272)	(0.270)
$2002 \times \ln\text{TPU}_j \times$ CN	0.597^b	0.570^c	0.794^a	0.787^b
	(0.301)	(0.298)	(0.308)	(0.307)
$2003 \times \ln\text{TPU}_j \times$ CN	0.418	0.348	0.483^c	0.504^c
	(0.289)	(0.283)	(0.287)	(0.287)
$2004 \times \ln\text{TPU}_j \times$ CN	0.581^b	0.553^b	0.647^b	0.682^b
	(0.272)	(0.263)	(0.278)	(0.276)
$2005 \times \ln\text{TPU}_j \times$ CN	0.620^b	0.569^b	0.809^a	0.840^a
	(0.300)	(0.290)	(0.298)	(0.300)
$2006 \times \ln\text{TPU}_j \times$ CN	0.566^c	0.542^c	0.660^b	0.684^b
	(0.315)	(0.302)	(0.311)	(0.313)
$2007 \times \ln\text{TPU}_j \times$ CN	0.743^b	0.703^b	0.983^a	1.015^a
	(0.356)	(0.340)	(0.353)	(0.358)
Observations	11196	873270	864396	622739
Adj. R^2	0.87	0.91	0.91	0.92
Fixed effects	t, j	nt, jt, jn	nt, jt, jn	nt, jt, jn
Other controls includes	*No*	*No*	*Yes*	*Yes*
Estimation	*DID*	*DDD*	*DDD*	*DDD*

Notes: The table reports generalized difference-in-differences (columnn 1) and triple difference-in-differences (columns 2-4) estimates of a regression of the inverse hyperbolic sine of patents on the interaction of the TPU exposure, the China indicator, and year dummies. Coefficients represent the TPU effect relative to the omitted year, 2000. Constant, time and sector fixed effects in column 1; constant and country-time, country-sector, and sector-time fixed effects in columns 2-4 are included but not reported. Column 3 includes additional controls: time-varying variables– China's MFA exposure, and foreign patent filings at the SIPO in each sector–and interactions of year dummies, the China indicator and time-invariant controls including an indicator of whether the sector faced non-tariff barriers and FDI restrictions in the pre-period, and China's 1995 import tariffs. Column 5 includes also China's imports from the rest of the world. Data span 1990 to 2007. Total sample in columns 5 is reduced because import data are not available before 1995. Robust standard errors are clustered at the 4-digit IPC sector-country level and displayed in parentheses. [a] significant at the 1 percent level, [b] significant at the 5 percent level, [c] significant at the 10 percent level.

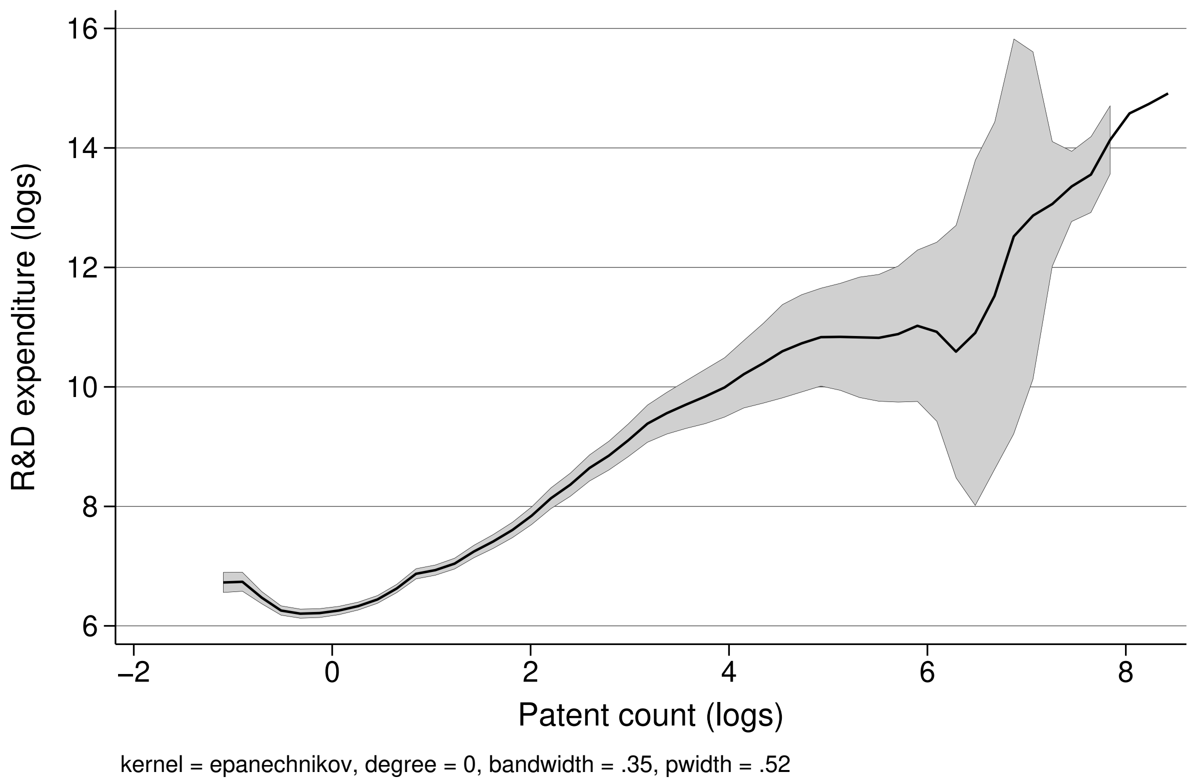

Figure 5: R&D expenditures and patenting. Intensive margin.

Note: The figure shows the average number of patent applications per year and average R&D expenditures per year (both in logs). R&D expenditures and patents refer to the period 2007-2009. The solid line is the local polynomial regression fit and the gray area represents the 95% confidence bands. The linear regression slope is 0.76 (s.e. 0.03).

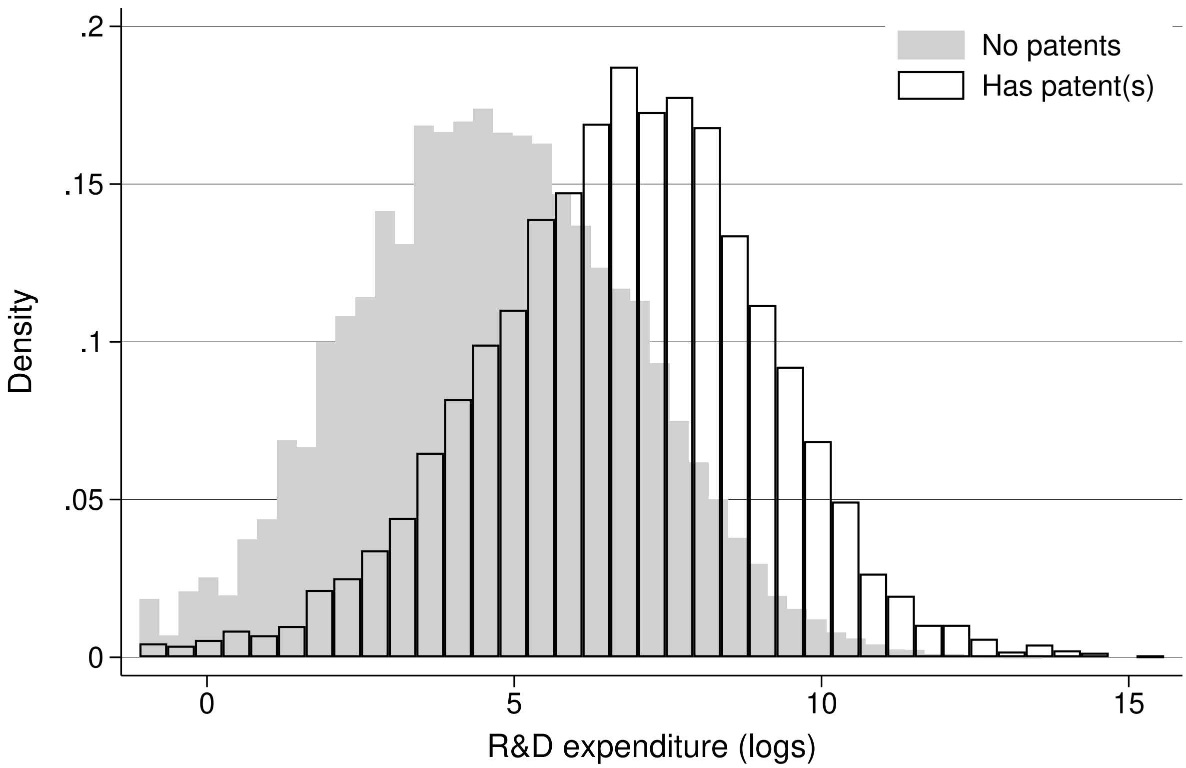

Figure 6: R&D expenditures and patenting. Extensive margin.

Note: The figure shows the distribution of firms' R&D expenditures (in logs) for firms with (white) and without (gray) patent applications in the period 2005-2007.

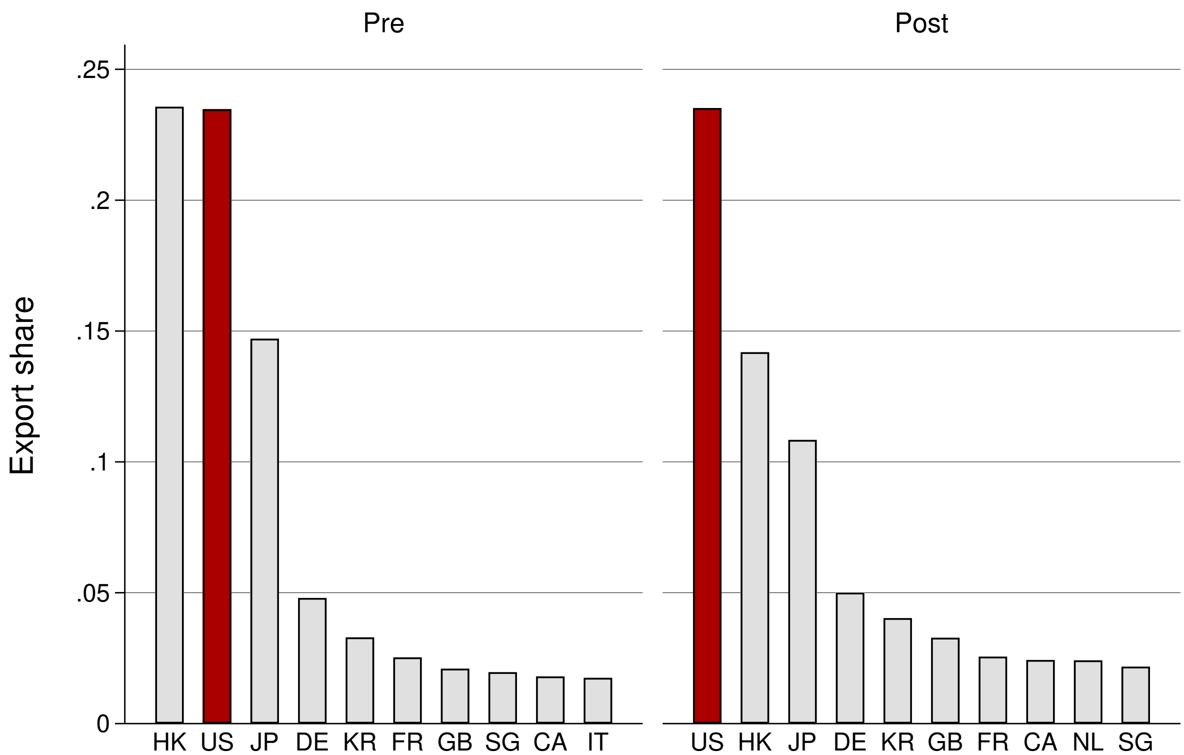

Figure 7: Share of China's export value by destination country.

Note: The figure shows the share of China's export value by destination country for the pre- and post-period. Export value is aggregated by pre-period (1995-2000) and post-period (2001-2007) to calculate the export share. Only top 10 destination countries are shown.