Trade policy uncertainty and innovation:
Evidence from China

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Abstract

This paper investigates the effect of trade policy uncertainty (TPU) on innovation using patent data. Access to large markets is an important driver of innovation, but uncertainty generates an option value of waiting which reduces investment, and may attenuate an important source of dynamic gains from trade. This paper exploits China's accession to the WTO, and the resulting conferral of permanent MFN status by the US, to estimate the causal effect of TPU on innovation in Chinese industries. Using a triple difference in differences, I find higher innovative activity in industries *ex-ante* exposed to larger potential profit losses than in industries exposed to lower potential profit losses, after the source of uncertainty is eliminated.

1 Introduction

Policy uncertainty varies a lot over time, but recent literature has documented an upwards trend since the 1960s, and particularly high average levels since 2008 compared to recent history (Baker et al., 2016). There is also emerging evidence that policy-related economic uncertainty matters for economic performance, and that firms' investment behavior is consistent with the theoretical mechanism highlighted by the real option literature[1]Baker et al. (2016): in the presence of sunk investment costs, uncertainty increases the range of inaction where the firm does not invest as it prefers a wait and see strategy

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[1]Baker et al. (2016) find that higher policy uncertainty is associated with reduced investment and employment in sectors highly exposed to government spending. Building on the approach of Baker et al. (2016), other authors have found that policy uncertainty is associated with sizable effects on economic performance. .

(Bernanke, 1983; Dixit and Pindyck, 1994; Bloom et al., 2007). But while recent work, such as the the news-based economic policy uncertainty (EPU) index developed by Baker et al. (2016), has made significant progress in measuring policy uncertainty, causal identification of the effect of policy uncertainty on investment behavior remains challenging because policy responds endogenously to economic conditions.

In this paper, I use a change in US trade policy towards China to establish causal evidence that reducing policy uncertainty increases investment in innovation. I study the impact of transitioning from annual to permanent MFN status[2] on innovation in Chinese industries. The conferral of Permanent Normal Trade Relations (PNTR) is particularly suitable to test empirically the cautionary effects predicted by the real option literature because it significantly reduced the probability that the US would revoke China's temporary MFN status and revert to the much higher column 2 tariffs assigned to non-market economies, but it didn't change the effective tariff rates applied to Chinese imported goods. Equally important for identification is the fact that 85% of the variation in the exposure to trade policy uncertainty comes from the column 2 tariffs, which were established in 1930 under the Smoot-Hawley Tariff Act, making the PNTR a plausibly exogenous shock.

Using trade policy to causally identify the effect of policy uncertainty is interesting for two reasons. First, the recent trade literature has emphasized the complementarities between improved access to foreign markets, innovation and technological upgrading in a deterministic framework (Lileeva and Trefler, 2010; Bustos, 2011; Coelli et al., 2018). In this paper I show that reducing uncertainty with respect to future foreign market access increases investment in technological innovation, and, more generally, that the role played by trade policy uncertainty is complementary to the role played by the level of protection.

Second, US trade policy and the increased protectionism are at the forefront of current political debate. The average level of the news-based trade policy uncertainty (TPU) index developed by Baker, Bloom and Davis is five times higher since Trump's election and the announcement of tariff hikes against China relative to the previous decade.[3] But the imposition of new tariffs on imports from China makes it challenging to disentangle the effect of increased policy uncertainty from the effect of an increased level of protection. The analysis I present in this paper can inform on the effect of uncertainty alone, because in the context of the PNTR I examine, applied tariffs did not change.

[2]Normal Trade Relations (PNTR) is the US term for MFN status, and Permanent Normal Trade Relations (PNTR) is often used to refer to the conferral of permanent MFN status to China. I will use these terms interchangeably.

[3]`http://www.policyuncertainty.com/index.html`

To guide empirical work, I introduce technology choice under uncertainty in a partial equilibrium model of trade with heterogeneous firms. The model is a variation of Handley and Limão (2017) and combines two mechanisms: the option value of waiting from the real option literature (Bernanke, 1983; Dixit, 1989; Dixit and Pindyck, 1994; Bloom et al., 2007), 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 only the most productive firms find paying the cost to innovate profitable. But unlike Bustos (2011), the cost to innovate is sunk, and, combined with uncertainty with respect to foreign market access, it generates a 'band of inaction' where the firm does not invest and keeps the low technology. In this set up, trade policy uncertainty requires firms to be more productive in order to innovate compared to deterministic scenario; a reduction in uncertainty reduces the option value of waiting, and induces more firms to innovate.

I test this mechanism within Chinese industries in the context of the conferral of permanent MFN status by the US in 2001. China obtained MFN status from the US in 1980, conditional on annual renewal. While nearly authomatic in the beginning, the renewal process became highly uncertain and politically contentious after the Tienanmen Square incident in 1989. 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,[4] although, in practice, China has never lost the MFN status.[5] 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 10 export markets.[6][7] The implied potential profit losses, proxied by the difference between column 2 and MFN tariffs, were also large. The average US applied MFN tariff was 4%, while the average column 2 tariff was 31%, with lots of heterogeneity across industries.

The model predicts that in industries where the difference between column 2 and MFN tariffs is larger, the productivity cutoff to invest in new technology falls more when uncertainty is eliminated. To take the model to the data, I use the fact that, although all firms faced the same probability of a trade policy shock, the difference between MFN

[4]Figure 5 in Appendix A shows Congress votes against the renewal of China's MFN status for all years in the period 1990-2001. Pierce and Schott (2017) provide extensive evidence that the US threat of revoking China's MFN status was concrete.

[5]China didn't lose its MFN status because of the lack of support by the US Senate.

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

[7]Table 8 and Figure 8 show China's export value shares to its main export markets before and after 2001.

tariffs and the much higher column 2 tariffs varied across industries, as tariffs are industry specific. Intuitively, firms in industries with larger gaps were more exposed to profit losses had the US reverted to column 2 tariffs, and are expected to respond more strongly to a reduction in TPU when the US grants permanent MFN status to China and source of uncertainty is eliminated.

The empirical identification is based on a generalized triple difference-in-differences estimation, where the source of variation is the difference between column 2 and MFN tariffs across industries, and where third countries' outcomes are used to remove industry specific trends in innovation. Empirically, I measure innovation using patent data. I use the comprehensive dataset Patstat, which allows me to 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 is 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, and compare patenting in sectors initially exposed to high *vs* low potential profit losses (1^{st} difference), before and after PNTR conferral (2^{nd} difference), across countries (3^{rd} difference).

The main advantage of this approach is that I can difference out technology and industry trends in patenting that could bias the estimated coefficient in a simple difference in differences. This is important because after WTO accession China implemented several reforms to liberalize its economy, and it is possible that industries with high and low potential losses have different trends in patenting after 2001 due to these reforms. Also, both the likelihood of patenting and the sunk R&D investment costs vary by industry and/or product, and industry fixed effects are suitable to eliminate these differences only to the extent that they constant over time.

Consistently with the theoretical predictions, I find a positive relationship between higher initial TPU exposure and subsequent innovation, which is statistically and economically significant. The baseline results show that a 1% increase in TPU exposure before the PNTR lead to 1% increase in patented innovation after uncertainty is reduced. This implies that moving from the first to the third tercile of the observed TPU distribution increases patenting by 0.24 log points. This result is robust to directly controlling for contemporaneous policy changes in China, which include the elimination of FDI restrictions, the phasing out of Multi-fiber Agreement (MFA) quotas, and the reduction of China's own import tariffs, and idiosyncratic demand shocks in China, using both China's import data and the aggregate patent application filed in China by foreign firms. While the triple difference in differences swipes out idiosyncratic trends in patenting that are common across countries within the same technology, these additional controls eliminate potentially remaining technology trends that are specific to China.

After establishing the effect of trade policy uncertainty on innovation, I use trade data from Comtrade to investigate the underlying mechanism, and show that there is a positive relationship between higher *ex-ante* exposure to TPU and increased export to the US.[8] I then perform a two-stage least square exercise, which uses TPU as instrument for export value, and where both the first stage and the reduced form equations are interesting in their own right. The effect of TPU on export is the first stage, the effect of TPU on innovation is the reduced form, and the IV estimate is the effect of (increased) export on innovation for those that are induced to export because uncertainty with respect to foreign trade policy is reduced or eliminated. Although the TPU exposure treatment is not binary, the two-stage least squares estimated coefficient can be interpreted in a similar way as a local average treatment effect (LATE), that is the effect of export on innovation for a particular group of compliers, those induced to export because of uncertainty reduction, which is a different group from the one identified e.g. in Lileeva and Trefler (2010).

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 contribution goes back to Bernanke (1983) andDixit (1989),[9] while more recent analyses of the impact of uncertainty on investment behavior include Bloom et al. (2007), Bloom (2009) and Bloom (2014).[10] Closer in spirit to this article are the papers exploring the implications of policy uncertainty on investment, which remain less well understood, partially due to the difficulties in measuring and quantifying policy uncertainty, and conducting causal inference. Baker et al. (2016) develop a news-based economic policy uncertainty (EPU) index and show that higher EPU is associated to reduced employment and investment in sectors highly exposed to government spending, while Handley and Limão (2017) exploit the PNTR to analyze the effect of TPU on the decision to export to an uncertain foreign market. The analysis I present in this paper differs from Baker et al. (2016) in that it exploits plausibly exogenous variation in exposure to policy uncertainty to provide causal evidence that reducing TPU increases investment in innovation. Compared to Handley and Limão (2017), the focus of this analysis is on the decision to invest in innovation, which is complementary to the export decision they analyze. Handley and Limão document some indirect evidence of technological upgrading that is specific to the export market.

[8] This is the main results obtained by Handley and Limão (2017).

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

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

The model and the empirical analysis I present in this paper are different in three aspects. First, in the model I present the investment in innovation is general in scope and increases firm's productivity as in Bustos (2011), whereas in Handley and Limão (2017) it is specific to the export market and reduces the marginal export cost. Second, investment in innovation is measured empirically using patent data, which represent a direct output-based measure of the innovation process, in the absence of reliable data on technology and R&D expenditures, whereas Handley and Limão (2017) provide indirect evidence. Third, the availability of patent data for countries other than China make it possible to implement a triple difference-in-differences to remove industry specific trends in innovation.

The second building block of this paper is the literature that examines the interaction between market size, exporting and investment in technology upgrade. The importance of market size for innovation has been known at least since Schmookler (1954). More recently, the literature on heterogeneous firms and trade has emphasized the complementarities between exporting and investing in productivity-enhancing activities Bustos (2011); Lileeva and Trefler (2010); Coelli et al. (2018). The main contribution to this literature is the introduction of uncertainty with respect to foreign market access, which isolates the effect of uncertainty on investment in innovation, and highlights a complementary channel to the reduction of the foreign level of protection examined in Bustos (2011); Lileeva and Trefler (2010). This also underlines the value of credible trade agreement for the dynamic gains from trade to fully materialize.

The paper also relates to a growing literature that looks more closely at TPU and at the PNTR shock as the work by Pierce and Schott (2016), Handley and Limão (2017), Feng et al. (2017), Handley and Limão (2015), Pierce and Schott (2017), and Amiti et al. (2017). Differently from these papers, that focus primarily on firm dynamic export decisions, I look at a different outcome, namely investment in R&D as measured by patent data.[11]

The uncertainty faced by China before obtaining permanent MFN status is unique. However, the framework used in this paper is useful to analyze the implications of other conditional trade preferences. Wealthier economies like the US, the European Union and Japan, often give developing countries unilateral preferential treatment. The largest program is the Generalised Scheme of Preferences (GSP), which allows to condition preferential market access on a country's compliance with human or labor rights practices or other requirements. For example, the European Union's Generalised System of Preferences Plus (GSP+) grants zero or reduced import tariffs to its beneficiaries in return for compliance with labour rights, human rights, good governance and environmental

[11] Pierce and Schott (2017) look at the manufacturing investment and capital stock in the US, and find that rising import competition from China resulting from reduced TPU decreases investment on average.

protection.[12] GSP involve a tariff reduction effect, and potentially an uncertainty effect due to the conditionality clause, and it is empirically difficult to disentangle the two. The example of China is useful because US applied tariffs didn't change after 2001, and therefore the admission to the WTO can be used to identify the effect of uncertainty on export and innovation.

The framework presented in this paper is also useful to better understand the effect of a large binding overhang, the gap between bound and applied MFN tariffs, for WTO members. When countries join the WTO or when WTO members negotiate tariff levels during trade rounds, they typically agree on bound tariff rates, and are free to increase their applied tariffs as long as they don't exceed their bound levels. A large binding overhang, makes a country's trade policy less predictable, and can make access to foreign markets less secure. However, bound rates are often endogenously chosen, and thus identification is challenging. The case of China allows to overcome this challenge, as column 2 tariffs where decided well in advance.

The rest of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 discusses the identification strategy and discusses the empirical model. Section 4 describes the data. Section 5 presents the empirical results. Section 6 discusses and provides evidence of the mechanism. Section 7 concludes.

2 Economic framework

To analyze the effect of trade policy uncertainty on innovation, I start by presenting a basic economic framework to describe the main mechanisms, and provide the intuition for the empirical strategy.

To do so, I consider a variation of Handley and Limão (2017), and focus on the firm's decision to invest in R&D. 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,[13] characterized by monopolistic competition,

[12]This conditionality has been enforced on three occasions agains Myanmar, Sri Lanka and Pakistan.

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

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.[14] The innovation choice is binary as in Bustos (2011): investment in R&D produces a high type technology,[15] 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,[16] or per-period fixed cost, which implies that all firms active in the domestic market also export to the foreign market.[17] 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 is a measure of domestic market size, and A_x is a measure of foreign market size.[18] p_{ix} is consumer price, inclusive of tariff;[19] 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

[14]"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).

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

[16]Including a sunk cost to enter the foreign market would generate an option value associated with entry. Although empirical evidence suggests that this sunk cost is relevant, I abstract from this to focus on the R&D investment decision. Handley and Limão (2017) analyze the effect of a sunk cost of exporting on firm's foreign market entry decision, and find that policy uncertainty substantially reduces firms' entry.

[17]There is also no endogenous exit.

[18]$A_n = E_n P_n^{\sigma-1}$, where E is the demand shifter, and $P_n^{\sigma-1}$ is the CES price index for the differentiated sector.

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

the low type technology, profits are:

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

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 for the firm 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, $T = \tau - 1$.[20] At any period t, the current value of τ_t is known, but future values τ_{t+1} are random variables. 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 is 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

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

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

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

[20]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.

$\mathbb{E}_s$ 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.

To understand the role of uncertainty, it is useful to consider the firm's dynamic problem 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. In the next period, the same choice will be available again. 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

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

Investment is optimal whenever

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

and waiting is optimal when the opposite is true.

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,[21] there is a unique threshold value of τ_s, $\tau_s^D(\varphi_i)$, which generates a clean division of the range of τ_s into a 'continuation region' and a 'stopping region': if $\tau_s > \tau_s^D(\varphi_i)$ it is optimal to wait; if $\tau_s < \tau_s^D(\varphi_i)$ if is optimal to invest. The cutoff $\tau_s^D(\varphi_i)$ must satisfy

$$\Pi_d^I(\varphi_1) - \Pi_d(\varphi_0) + \Pi_x^I(\tau_s^D, \varphi_1) - \Pi_x(\tau_s^D, \varphi_0) - I = \beta \mathbb{E}_s F(\tau_s'^D, \varphi). \tag{12}$$

Thus, under uncertainty, the investment indifferent condition becomes:

$$F(\tau_s^D, \varphi) = \Pi_d^I(\varphi_1) - \Pi_d(\varphi_0) + \Pi_x^I(\tau_s^D, \varphi_1) - \Pi_x(\tau_s^D, \varphi_0) - I. \tag{13}$$

To understand the role of uncertainty, it is useful to rearrange (10) by subtracting $\Pi_d^I(\varphi_1) - \Pi_d(\varphi_0) + \Pi_x^I(\tau_s, \varphi_1) - \Pi_x(\tau_s, \varphi_0) - I$ from both sides of the equal sign to obtain[22]

$$\begin{aligned}
F(\tau_s,\varphi) - \Pi_d^I(\varphi_1) + \Pi_d(\varphi_0) - \Pi_x^I(\tau_s, \varphi_1) + \Pi_x(\tau_s, \varphi_0) + I& \\
= \max\{0, \beta \mathbb{E}_s \Big[F(\tau_s', \varphi) - \Pi_d'^I(\varphi_1) + \Pi_d'(\varphi_0) - \Pi_x^I(\tau_s', \varphi_1) + \Pi_x(\tau_s', \varphi_0)\Big]& \\
- [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_s, \varphi_1) - \pi_x(\tau_s, \varphi_0)] + I\}& \qquad (14) \\
V_s = \max\{0, \beta \mathbb{E}_s V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_s, \varphi_1) - \pi_x(\tau_s, \varphi_0)]& \\
+ (1-\beta) I\}& \qquad (15)
\end{aligned}$$

where $V_s \equiv F(\tau_s, \varphi) - \Pi_d^I(\varphi_1) + \Pi_d(\varphi_0) - \Pi_x^I(\tau_s, \varphi_1) + \Pi_x(\tau_s, \varphi_0) + I$ 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

[21] Under reasonable assumption the cutoff value of $\tau_s^D(\varphi_i)$ is unique. First, it is required to assume persistence in uncertainty. Second, the flow payoff from continuation, zero in this case, relative to the termination payoff, must be a monotonic function; when this function is increasing in τ_s, then investment is optimal when $\tau_s^D(\varphi_i)$.

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

R&D. When $\tau_s = \tau_s^D(\varphi_i)$ 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

To understand the effect of TPU on innovation, it is useful to think about China's MFN temporary status in the 90's as an intermediate policy state. Each year, there is a probability γ that this status changes, giving rise to a high protection state, in which column 2 tariffs apply, with probability λ, or to a low protection state (credible trade agreement) with probability $1-\lambda$.[23]

There is only trade policy uncertainty in the intermediate state ($\gamma > 0$), whereas γ=0 after the US reverts to column 2 tariffs or after a credible trade agreement between the US and China is signed.

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

Formally, the trade policy regime is characterized by a Markov process with three possible policy states as in Handley and Limão (2017). The policy states are: column 2 tariffs (s=2), temporary MFN tariffs (s=1), and a credible trade agreement (s=0), with the associated tariff values $\tau_2 \geq \tau_1 \geq \tau_0$. The extreme states (s=2 and s=0) are assumed to be absorbing. Let $\lambda_{ss'}$ denote the transition probability from state s to s'. The policy

[23] The same qualitative predictions can be obtained if the probability of a trade agreement 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).

transition matrix S summarizes the transition probabilities for all possible states:

$$S = \begin{bmatrix} \lambda_{00} & 0 & 0 \\ \lambda_{10} & \lambda_{11} & \lambda_{12} \\ 0 & 0 & \lambda_{22} \end{bmatrix}, \tag{16}$$

where $\lambda_{11} = (1-\gamma)$, $\lambda_{12} = \gamma\lambda$, and $\lambda_{10} = \gamma(1-\lambda)$. In this specific context, $\gamma \in (0,1)$ in the 90s, while it becomes zero after China joins the WTO in 2001, and thus uncertainty with respect to US trade policy is resolved. I will use this change in γ after 2001 as a policy shock to identify the effect of uncertainty on innovation. This shock is common across industries, but the relative difference in profits under temporary MFN and column 2 tariffs status varies across industries, and provides the source of variation for the empirical analysis.

2.3 Partial equilibrium

To understand the effect of TPU on firms' R&D investment, it useful to find and compare the productivity threshold level that induces firms to innovate under a deterministic scenario and under uncertainty. Consider a partial equilibrium in which applied tariffs τ_s are the only source of uncertainty, and changes in trade policy state leave the aggregate variables E_n and P_n unchanged. 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):

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

$$\varphi_s^D = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)(B_d + B_x\tau_s^{-\sigma})}\right)^{\frac{1}{\sigma-1}} \tag{17}$$

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.1), 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 (13):

$$F(\tau_s, \varphi_s^U, \gamma) = \Pi_d^I(\eta\varphi_s^U) - \Pi_d(\varphi_s^U) + \Pi_x^I(\tau_s, \eta\varphi_s^U, \gamma) - \Pi_x(\tau_s, \varphi_s^U, \gamma) - I. \tag{18}$$

By rewriting the Bellman as in (14), the marginal firm has an option value of waiting equal to zero, that is:

$$\begin{aligned} V_s\left(\varphi_s^U\right) &= 0 \\ &= \max\{0, \beta\mathbb{E}_s V_s'\left(\varphi_s^U\right) - \left[\pi_d(\eta\varphi_s^U) - \pi_d(\varphi_s^U)\right] - \left[\pi_x(\tau_s, \eta\varphi_s^U) - \pi_x(\tau_s, \varphi_s^U)\right] \\ &\quad + (1-\beta)I\}, \end{aligned} \tag{19}$$

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

$$\varphi_1^U = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)\left(B_d + B_x\tau_1^{-\sigma}U(\gamma,\omega)\right)}\right)^{\frac{1}{\sigma-1}} \tag{20}$$

$$U(\gamma,\omega) \equiv \frac{1+u(\gamma)\omega}{1+u(\gamma)}. \tag{21}$$

$U(\gamma, \omega)$ 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 $\varphi_1^U =$

φ_1^D. Second, $u(\gamma) > 0$, which implies $\gamma > 0$ and $\lambda > 0$: if $\gamma = 0$, then 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 TPU, whereby more firms find it profitable to innovate when TPU 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.

3 Estimation and identification

I use China accession to the WTO and the conferral of Permanent Normal Trade Relations by the US as a quasi-natural experiment to identify the causal effect of TPU reduction on innovative activity. The empirical strategy exploits time-sector-country variation in a triple difference in differences.

3.1 Identification

The economic framework presented in section 2 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 uncertainty about foreign market conditions is reduced. This should translate in an increase in innovative activity observed in the data after 2001, which I measure using patent data.

The model provides the intuition for one sector, while the identification strategy exploits the fact that sectors are heterogeneous in the difference between column 2 and MFN tariffs, because tariffs are product specific. Industries that are relatively more exposed to TPU before 2001 are expected to innovate more than industries relatively less exposed to TPU when uncertainty is reduced. This is because a larger difference between MFN and column 2 tariffs implies higher profit losses if the US reverts to column 2 tariffs. While the probability of reverting to non-market economy status is the same for all sectors, the potential profit losses in this worst case scenario vary across sectors, because both MFN and column 2 tariffs vary across products. I exploit variation in the log difference between

MFN and column 2 tariffs across products as a source of variation to identify the effect or reduced TPU on innovation.

Identification relies on the assumption that, in the absence of PNTR, firms in sectors relatively more exposed to TPU would have experienced the same trend in patenting/innovation as firms in sectors relatively less exposed to TPU. If this assumption holds, then a difference in differences strategy can be used to identify the causal effect of TPU on innovation.

Identifying the effect of interest may be challenging. The common trend assumption may be violated if firms in expanding sectors are more likely to start exporting and innovating, and are also more likely to face higher potential profit losses, 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 is expected from China. Reassuringly, more than 80% of the variation in the uncertainty exposure measure is explained by variation in the column 2 tariffs, which were set in 1930 under the Smoot-Hawley Tariff Act, while the average MFN tariffs are stable around 4% during the 1990-2001 period.[24]

Another concern is that 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, comparing patenting in sectors exposed to high *vs* low potential profit losses before and after PNTR conferral may lead to a biased estimate of the effect of interest. 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 technical class available in the dataset. The simple difference-in-differences removes time varying trends that are common across sectors within the same country. Adding a third difference allows to remove sector-specific trends that are common across countries. Then, I compare innovation in industries exposed to high *vs* low potential profit losses (1^{st} difference), before and after PNTR conferral (2^{nd} difference), across countries (3^{rd} difference).

Still, the concern remains that contemporaneous policy changes in China are correlated with the PNTR, even after controlling for 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 reduction of its import tariff rates, which are bound at an average of 9 percent, removal of restriction on exporting, importing, and barriers to foreign investment. Finally, China's

[24]The results are robust to using the log of column 2 tariffs as instrument for $lnTPU_j$.

WTO accession coincides with the elimination of quotas for textiles exports under the MFA in 2002 and 2005. If these reforms are disproportionately targeted towards sectors that are both more exposed to potential profit losses and that face higher export and innovation opportunities, for example globally expanding sectors, then sector specific trends in patenting may arise. In other words, it is possible that industries exposed to higher potential losses would have different trends in patenting than industries exposed to lower potential losses, had the PNTR not happened. I explicitly control for the policy changes associated with China's WTO accession to eliminate remaining sectoral trends that are specific to China. Specifically, I include dummies for all Chinese sectors that faced FDI restrictions before 2001,[25] dummies for all product codes subject to MFA quota restrictions before 2001, and the log of China's import tariffs in 1995. All of these controls are measured in the pre-period, and interacted with an indicator for the post-PNTR period and China.[26]

A last remaining concern is that there may be unobserved demand 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[27] for each sector. This controls for both the inflow of goods as a response to increased demand, and the inflow of both patented and non-patented 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.

3.2 Empirical model

To compare innovation in sectors exposed to high *vs* low potential profit losses (1^{st} difference), before and after PNTR conferral (2^{nd} difference), across countries (3^{rd} difference), I estimate the following generalized difference in difference in differences model:

$$\ln(p_{jnt}) = \alpha + \delta_{nt} + \delta_{jn} + \delta_{jt} + \beta PostPNTR_t \times \ln(TPU_j) \times \mathbb{1}\{n = CN\} + \epsilon_{jnt}, \qquad (22)$$

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

[26]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 (23) and construct a weighted average for each IPC patent class.

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

where the dependent variable, $\ln(p_{jnt})$, is the log[28] number of granted patents[29] filed in technology j and year t by all applicants resident in country n. δ_{nt}, δ_{jn}, and δ_{jt} are country-time, country-technology, and technology-time dummies respectively. $PostPNTR_t$ is a dummy denoting the period after China's WTO accession, $\ln(TPU_j)$ is a weighted average of the log difference between column 2 tariffs that the US applies to non-market economies, and MFN tariffs that the US levies on WTO members' goods, and $\mathbb{1}\{n = CN\}$ is an indicator variable equal to one for China, and zero otherwise. The coefficient β identifies the effect of uncertainty, and ϵ_{jnt} is the error term.

The uncertainty exposure measure, $\ln(TPU_j)$, is constructed as follows:

$$\ln(TPU_j) = \sum_h \omega_{jh} ln\left(\frac{\tau_{h2}}{\tau_{h1}}\right), \tag{23}$$

where $\tau_{h2} = 1 + T_{h2}$, and $\tau_{h1} = 1 + T_{h1}$,[30] are the iceberg-equivalent column 2 and MFN tariff lines respectively, aggregated at the HS 6-digit level. I use the τ_{h2} and τ_{h1} for 1999,[31] but both MFN and column 2 tariffs for China are stable over the period.[32] 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 researcher's uncertainty when mapping a patented technology into a specific product.

4 Data

4.1 Tariffs

The source of tariff data is the UNCTAD Trade Analysis Information System (TRAINS). I extract average applied MFN and column 2[33] tariff lines disaggregated at 6-digits level of the Harmonized System (HS) for the US. All tariff lines are converted to their iceberg form, so $\tau_h = 1 + T_h$, where T_h is the *ad-valorem* tariff.

[28] 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.

[29] I use only patents of inventions, and exclude utility models.

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

[31] In November 1999 the US and China sign the bilateral agreement on China's entry into the WTO.

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

[33] 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.

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 can be matched to patent technical classes.

4.2 Patents

I use patents from PATSTAT[34] to measure industries' innovative activity. PATSTAT contains the population of all patents filed globally since the Mid-19th century, and collects a wide range of information (bibliographic information, family links, citations, etc.) of 100 million patent applications from 90 patent authorities. I observe the name and the address of patent applicants. This allows me to identify the population of all applicants resident in a country in the period of analysis. For each application, I observe the filing date, the publication date, and whether, when, and by which patent authority the patent was granted.

To measure the innovative activity in a technology area j in country n in year t, I count patents by application filing year (p_{jt}). 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.[35]

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 Chinese firms.

I use patent families[36] to identify unique inventions, that is identical inventions filed in multiple locations are not double counted. To ensure that patents by Chinese applicants are comparable in terms of quality, validation procedure, and duration of IP protection to patents in other countries, I only use granted[37] patents of inventions, and exclude utility models. 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.

Patents are organized according to their technical features by the International Classification System (IPC), while tariffs are levied on products available in the HS classification. To measure the potential profit losses faced by a firm that considers to invest in a

[34] The European Patent Office's (EPO) Worldwide Patent Statistical Database (henceforth PATSTAT), the October 2016 version.

[35] Patent applications are usually published 18 months after the first application.

[36] I use DOCDB patent family.

[37] 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.

technology and plans to export, it is necessary to link IPC technical classes to HS product codes. I use the Algorithmic Links with Probabilities approach as in Lybbert and Zolas (2014) to match patents to products. I map IPC 4-digit classes to HS 6-digit products. For example, a patent on semiconductors (IPC class H01L) is linked to all products that use semiconductors. For each IPC-HS match, a weight w_{jh} is provided, which defines the quality of the match.[38] I use these weights to construct the uncertainty exposure measure in (23)

4.3 Descriptives

Figure 1 shows the distribution of $ln(TPU_j)$ in 1999, which proxies for industries' differential exposure to uncertainty, and provides the source of variation in the analysis. Table 1 shows mean and standard deviation of $ln(TPU_j)$ in 1999. The potential profit loss faced by Chinese inventors willing to export to the US market is high on average, and there is considerable variation across industries. The average $ln(TPU_j)$ is 0.22, with a standard deviation of 0.12. It is also worth noting that, while log MFN tariff lines are relatively low for all industries, averaging around 0.03, with a standard deviation of 0.03, column 2 tariff lines are very high. The average log column 2 tariff is 0.24, with a large standard deviation of 0.13.

	$ln(\tau_2/\tau_1)$	$ln\tau_2$	$ln\tau_1$
Mean	0.218	0.243	0.025
St. deviation	0.115	0.133	0.030

Notes: 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 (23).

Table 1: Tariffs in 1999

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 potential profit losses within each tercile. Firms investing in technologies in the bottom tercile of $ln(TPU_j)$ faced relatively lower potential losses in the pre WTO phase. The table shows that patent growth is higher in technology areas initially exposed to higher uncertainty, and the difference relative to the lowest tercile is statistically significant.

[38] If no HS product is match to an IPC technology, then the weight w_{jh} is zero.

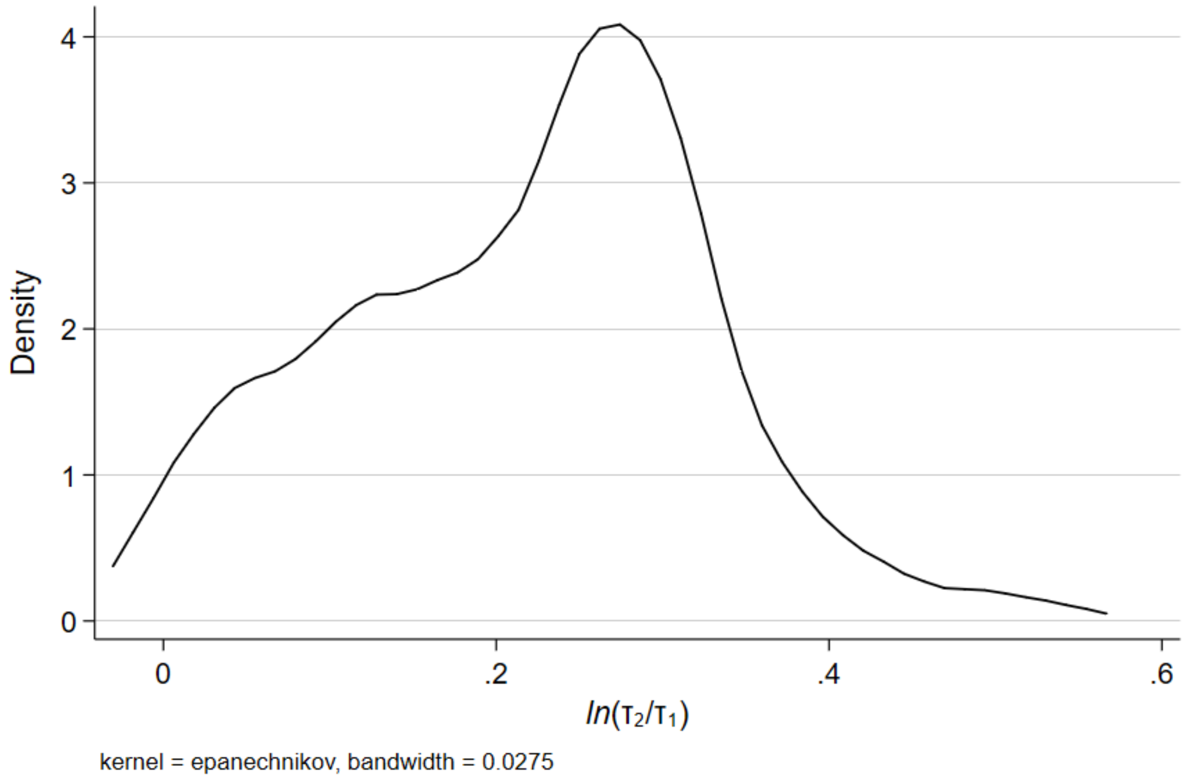

Figure 1: Distribution of TPU_j, 1999.

5 Results

I estimate the triple difference model presented in equation (22). As described in Section 3.1, 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 $\ln(p_{jnt})$ calculated for all countries and sectors available in Patstat, and I exclude the US as they could be themselves affected by the PNTR shock.

Column 1 of Table 3 includes only the DID variable, along with time and sector fixed effects, and thus shows the results obtained by simply comparing high *vs* low potential profit losses sectors, before and after the PNTR. The remaining columns show the results for the triple difference in differences estimation. The second column includes country-time, country-sector, and sector-time dummies. The third column includes controls for contemporaneous policy changes implemented as part of China's WTO accession: FDI barriers, MFA quota elimination, and China import tariffs. The last columns includes controls for unobserved demand shocks: China's sector imports from the rest of the world, and aggregate patenting by foreign applicants in China for each sector. As

		Terciles of $ln(TPU_j)$			
		Lowest	Middle	Highest	All
Uncertainty exposure	Mean	0.09	0.23	0.33	0.22
($lnTPU_j$)	St. dev.	0.05	0.03	0.06	0.11
Patent growth	Mean	2.04	2.32	2.34	2.23
($\Delta ln\bar{p}$)	St. dev.	0.71	0.73	0.72	0.73
Total patents					
(1994-2000)		30188	18553	11684	60425
(2001-2007)		205233	167226	121677	494136

Notes: Patent growth $\Delta ln\bar{p}$ is calculated as the difference in the log average patents between the pre- and post-period.

Table 2: Descriptives patents

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 potential losses coincides 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 TPU in the pre-WTO period leads to a 1% mode 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 TPU distribution is 0.09, while the average $\ln(TPU_j)$ in the highest tercile in 0.33. This indicates that moving from the first to the third tercile of the observed distribution increases patenting by $1 \times (0.33 - 0.09) = 0.24$ log points.

Estimation of model (22) indicates that higher *ex-ante* exposure to TPU is associated with increased patenting activity after uncertainty is eliminated. Nevertheless, one may argue that patents remain an imprecise measure of innovation, and the quality of patents is highly heterogeneous. To mitigate this concern, all specifications use only patents of invention that are successfully granted, and exclude utility models,[39] which are easier and cheaper to obtain and maintain, and less comparable across countries. To further mitigate this concern, column 2, 3, and 4 of Table 3 report the result when using quality adjusted measures in the outcome variable, while column 1 repeats the baseline estimates as reference. I use three proxies for quality that are generally used in the literature: the number of citations, the size of the research team behind a patent, and the patent family

[39]Compared to patents of invention, the requirements to obtain utility models are less stringent, IP protection is usually shorter, generally between 7 and 10 years, and the costs to obtain and maintain them are lower. Utility models are ofter used to patent incremental innovations.

	$ln(p_{jt})$	$ln(p_{jnt})$	$ln(p_{jnt})$	$ln(p_{jnt})$	$ln(p_{jnt})$
$Post \times \ln(TPU_j) \times CN$	1.091^a	0.990^a	1.330^a	1.045^a	1.233^a
	(0.269)	(0.224)	(0.248)	(0.226)	(0.245)
$X_{jCN} \times Post \times CN$	No	No	Yes	Yes	Yes
$X_{jt} \times CN$	No	No	No	Yes	Yes
Observations	11304	880308	868950	868950	626028
Fixed Effects	t, j	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn
Control countries group	–	$all, noUS$	$all, noUS$	$all, noUS$	$all, noUS$

Standard errors clustered by sector-country in parentheses.
^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$

Table 3: Baseline results, DDD

	$ln(p_{jnt})$	$ln(p^C_{jnt})$	$ln(p^I_{jnt})$	$ln(p^F_{jnt})$
$Post \times \ln(TPU_j) \times CN$	1.045^a	0.543	1.288^a	1.122^a
	(0.226)	(0.377)	(0.234)	(0.222)
$X_{jCN} \times Post \times CN$	Yes	Yes	Yes	Yes
$X_{jt} \times CN$	Yes	Yes	Yes	Yes
Observations	868950	868950	868950	868950
Fixed Effects	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn
Control countries group	$all, noUS$	$all, noUS$	$all, noUS$	$all, noUS$

Standard errors clustered by sector-country in parentheses.
^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$

Table 4: Innovation quality, DDD

size.[40] Patents are then weighted by the number of citations (column 2), the number of inventors (column 3), and the family size (column 4). In this way, higher value inventions receive more weight. The results for these quality adjusted measures confirm the findings in the baseline estimation.

5.1 Robustness

This sections 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 the exposure to TPU after the

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

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 (22) with a full set of year dummies:

$$\ln(p_{jnt}) = \alpha + \delta_{nt} + \delta_{jn} + \delta_{jt} + \sum_{y \neq 2000} \beta_y \mathbb{1}\{y = t\} \times \ln(TPU_j) \times \mathbb{1}\{n = CN\} + \epsilon_{jnt}, \tag{24}$$

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

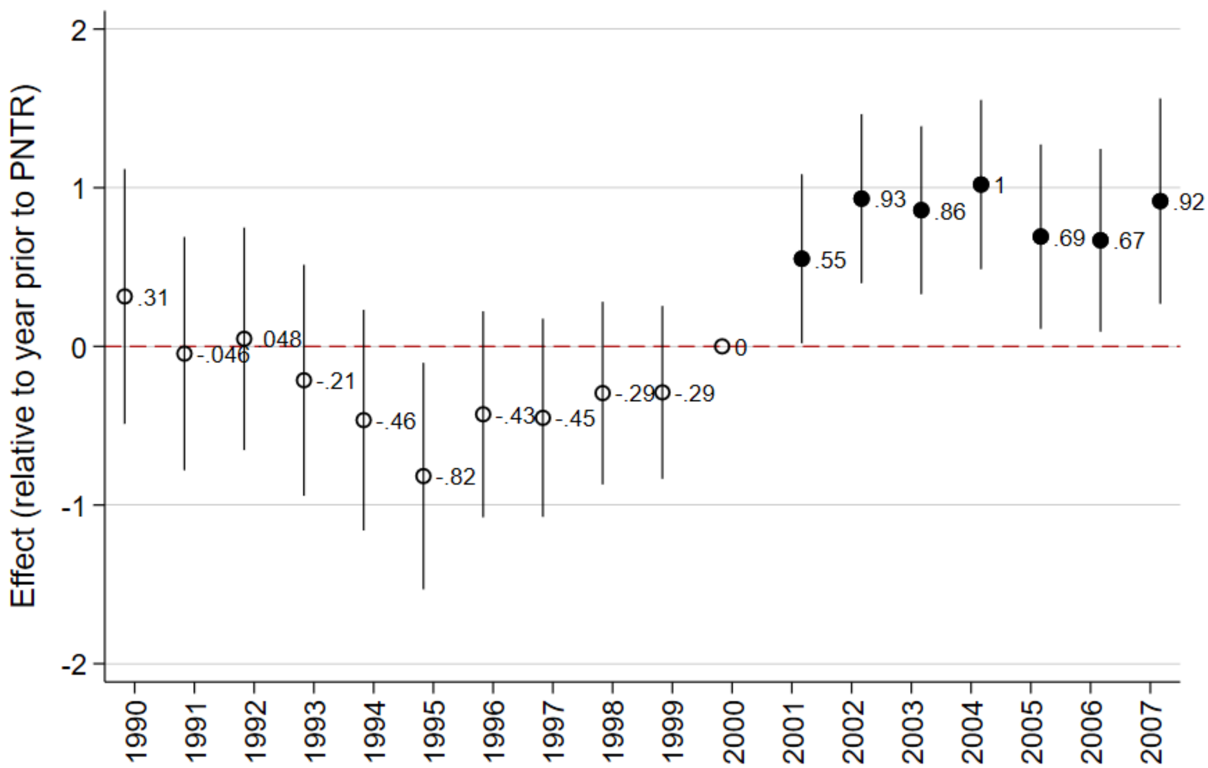

Figure 2: Event timing relative to year prior to PNTR

Placebo reforms: As an additional test of the validity of the empirical strategy, I estimate the effect of placebo reforms before and after the PNTR. Precisely, I estimate the model in equation (22) introducing leads and lags of the reform. While lags indicated a lagged innovation response, the leads should not be significant as they indicate an anticipated effect of the reform. The point estimates are displayed visually in Figure 3. Consistently with the identifying assumption, PNTR leads are statistically insignificant at conventional level.

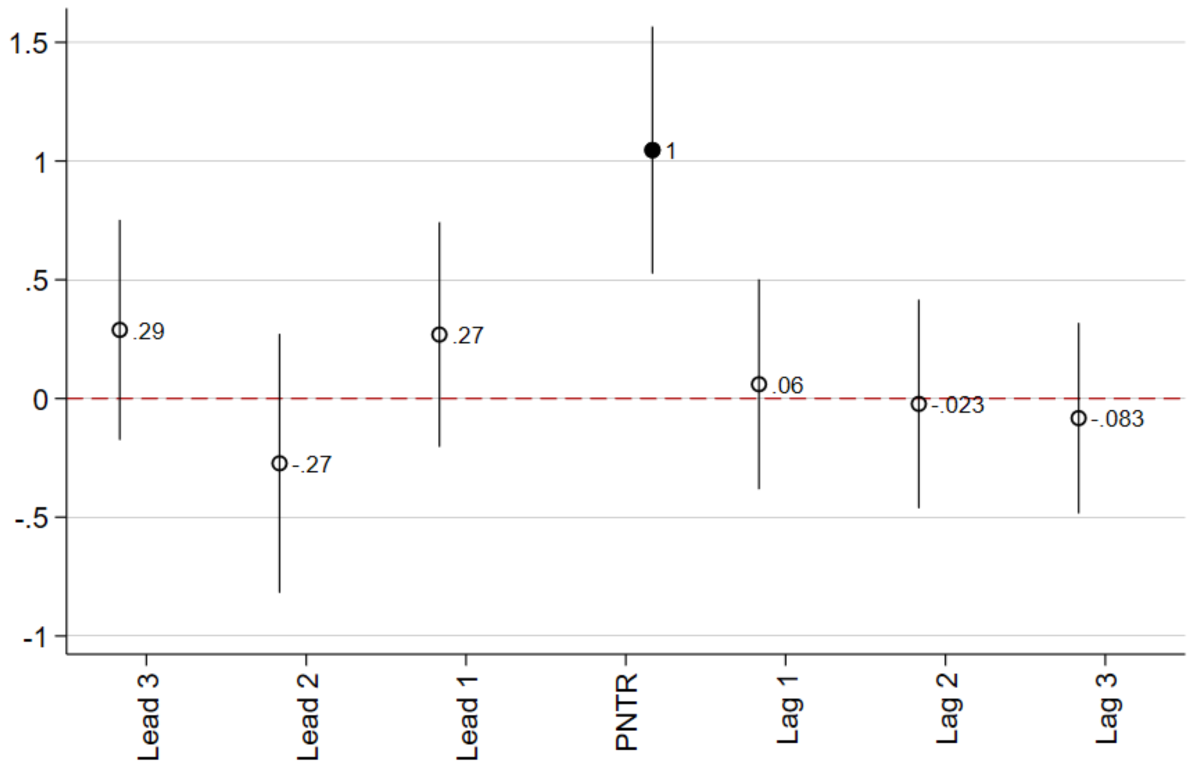

Figure 3: Placebo PNTR, with controls.

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 $lnTPU_j$ with the column 2 tariffs established under the Smoot-Hawley Act. Table 5 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.

Control group: The baseline estimations 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:

	OLS	FS	IV	RF
$Post \times \ln(TPU_j) \times CN$	1.045^a	0.923^a	1.043^a	0.963^a
	(0.226)	(0.010)	(0.223)	(0.205)
$X_{jCN} \times Post \times CN$	Yes	Yes	Yes	Yes
$X_{jt} \times CN$	Yes	Yes	Yes	Yes
Observations	868950	868950	868950	868950
Fixed Effects	nt, jt, jn	nt, jt, jn	nt, jt, jn	nt, jt, jn
Control countries group	$all, noUS$	$all, noUS$	$all, noUS$	$all, noUS$

Standard errors clustered by industry-country in parentheses.
^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$

Table 5: IV

the EU 15 member countries,[41] the Asean economies[42], the Brics,[43], the Eagle,[44] and an additional group of emerging economies which includes the Brics, Mexico, and Turkey. Figure 4 shows graphically how the baseline result is sensitive to the choice of the control group of countries.

6 The Mechanism

In this section, I provide some evidence of the two mechanisms in place that generate the results predicted by the model, namely increased export revenues and the the sunk cost to innovate.

Export: According to the model, reducing trade policy uncertainty increases innovation because it increases export revenue, and firms that have a high option value of waiting would only innovate after access to a large export market is secured. To verify this mechanism, I use data from Comtrade to construct China's and other countries exports to the US over the period 1995-2007.[45] I use the same country-sector-time variation as in model (22), and the same set of controls, to test whether export is higher in sectors

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

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

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

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

[45] The baseline analysis uses data from 1990 to 2007, but export data for China are only available starting in 1995.

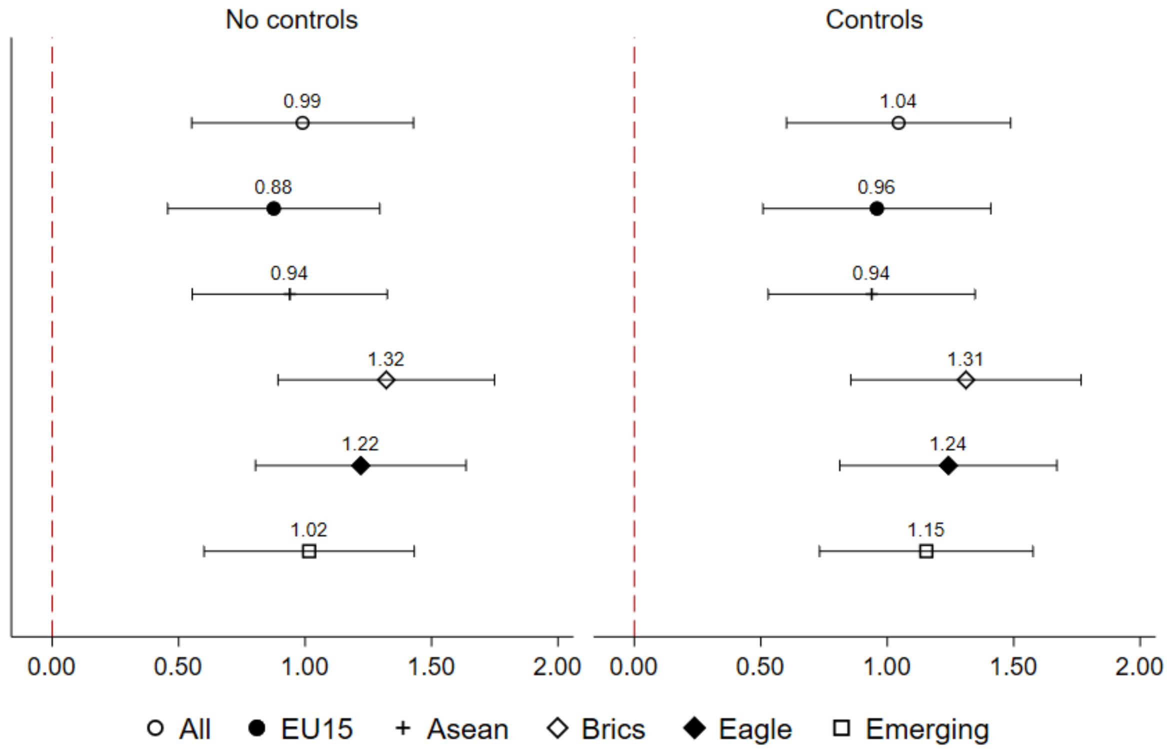

Figure 4: Changing control group

that were exposed to higher TPU before 2001, and estimate the following model:

$$\ln(export^{US}_{jnt}) = \mu + \theta_{nt} + \theta_{jn} + \theta_{jt} + \rho PostPNTR_t \times \ln(TPU_j) \times \mathbb{1}\{n = CN\} + v_{jnt}, \qquad (25)$$

where μ is the constant term, and θ_{nt}, θ_{jn}, and θ_{jt} are country-time, country-technology, and technology-time dummies respectively. The results in Table 6 shows a positive relationship between higher potential profit losses and exporting: a one percent increase in exposure to TPU leads to 0.63 percent more export, a statistically significant effect.

Given the positive and statistically significant effect of TPU reduction on exporting, I use the predicted log export from Equation (25) as a first stage in a two-stage least square estimation of the effect of exporting on innovation. In this framework, the differential exposure to TPU, $ln(TPU_j)$, is used as an instrument for the log export value, and both the first stage and the reduced form become interesting in their own right: the first stage in equation (25) represents the effect of TPU on exporting, which has been assessed by Handley and Limão (2017), and the reduced form, equation (22), represents the effect of uncertainty on innovation. Then, the two-stage least squares results reported in column

Dependent variable	FS $ln(export^{US}_{jnt})$	RF $ln(p_{jnt})$	IV $ln(p_{jnt})$
Instrumented $ln(export^{US}_{jnt})$			1.952^{b}
			(0.846)
$Post \times ln(TPU_j) \times CN$	0.632^{b}	1.233^{a}	
	(0.257)	(0.215)	
$X_{jCN} \times Post \times CN$	Yes	Yes	Yes
$X_{jt} \times CN$	Yes	Yes	Yes
Observations	626028	626028	626028
Fixed Effects	nt, jt, jn	nt, jt, jn	nt, jt, jn
Control countries group	$all, noUS$	$all, noUS$	$all, noUS$

Standard errors clustered by industry-country in parentheses.
^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$

Table 6: The mechanism: export

3 of Table 6 can be interpreted as a local average treatment effect (LATE): the effect of exporting on innovation for a specific group of compliers, those that are induced to export because of the reduction in TPU, but wouldn't have exported to the US otherwise.

Sunk cost: The other key insight of the model is that the presence of a sunk cost to invest in innovation generates an option value of waiting, which reduces innovation when uncertainty is high. The literature documents that sunk costs to undertake new R&D project exist and can be high. For example, Stiglitz et al. (1987, p. 928) claim that "*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*". Although I do not have data on sunk cost for each sector, I provide some indirect evidence which exploits some specific characteristics of patent data. More precisely, I perform the same analysis using utility models to verify that the estimated effect is lower in magnitude.

Compared to patents of invention, the patentability requirements[46] of utility models are less stringent; in particular the inventive step or non-obviousness requirement may be much lower or absent, so that utility models are often used to patent incremental innovations. Table 7 compares the estimated coefficient of equation (22), including all controls, when using utility models in (column two) to the baseline (column one), and shows that the estimated effect for utility models is smaller in magnitude.

[46]To be granted, a patent needs to be novel, non-obvious or represent an inventive step, and useful or susceptible of industrial application.

	$ln(p_{jnt})$	$ln(um_{jnt})$
$Post \times \ln(TPU_j) \times CN$	1.233^a	0.677^a
	(0.245)	(0.219)
$X_{jCN} \times Post \times CN$	Yes	Yes
$X_{jt} \times CN$	Yes	Yes
Observations	626028	626028
Fixed Effects	nt, jt, jn	nt, jt, jn
Control countries group	$all, noUS$	$all, noUS$

Standard errors clustered by sector-country in parentheses.
^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$

Table 7: The mechanism: sunk cost

7 Conclusion

I examined the impact of policy uncertainty on innovation. I used a trade policy shock, a change in US trade policy towards China, to link the end of the US threat to impose high tariffs on Chines imported goods, to the rapid growth of innovation, in China, measured by patenting activity.

I combined two mechanisms, the access to larger markets as a driver of innovation, and the option value of waiting generated by uncertainty, and explored their interaction to understand to which extent the dynamic gains from trade documented in the literature are sensitive to a secure economic environment.

Using a triple difference in differences, I found that industries *ex-ante* more exposed to uncertainty innovate more than industries relatively less exposed to uncertainty. The effects are large and robust to controlling for other contemporaneous policy changes. Overall, the analysis highlights the importance policy uncertainty for economic activity, and to ensure that the dynamic gains from trade liberalization fully materialize.

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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,[47] 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 incident 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 34%, while the average applied MFN tariff was 4.6%. Figure 5 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 status (PNTR). 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

B.1.1 Deterministic cutoff

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

[47] 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.

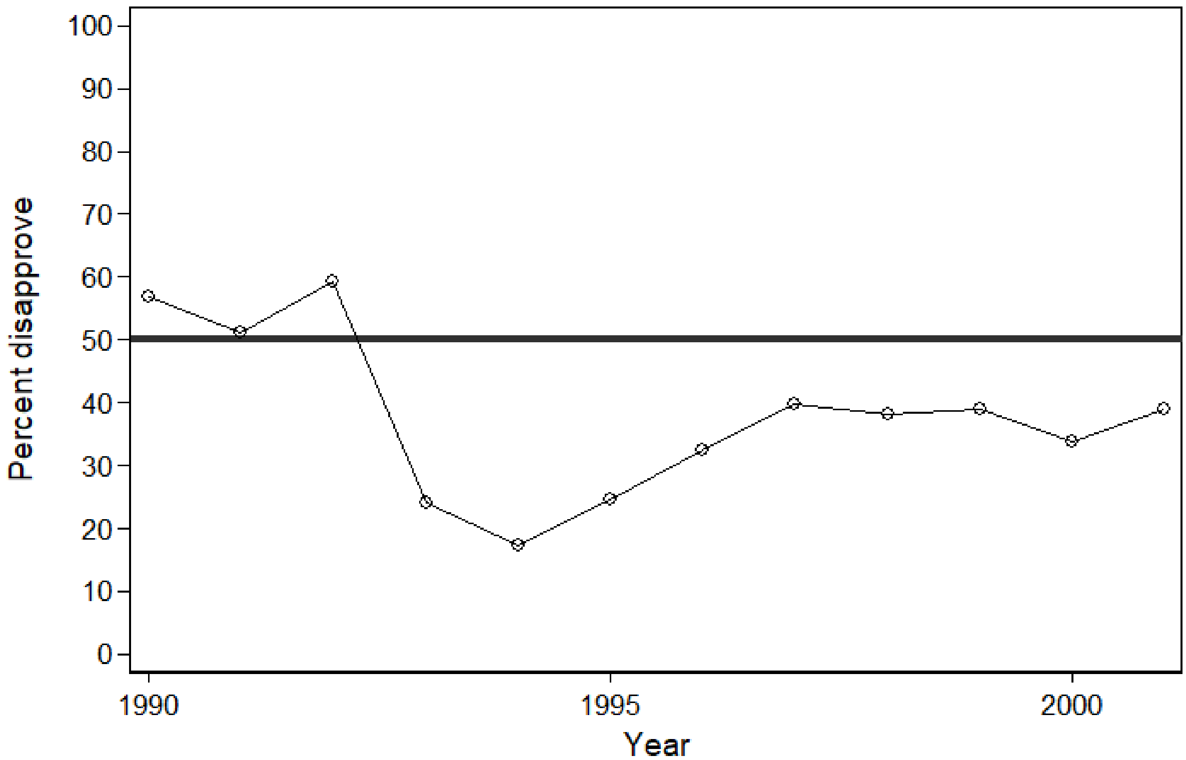

Figure 5: House votes to renew China's temporary MFN status (1990-2001).

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

case:

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

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

$$\iff \varphi_s^D = \left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)(B_d + B_x\tau_s^{-\sigma})}\right)^{\frac{1}{\sigma-1}} \tag{26}$$

B.1.2 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 (14), the marginal firm has

$$
\begin{aligned}
V_s\left(\varphi_s^U\right) &= 0 && (27)\\
&= \max\{0, \beta\mathbb{E}_s V_s'\left(\varphi_s^U\right) - \left[\pi_d(\eta\varphi_s^U) - \pi_d(\varphi_s^U)\right] - \left[\pi_x(\tau_s, \eta\varphi_s^U) - \pi_x(\tau_s, \varphi_s^U)\right] \\
&\qquad + (1-\beta)I\}, && (28)
\end{aligned}
$$

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 (14) as follows:

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

Starting with (14)

$$
\begin{aligned}
\mathbb{E}_s V_s' &= \lambda_{s,s+1}\Bigg[\beta\mathbb{E}_{s+1} V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1}, \varphi_1) - \pi_x(\tau_{s+1}, \varphi_0)] \\
&\qquad + (1-\beta)I\Bigg] \qquad \text{if } \varphi_s^U \le \varphi < \varphi_{s+1}^U \\
&= \lambda_{s,s+1}\Bigg[\beta\Bigg(\frac{\lambda_{s+1,s+1}}{1-\beta\lambda_{s+1,s+1}}\Big[I(1-\beta) - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1}, \varphi_1) - \pi_x(\tau_{s+1}, \varphi_0)]\Big]\Bigg) \\
&\qquad - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1}, \varphi_1) - \pi_x(\tau_{s+1}, \varphi_0)] + (1-\beta)I\Bigg] \\
&= \frac{\lambda_{s,s+1}}{1-\beta\lambda_{s+1,s+1}}\Big[I(1-\beta) - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1}, \varphi_1) - \pi_x(\tau_{s+1}, \varphi_0)]\Big], && (29)
\end{aligned}
$$

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

$$
\begin{aligned}
\mathbb{E}_{s+1} V_s' &= \lambda_{s+1,s+1}\Bigg[\beta\mathbb{E}_{s+1} V_s' - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1}, \varphi_1) - \pi_x(\tau_{s+1}, \varphi_0)] \\
&\qquad + (1-\beta)I\Bigg] \qquad \text{if } \varphi_s^U \le \varphi < \varphi_{s+1}^U \\
&= \frac{\lambda_{s+1,s+1}}{1-\beta\lambda_{s+1,s+1}}\Big[I(1-\beta) - [\pi_d(\varphi_1) - \pi_d(\varphi_0)] - [\pi_x(\tau_{s+1}, \varphi_1) - \pi_x(\tau_{s+1}, \varphi_0)]\Big] && (30)
\end{aligned}
$$

Using (29) in (27) gives:

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

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:

$$\begin{aligned}
&\left(\varphi_1^U\right)^{\sigma-1}\left[\left(1+\frac{\beta\lambda_{12}}{1-\beta\lambda_{22}}\right)B_d(\eta^{\sigma-1}-1)+\frac{\beta\lambda_{12}}{1-\beta\lambda_{22}}B_x\tau_2^{-\sigma}(\eta^{\sigma-1}-1)+B_x\tau_1^{-\sigma}(\eta^{\sigma-1}-1)\right]\\
&\qquad=(1-\beta)I\left(1+\frac{\beta\lambda_{12}}{1-\beta\lambda_{22}}\right)\\
&\left(\varphi_1^U\right)^{\sigma-1}\left[(1+u(\gamma))B_d(\eta^{\sigma-1}-1)+u(\gamma)B_x\tau_2^{-\sigma}(\eta^{\sigma-1}-1)+B_x\tau_1^{-\sigma}(\eta^{\sigma-1}-1)\right]\\
&\qquad=(1-\beta)I\,(1+u(\gamma))\\
&\left(\varphi_1^U\right)^{\sigma-1}\left[(1+u(\gamma))B_d(\eta^{\sigma-1}-1)+(\eta^{\sigma-1}-1)B_x\tau_1^{-\sigma}\left(u(\gamma)\left(\frac{\tau_2}{\tau_1}\right)^{-\sigma}+1\right)\right]\\
&\qquad=(1-\beta)I\,(1+u(\gamma))\\
&\qquad\varphi_1^U=\left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)\left(B_d+B_x\tau_1^{-\sigma}\frac{1+u(\gamma)\omega}{1+u(\gamma)}\right)}\right)^{\frac{1}{\sigma-1}}\\
&\qquad\quad=\left(\frac{I(1-\beta)}{(\eta^{\sigma-1}-1)\left(B_d+B_x\tau_1^{-\sigma}U(\gamma,\omega)\right)}\right)^{\frac{1}{\sigma-1}}
\end{aligned}\tag{31}$$

$U(\gamma,\omega)\equiv\frac{1+u(\gamma)\omega}{1+u(\gamma)}$ 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).[48] Patents are linked to Chinese firms using the concordance provided by He et al. (2018). I keep all firms that are active[49] in the period.

On the intensive margin, I find that firms that spend more on R&D also apply for more patents. Figure 6 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[50], and firms that did not, and look at the distribution of their R&D expenditures. Figure 7 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

[48] 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.

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

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

Destination country	Export value share	
	Pre	Post
Hong Kong	.236	.142
US	.235	.235
Japan	.147	.108
Germany	.048	.050
South Korea	.033	.040
France	.025	.026
United Kingdom	.021	.033
Singapore	.020	.022
Canada	.018	.024
Italy	.017	
The Netherlands		.024
Total export value (yearly average)	267377936	796623232

Table 8: Relative export shares

Note: The table reports 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. The total export value in the last row is the yearly average of total export value in the pre- and post-period. Only top 10 destination countries are shown.

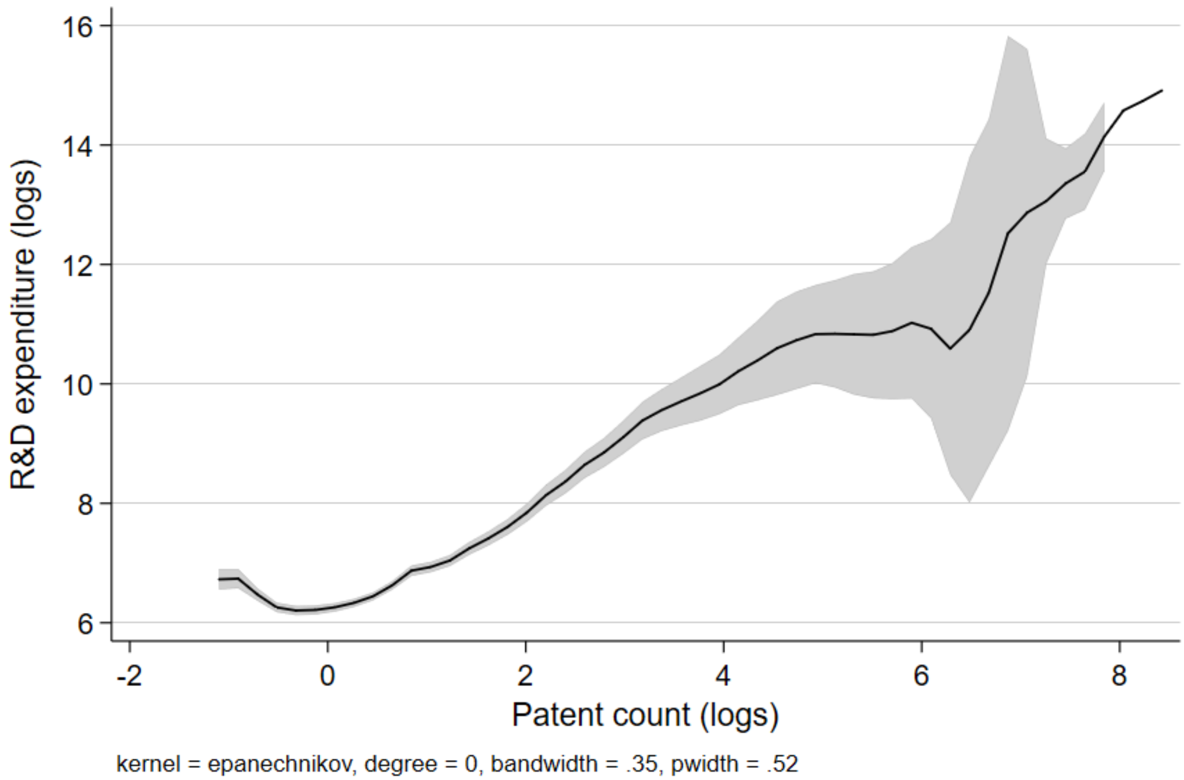

Figure 6: R&D expenditures and patenting. Intensive margin.

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).

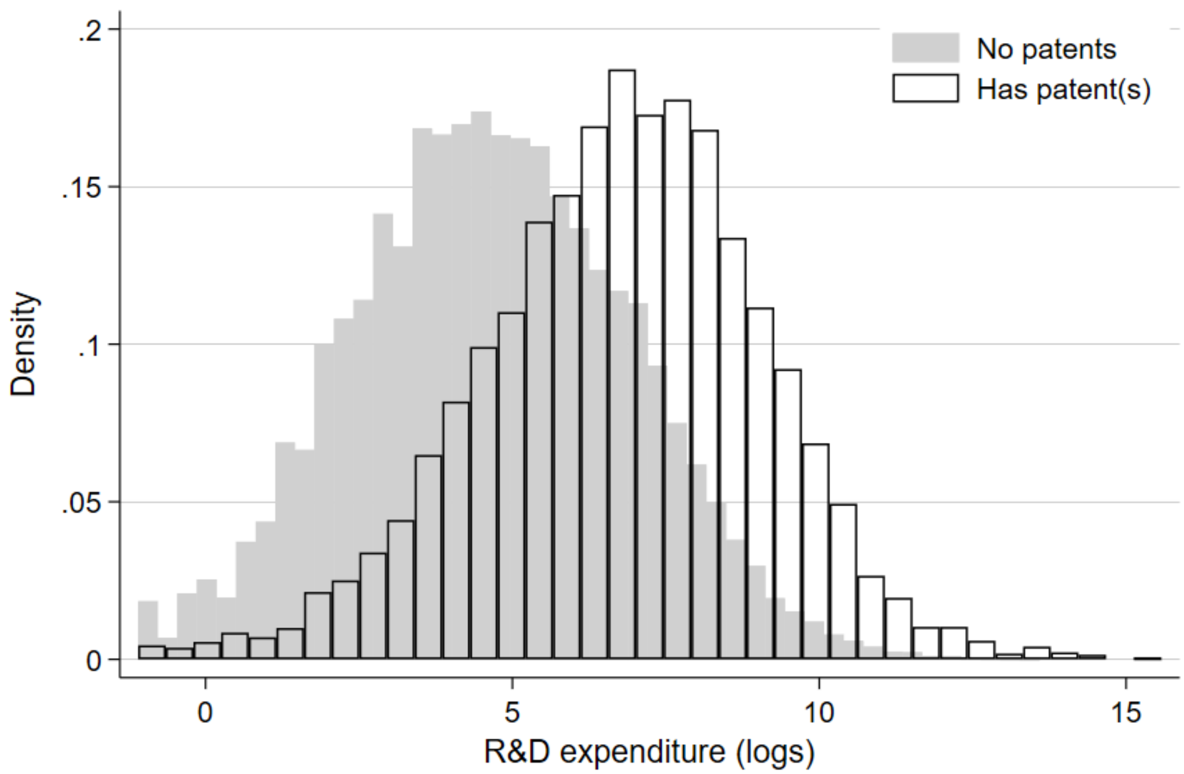

Figure 7: R&D expenditures and patenting. Extensive margin.

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.

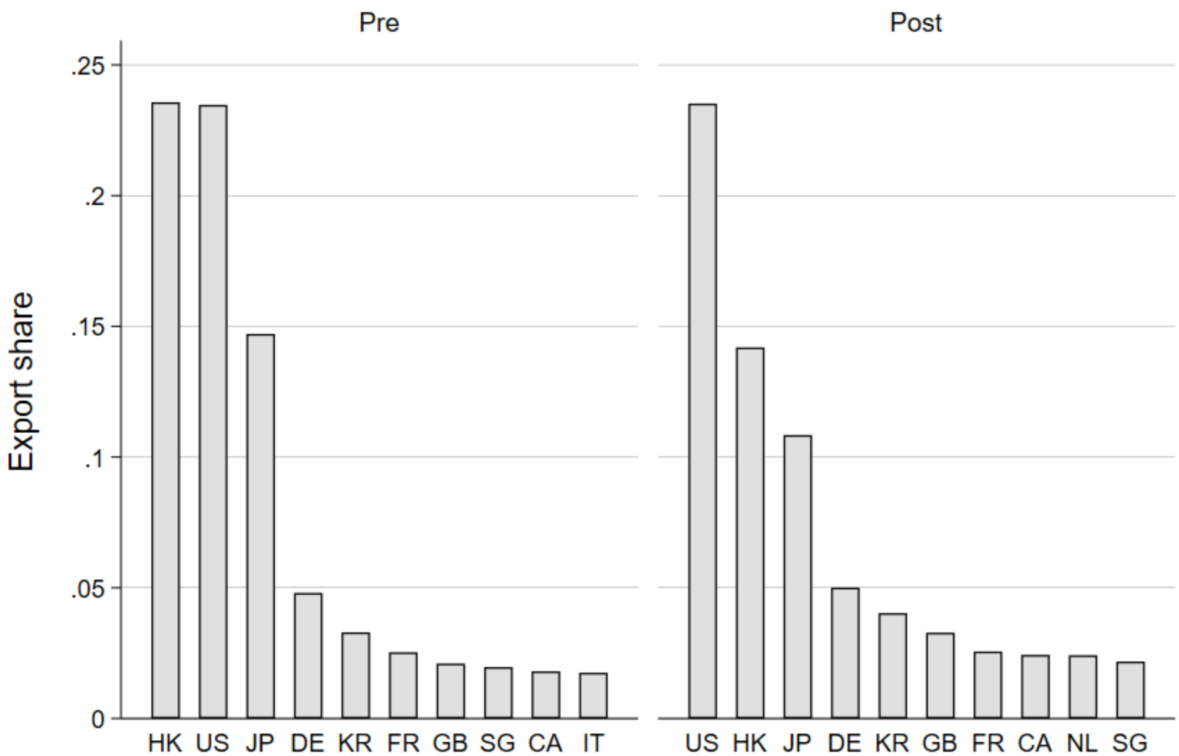

Figure 8: Share of China's export value by destination country.

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.