Journal of Empirical Finance 62 (2021) 12–27

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

Tariff uncertainty and firm innovation: Evidence from the U.S.–China Permanent Normal Trade Relation☆

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ARTICLE INFO

JEL classification:
G38
O31

Keywords:
Permanent Normal Trade Relations
Tariff uncertainty
Innovation
Patents
Imports
China

ABSTRACT

We examine the effect of the tariff uncertainty associated with Chinese imports on U.S. firm innovation. Our test exploits the U.S. conferral of Permanent Normal Trade Relations (PNTR) on China—a policy that reduces the uncertainty of future tariff increases for Chinese goods. We find a significant increase in the number of patents and patent citations for U.S. firms affected by PNTR relative to other firms. This result is stronger for firms with more irreversible investments and for firms that experience a greater increase in Chinese goods following PNTR. Overall, our evidence is consistent with the view that lowering the tariff uncertainty of Chinese imports boosts the attractiveness for U.S. firms to make long-term irreversible investment (such as technological innovation) and thus induces U.S. firms to innovate more.

1. Introduction

A growing strand of literature has examined the effect of tariff rate reduction on corporate policies (e.g., Valta (2012), Xu (2012) and Frésard (2010)). Among them, the most recent studies focus on the consequences of tariff rate reduction for Chinese imports, such as the effects on operation profit and employment of U.S. firms (e.g., Acemoglu et al. (2016), McManus and Schaur (2016), Gutiérrez and Philippon (2017) and Greenland et al. (2020)). While these studies enhance our understanding concerning the effect of the tariff rate level, the real effect of tariff rate uncertainty is relatively under-examined. In this paper, we intend to fill the void by examining how the tariff uncertainty of Chinese imports influences U.S. firm innovation.

Our test exploits the U.S. granting China Permanent Normal Trade Relations (PNTR) as a quasi-natural experiment—a policy that reduces the uncertainty of future tariff increases for Chinese goods. The PNTR, which was finally implemented on January 1, 2002, pushed the U.S. market to be more open to Chinese products by reducing the threat of large tariff increases on Chinese imports. The conferral of PNTR was unique in history in that it did not change the actual tariff rates applied to Chinese imports but reduced the uncertainty of the tariff rates Pierce and Schott (2016). Since 1980, U.S. imports from China had already enjoyed the Normal Trade Relations (NTR) tariff rates,[1] but these low rates had to be renewed every year by the U.S. Congress. The renewals

☆ We are grateful for the helpful comments from Kewei Hou (the Editor), the Associate Editor, an anonymous referee, Hao Liang, Jun-koo Kang, Chuan Yang Hwang, Faqin Lin, Kevin Tseng, Yiming Qian, Shang-Jin Wei, seminar participants from Nanyang Technological University, University of International Business and Economics, the 2016 Singapore Scholar Symposium, the 2017 China Financial Research Conference, and the 2018 CICF meeting. Gao acknowledges financial support from the Program for Professor of Special Appointment (Eastern Scholar) at Shanghai Institutions of Higher Learning, China (Grant No. TP2018001), the National Natural Science Foundation of China (Grant No. 71973029), and Shanghai Institute of International Finance and Economics, China. Chen acknowledges the financial support from Singapore Ministry of Education Academic Research Fund Tier 1 (Official Number: RG58/15) and Academic Research Fund Tier 2, Singapore (Official Number: MOE2015-T2-1-118). All errors are our own.

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[1] Normal Trade Relations is a U.S. term for Most Favored Nation.

https://doi.org/10.1016/j.jempfin.2021.02.002
Received 15 March 2020; Received in revised form 1 February 2021; Accepted 10 February 2021
Available online 15 February 2021
0927-5398/

were uncertain and politically contentious. If the Congress did not approve the renewal in any particular year, a much higher tariff rate (non-NTR rate) would be applied to Chinese imports. For example, in 1999, the average NTR rate was only 4 percent, but the average non-NTR rate was 37 percent. To sum up, the passage of PNTR reduced a great amount of the uncertainty in importing goods from China by permanently setting the U.S. tariff rates on Chinese goods at NTR levels. Considering that the tariff uncertainty about Chinese goods increases the value of waiting before undertaking irreversible risky investments in new technology, we expect PNTR to foster innovation in U.S. firms by reducing such uncertainty.[2]

We empirically test the effect of PNTR on corporate innovation using a panel of 6209 U.S. public firm–year observations from 1995 to 2005 and a difference-in-differences approach. We find that PNTR leads to a significant increase in innovation outputs. On average, firms that are affected by PNTR experience an increase in the number of patents by 31% (or by 3% per year) and an increase in the number of patent citations by 40% (or by 4% per year), relative to firms that are unaffected by PNTR.

The identifying assumption central to the difference-in-differences estimation is that the treated and control firms share parallel trends prior to PNTR. Our tests show that their pre-treatment trends are indeed indistinguishable. Moreover, most of the impact of PNTR on innovation occurs several years after PNTR takes effect, which suggests a causal effect.

To provide further evidence that the effects of PNTR on innovation are indeed tied to the tariff uncertainty associated with Chinese imports, we examine heterogeneous treatment effects. We find that the treatment effects are stronger for firms that have greater irreversible investment and for firms in industries that experience a greater increase in Chinese goods following PNTR. These cross-sectional variations in the treatment effects further increase our confidence that the positive impact of PNTR on innovation is likely due to the reduced tariff uncertainty associated with Chinese goods.

Moreover, we implement two placebo tests to investigate the possibility that our results are purely driven by chance. In our first placebo test, we randomly select a group of firms as pseudo-treated firms and the rest of the firms as pseudo-control firms. We repeat this procedure 5000 times. We find that the maximum coefficient estimated in the placebo test is substantially smaller than the actual coefficient estimated from the main test. In the second placebo test, we re-estimate our baseline regression based on pseudo-treatment years and find no positive effect on corporate innovation. These results indicate that the effects of PNTR on innovation documented in our main tests are unlikely to be spurious.

We further investigate an alternative explanation of our results that the admission of China into the WTO in 2000 removes the barriers to invest in China, and U.S. firms have stronger incentives to outsource low-tech productions to other countries and focus more on innovation. Using outsourcing information from Moon and Phillips (2021), we find that the positive effect of PNTR on U.S. firms' innovation remains significant after controlling for firms' outsourcing activities, and that PNTR leads to a significant increase in corporate innovation in the subsample of firms that have no outsourcing. The results indicate that outsourcing is unlikely the main driving force for our results.

This paper provides at least four major contributions to the existing literature. First, our study contributes to the vast literature on the relationship between uncertainty and investment. Although economic theory predicts that uncertainty could affect investment in either a positive way (i.e., increasing investment) or a negative way (i.e, decreasing investment),[3] the overall empirical evidence suggests a negative uncertainty–investment relation (e.g., Leahy and Whited (1996), Gulen and Ion (2016) and Kim and Kung (2016)). However, firms face uncertainty from various aspects, including economic condition, political environment, policy, product price, customer demand, wages and so on. Existing literature finds it difficult to construct clean uncertainty measures and/or to isolate the portion of uncertainty concerning a specific source. By focusing on PNTR, we can better isolate the uncertainty in future tariff rates, which is a nontrivial portion of the overall uncertainty for U.S. firms (at least for U.S. firms facing competitions from Chinese imports).

Second, our paper adds to the literature that examines the drivers of innovation. This strand of literature is important to the economy, as innovation is widely believed to be crucial for sustainable growth and economic development (Solow, 1957; Romer, 1986). Our paper suggests that reducing tariff uncertainty and better integrating the U.S. and Chinese economies have a significant impact on corporate innovation for U.S. firms.

Third, our paper contributes to the literature on the effect of U.S. tariff rate policy. Extant literature has examined the effect of tariff rate reduction on the cost of debt (e.g., Valta (2012)), capital structure (e.g., Xu (2012)), and the link between cash holding and product market structure (e.g., Frésard (2010)). The recent bourgeoning literature focuses on the consequences of Chinese import competition, such as the effects on manufacturing unemployment (e.g., Acemoglu et al. (2016)), public health (e.g., McManus and Schaur (2016)), relative decline of investment, operation profit and employment of small U.S. firms (Gutiérrez and Philippon, 2017; Greenland et al., 2020), and the increased prices of inputs and consumer products in the U.S. (Wang et al., 2018; Amiti et al., 2020). Most of these studies examine the effect of the level of tariff rate. Complementing these studies, we focus on the uncertainty of tariff rate (considering that PNTR does not affect the level of tariff rate, but reduces the tariff uncertainty) and provide evidence that such uncertainty also has significant impacts on business decisions.

[2] There exists an extensive literature on trade deals between the U.S. and other countries, such as the Canada–U.S. Free Trade Agreement (e.g., Trefler (2004)) and the North American Free Trade Agreement between the U.S., Canada, and Mexico (e.g., Burfisher et al. (2001)). Unlike PNTR that only affects tariff uncertainty (not the level of tariff rate), these agreements lead to a significant decrease in the tariff rate for goods traded among these countries. Therefore, PNTR enables us to better identify the effect of tariff uncertainty on firm decision making.

[3] The economic models predicting a positive uncertainty–investment relation include Hartman (1972) and Abel (1983, 1984), while the economic models predicting a negative uncertainty–investment relation include Dixit and Pindyck (1994), Bloom (2007) and Bloom et al. (2007). The former group argues that when marginal product of capital is convex in product price, a mean-preserving increase in the price uncertainty raises the expected return on a marginal unit of capital and thus induces firms to invest more. The latter group argues that when the investment is irreversible, uncertainty raises the value of the real option to defer the investment.

Fourth, our study sheds light on the real consequences of PNTR. As pointed out by Pierce and Schott (2016), PNTR has a significant impact on the U.S. manufacturing firms, in that it leads to massive layoffs in these firms. They find that the number of workers in the U.S. manufacturing industry plunges by 18% from 2001 to 2007 and that this decline in employment is attributed to the passage of PNTR. Our paper complements this study and provides evidence that there is a bright side to PNTR: It promotes innovation.

It is worth noting that our study is closely related to Bena and Simintzi (2019), which examines how an improvement in the U.S.–China contracting environment affects U.S. firm innovation. Based on the 1999 U.S.–China bilateral agreement that enables U.S. firms to better access cheap and abundant offshore labor in China, they find that U.S. firms with a subsidiary in China experience a significant decrease in process innovation (the type of innovation aimed at lowering production cost) than U.S. firms with a subsidiary in a low-wage Asian country other than China. Although both our study and theirs show that the U.S.–China economic integration has significant effects on U.S. firms' innovation, the two articles differ in the following ways. First, the focal policy change is different. Different from the 1999 U.S.–China bilateral agreement, our study is based on the 2001 conferral of PNTR, which does not affect U.S. firms' access to Chinese labor but reduces the tariff uncertainty associated with Chinese imports. Second, the underlying mechanism is different. The results in Bena and Simintzi (2019) are due to better contracting with cheap Chinese labor, which induces U.S. firms to direct R&D away from devising new production methods that save costs. Our results are due to reduced tariff uncertainty associated with PNTR, which makes U.S. firms more willing to make irreversible investment (such as R&D). Moreover, as detailed in Table 8, we provide evidence that our results are unlikely driven by outsourcing activities.

The remainder of the paper is organized as follows. Section 2 reviews the background on PNTR and develops our hypothesis. Section 3 describes our sample and key variable construction. Section 4 presents the empirical results. We conclude in Section 5.

2. Background on PNTR and hypothesis development

We use the passage of PNTR as a natural experiment to study the effect of tariff uncertainty associated with Chinese imports on U.S. corporate innovation. Since the Smoot–Hawley Tariff Act of 1930, U.S. imports from non-market economies, including China, had been subject to high "non-NTR" tariff rates, which were significantly larger than "NTR" rates offered to WTO members. The U.S. Trade Act of 1974 gave the U.S. President power to grant NTR tariff rates to non-market countries, and the U.S. started granting low tariff rates to China annually in 1980. However, these low tariffs were subject to annual approval by the U.S. Congress. This created uncertainty about whether the low tariff rates would be sustained in the future and could be easily influenced by political contention. Indeed, from 1990 to 2001 the U.S. House of Representatives voted on legislation to revoke China's temporary NTR status every year and the votes were successful in 1990, 1991 and 1992.[4] Fig. 1 plots the percentage-disapproving vote of the U.S. House of Representatives on China's temporary NTR status during 1990–2001. Consistent with Pierce and Schott (2016), the average House vote against an annual NTR renewal was 38%. Even in 2001 (the year right before the PNTR became effective), the percentage of disapproving vote was 40%. These facts indicate that there exists considerable uncertainty about China's NTR status.[5] If the U.S. decided to withdraw China's NTR status, the consequences would be catastrophic—tariff rates could easily jump by 60 percentage points.

Two decades later, in October 2000, the U.S. Congress passed a bill granting PNTR status to China following China's entry into the WTO. The new trade status was finally implemented on January 1, 2002. This effectively ended the uncertainty associated with annual renewals of China's NTR status. Following Pierce and Schott (2016), we define the "NTR gap" to quantitatively capture the effect of PNTR, calculated as the difference between non-NTR rates and NTR rates. Non-NTR rates refer to the tariff rates that would have jumped if annual renewal had failed, while NTR rates refer to the rates locked in by PNTR. On average, the non-NTR rate is 37% and the NTR rate is 4% in 1999. Therefore, the NTR gap averages 33%. More importantly, the NTR gap has a large cross-sectional variation across different industries, as indicated by a standard deviation of 14%. The impact of PNTR is larger in industries with higher NTR gaps, and we expect the responses from firms to be larger as well.

One paramount advantage of this natural experiment is its exogeneity to corporate innovation activities. First, the conferral of PNTR status was unique in that it did not change the import tariff rates that were actually applied to Chinese imports over this period, which effectively rules out the concern that tariff rate changes might be influenced by policy considerations and corporate lobbying activities. Second, according to Pierce and Schott (2016), over 79% of the variation in the NTR gap comes from non-NTR rates, which were set under the Smoot–Hawley Tariff Act of 1930. This makes it highly unlikely that corporate innovation could have influenced the setting of non-NTR rates seven decades ago.

Uncertainty increases the value of waiting before undertaking irreversible risky investments (such as investment in new technology) and firms are more likely to undertake such investments after ambiguity resolves (e.g., McDonald and Siegel (1986), Pindyck (1993), Dixit and Pindyck (1994) and Schwartz and Zozaya-Gorostiza (2003)). The value of the option to wait under uncertainty is particularly important for corporate innovation, because innovation is about exploring unknown approaches and untested methods and usually has higher tail risk (Holmstrom, 1989; Ferreira et al., 2014; Bhattacharya et al., 2017). The conferral of PNTR eliminates the tariff uncertainty of Chinese imports faced by U.S. manufacturing firms, which boosts the attractiveness of investment in innovations.

The following example illustrates this point. Suppose that a U.S. firm is considering making an irreversible investment in a new technology to produce an innovative product (to replace its conventional products that face competition from Chinese imports). The

[4] Ultimately, the U.S. Senate failed to support the House votes and China's NTR status was not overturned in these years.

[5] Pierce and Schott (2016) also provided substantial anecdotal evidence in a Congressional testimony about this threat of uncertainty, and it was taken seriously by firms and government sources alike.

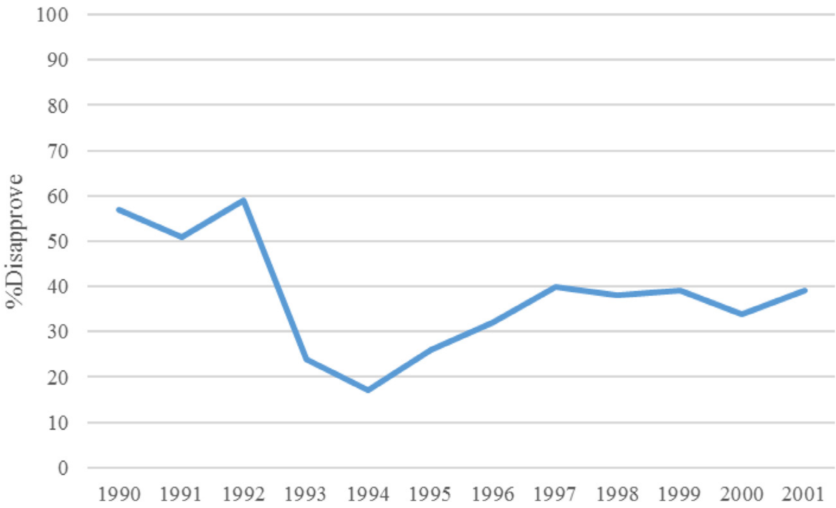


Fig. 1. Average House Vote Against China's Annual Temporary NTR Status. This figure plots the outcome of the U.S. House of Representatives' vote on China's temporary NTR status. The *y*-axis represents the percentage-disapproving vote by year from 1990 to 2001. The votes to revoke China's temporary NTR status succeeded in 1990, 1991 and 1992, consecutively.

profitability of this new technology depends on the tariff rate associated with Chinese imports. If China's NTR status is revoked and the tariff rate of Chinese imports is increased accordingly, the profitability of innovative product over conventional product would be smaller. When there is uncertainty about China's NTR status, the company may wish to postpone this investment decision until the uncertainty about China's NTR status is resolved.

Based on the discussion above, we expect a positive effect of PNTR for innovation in U.S. manufacturing firms, because PNTR helps reduce the tariff uncertainty associated with Chinese imports.

3. Sample formation and variable construction

We start with all U.S. public firms in Compustat during the 1995–1998 and 2002–2005 periods. Following Pierce and Schott (2016), we then construct our sample of manufacturing firms that have SIC codes between 2000 and 3999. Our final sample consists of 6209 firm–year observations.

We define a firm as in the treated group if the firm belongs to an industry in the top tercile of NTR Gap values, and in the control group if the firm belongs to an industry in the bottom tercile of NTR Gap values. We calculate NTR gaps as the difference of *ad valorem* equivalent tariff rates between a non-NTR country and an NTR country, obtained from Feenstra et al. (2002). Table 1 presents the distribution of NTR gap value across industry. The industries in the treated group include rubber and miscellaneous plastics products (SIC code 30), apparel and other finished products made from fabrics and similar materials (SIC code 23), miscellaneous manufacturing industries (SIC code 39), leather and leather products (SIC code 31), textile and mill products (SIC code 22), electronic and other electrical equipment and components, except computer (SIC code 36) and measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks (SIC code 38). The industries in the control group include stone, clay, glass and concrete products (SIC code 32), primary metal industries (SIC code 33), transportation equipment (SIC code 37), food and kindred products (SIC code 20), paper and allied products (SIC code 26), printing, publishing and allied industries (SIC code 27), and petroleum refining and related industries (SIC code 29).

We further define an indicator variable *Post*, which takes the value of one for the 2002–2005 period (i.e., post-PNTR period), and zero for the 1995–1999 period (i.e., pre-PNTR period). The U.S. Congress passed the bill granting PNTR status to China in October 2000, after the November 1999 agreement governing China's eventual entry into the WTO. PNTR became effective in December 2001 and was implemented on January 1, 2002. To alleviate any confounding effects, we drop the years 1999, 2000, and 2001, as PNTR was foreseeable in 1999 and was eventually implemented in 2002.[6]

We collect patent information from the National Bureau of Economic Research (NBER) Patent Citations Data File (Hall et al., 2005). This database provides detailed information on more than three million patents granted by the United States Patent and Trademark Office from 1976 to 2006. For each patent, this database also provides information regarding the number of citations received by the patent. However, considering the average of a two-year lag between patent application and patent grant, and that the latest year in the NBER patent database is 2006, patents applied for between 2005 and 2006 may not appear in the database. To address this concern, we supplement the information for patents granted over the period of 2007–2010 from the Harvard Business School (HBS) U.S. Patent Inventor Database (Li et al., 2014).[7]

[6] In untabulated tests, we find that our results remain robust without dropping the three years of observations.

[7] The HBS patent database is constructed in a similar manner as the NBER patent database, and has more recent patent data.

Table 1
NTR gap by industry. This table presents the NTR Gap by all manufacturing industries (SIC codes between 2000 and 3999).

Industry	SIC	NTRGAP
Rubber and Miscellaneous Plastics Products[a]	30	0.581
Apparel and Other Finished Products Made From Fabrics and Similar Materials[a]	23	0.578
Miscellaneous Manufacturing Industries[a]	39	0.507
Leather and Leather Products[a]	31	0.490
Textile Mill Products[a]	22	0.462
Electronic and Other Electrical Equipment and Components, Except Computer Equipment[a]	36	0.455
Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical[a] Goods; Watches and Clocks	38	0.414
Furniture and Fixtures	25	0.411
Fabricated Metal Products, Except Machinery and Transportation Equipment	34	0.405
Chemicals and Allied Products	28	0.381
Lumber and Wood Products, Except Furniture	24	0.349
Industrial and Commercial Machinery and Computer Equipment	35	0.319
Tobacco Products	21	0.232
Stone, Clay, Glass, and Concrete Products[b]	32	0.209
Primary Metal Industries[b]	33	0.209
Transportation Equipment[b]	37	0.185
Food and Kindred Products[b]	20	0.160
Paper and Allied Products[b]	26	0.130
Printing, Publishing, and Allied Industries[b]	27	0.055
Petroleum Refining and Related Industries[b]	29	0.052

[a]Denote the treated industry.
[b]Denote the control industry.

We mainly use two measures for innovation output. The first measure is the number of patent applications filed in a year that are eventually granted. This measure captures the quantity of innovation output. Our second measure of innovation is the sum of citation counts across all patents filed by the firm in a given year, which captures the significance of the patent outputs. Because citations are received many years after a patent is created, patents created near the end of the sample period have less time to accumulate citations. To address this truncation bias, we follow the recommendations of Hall et al. (2001, 2005) and scale the citation count of each patent by the average citation count of all firms' patents that are filed in the same year. The use of patenting to measure a firm's innovativeness has been widely used in the literature since Scherer (1965) and Griliches (1981).

We control for a vector of firm and industry characteristics that may affect a firm's innovation productivity, and these controls are motivated by prior literature (e.g., Aghion et al. (2005)). These variables include firm size, firm age, asset tangibility, leverage, cash holding, R&D expenditure, capital expenditure, ROA, and Tobin's *Q*.

We control for several time-varying industry characteristics. Specifically, we control for industry concentration (the Herfindahl index (*H-index*) based on sales) and the squared Herfindahl index (*H-index*^{2}) (which controls for non-linear effects of product market competition on innovation outputs). There is a potential concern that the increase in innovation might be correlated with an increase in the competitiveness of U.S. technology-intensive industries rather than the change in trade policy. To address this issue, we control for industry skill intensity and capital intensity. The variable *Skill Intensity* is measured by the ratio of non-production workers to total employment in one industry, while the variable *Capital Intensity* is calculated as the ratio of capital to total employment in one industry. An alternative strategy in response to PNTR is to shift operations to China. We control for this possibility by including a measure of China's barriers to foreign investment: *Contract Intensity*, which is measured by the proportion of intermediate inputs that require relationship-specific investments to capture the nature of contracting in the industry, as China's reduction of barriers to foreign investment may have affected industries differently. We further control for advanced technology products (*ADT*)—a dummy variable that equals one if the industry produces advanced technology products, and zero otherwise. We also control for the elimination of import quotas on some textile and clothing imports in 2002 and 2005 under the global Multi-Fiber Arrangement (*MFA*). Third, we control for the steady decline in union membership in the U.S. in the manufacturing sector. Furthermore, we also include industries' NTR rates.

All these control variables are lagged by one year. To minimize the effect of outliers, we winsorize all continuous variables at the 0.5th and 99.5th percentiles. Detailed variable definitions are provided in Appendix.

Table 2 Panel A provides summary statistics. On average, firms in our sample have 8 patents filed (and subsequently granted) per year and receive 33 total citations. Our average sample firms have a book value of total assets of $2.11 billion and are 18 years old. The average R&D and capital expenditure account for 5.4% and 5.1% of total assets, respectively. The average firms are moderately leveraged with a book leverage ratio of 18.9%, and tangible assets account for 26% of total assets in the average firms. In terms of performance, sample firms perform well, with an average ROA of 6.2% and Tobin's Q of 2.15.

Table 2 Panel B compares the pre-event firm characteristics between the treated and control groups. We show that the treated firms are on average more innovative, smaller and younger. In addition, they have more cash holding, higher R&D expenditure, higher Tobin's Q, lower leverage, lower capital expenditure and lower ROA. As pointed out by Roberts and Whited (2013), it is ideal for the treatment and controls to be relatively similar among observable dimensions before the treatment. However, if not, one can directly incorporate control variables in the regression specification.

Table 2
Summary statistics. Panel A presents the summary statistics of the full sample, which consists of 6209 firm–year observations from 1995 to 2005, excluding 1999–2001. We obtain patent information from the NBER patent database and HBS patent database, and financial information from Compustat. Definitions of all variables are detailed in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. Panel B compares the firm characteristics between the treated and control groups in the pre-treatment period.

Panel A: Summary statistics of the full sample

	Mean	SD	P25	Median	P75
Patent	8.070	44.882	0.000	0.000	2.000
Citation	33.493	211.404	0.000	0.000	3.200
Total assets (in billion $)	2.114	7.341	0.035	0.154	0.864
# of employees (in 1000s)	6.193	15.809	0.185	0.991	4.400
Firm age (in years)	17.516	14.282	7.000	12.000	26.000
Cash	0.177	0.213	0.022	0.088	0.255
R&D	0.054	0.095	0.000	0.016	0.067
ROA	0.062	0.232	0.048	0.119	0.175
PPE	0.260	0.187	0.116	0.215	0.362
Leverage	0.189	0.172	0.024	0.164	0.308
Capex	0.051	0.048	0.021	0.038	0.066
Tobin's Q	2.153	1.882	1.152	1.558	2.371
H-index	0.054	0.038	0.040	0.044	0.049
H-index^2	0.004	0.010	0.002	0.002	0.002
Capital intensity	126.239	213.226	35.837	43.556	95.393
Skill intensity	0.349	0.169	0.238	0.351	0.506
Contract intensity	0.597	0.257	0.402	0.694	0.808
ADT	0.408	0.492	0.000	0.000	1.000
NTR	0.021	0.050	0.000	0.009	0.021
Union membership	0.118	0.094	0.048	0.088	0.175
MFA	0.001	0.030	0.000	0.000	0.000

Panel B: Comparison of firm characteristics between the treated and control groups in the pre-treatment period

	Control firms		Treated firms		Test of differences	
	Mean (1)	Median (2)	Mean (3)	Median (4)	t-test(3)-(1)	Wilcoxontest (4)-(2)
Patent	4.919	0.000	7.958	0.000	3.039**	0.000***
Citation	15.977	0.000	42.770	0.000	26.793***	0.000***
Total assets (in billion $)	3.521	0.442	0.564	0.069	−2.957***	−0.373***
# of employees (in 1000s)	9.442	2.247	3.145	0.471	−6.297***	−1.776***
Firm age (in years)	19.616	12.000	13.938	10.000	−5.678***	−2.000***
Cash	0.096	0.039	0.205	0.104	0.109***	0.065***
R&D	0.014	0.000	0.075	0.034	0.061***	0.034***
ROA	0.112	0.133	0.041	0.123	−0.071***	−0.010***
PPE	0.374	0.367	0.218	0.193	−0.156***	−0.174***
Leverage	0.240	0.228	0.179	0.135	−0.061***	−0.093***
Capex	0.068	0.056	0.056	0.042	−0.012***	−0.093***
Tobin's Q	1.723	1.385	2.376	1.664	0.653***	0.279***
H-index	0.053	0.037	0.052	0.046	−0.001	0.009***
H-index^2	0.006	0.001	0.003	0.002	−0.003***	0.001***
Skill intensity	0.235	0.239	0.397	0.395	0.161***	0.156***
Capital intensity	243.808	108.106	65.996	38.664	−177.812***	−69.442
ADT	0.007	0.000	0.578	1.000	0.571***	1.000***
Contract intensity	0.421	0.348	0.681	0.716	0.260***	0.368***
NTR	0.039	0.014	0.015	0.009	−0.024***	−0.005***
Union membership	0.202	0.118	0.091	0.048	−0.111***	−0.070***
MFA	0.000	0.000	0.000	0.000	0.000	0.000

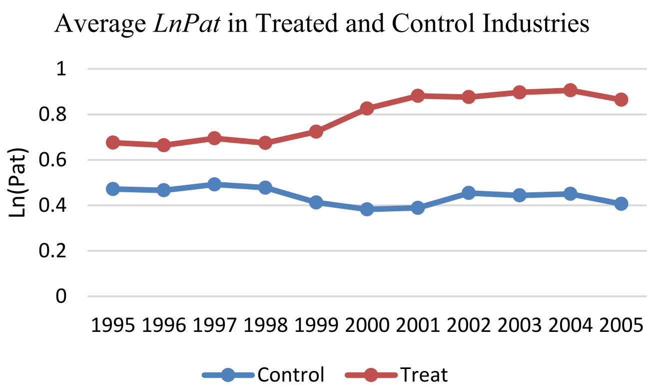
4. Empirical results

4.1. Visual illustration

Fig. 2 plots the corporate innovation during 1995–2005 for firms in the treated and control industries, respectively. There are two facts worth highlighting. First, the pre-PNTR trend in *LnPat* and *LnCit* in treated industries is largely parallel to that of control industries, supporting the parallel trend assumption associated with the difference-in-differences estimation.[8] Second, although the treated industries are more innovative than the control industries over the whole period, the difference becomes larger in the post-PNTR period (i.e., firms in treated industries become even more innovative than the ones in control industries in the post-PNTR period).

[8] It is worth noting that the parallel trends assumption does not require the level of corporate innovation to be the same between the treatment group and the control group during the pre-PNTR period because these distinctions are differenced out in the estimation. Instead, this assumption requires a similar trend in corporate innovation in the pre-PNTR period for both groups (see, e.g., Lemmon and Roberts (2010) and Kim and Valentine (2020)).

A: Number of Patents



B: Number of Patent Citations

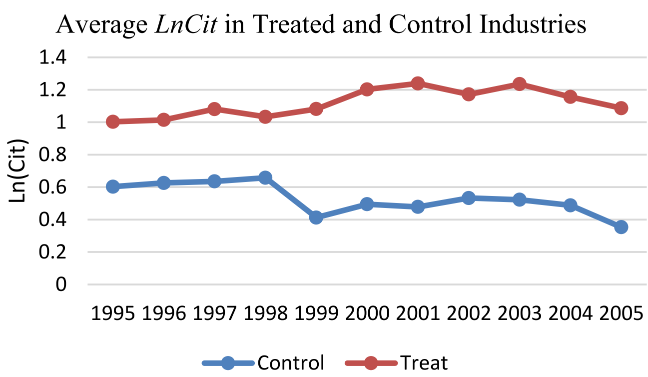


Fig. 2. Visual Illustration. This figure shows corporate innovation during 1995–2005 for firms in the treated and control industries, respectively.

Overall, Fig. 2 indicates that treated firms become more innovative after PNTR, compared to the control firms. This result provides suggestive evidence supporting the positive effect of PNTR on U.S. firm innovation.

4.2. Baseline regression

We implement a standard difference-in-differences test through the following regression:

$$Innovation = \alpha + \beta_1 Treat \times Post + Firm\ Characteristics + Industry\ Characteristics + Industry\ FE + Year\ FE + \varepsilon. \tag{1}$$

The dependent variable is a proxy for innovation performance. The indicator variable *Treat* takes the value of one for the treated firms, and zero for control firms. The indicator variable *Post* takes the value of one for the 2002–2005 period (i.e., post-PNTR period), and zero for the 1995–1999 period (i.e., pre-PNTR period). We include industry and year fixed effects, as well as a set of control variables that could affect firms' innovation output, as discussed in Section 3. Because we control for industry fixed effects and year fixed effects in the regression, we do not include *Treat* and *Post* in the regression due to the collinearity problem. Given that our treatment is defined at the industry level, we cluster standard errors by industry.

The coefficient of interest in this model is the β_1 coefficient, which captures the differences in innovation in treated firms before and after PNTR as opposed to the corresponding before-after differences in control firms.

It is helpful to consider an example. Suppose we want to estimate the effect of PNTR on innovation. We can subtract the number of innovations in the pre-PNTR period from the number of innovations in the post-PNTR period for firms affected by PNTR. To eliminate any confounding factors, we calculate the same difference in innovations in firms that are unaffected by PNTR. Finally,

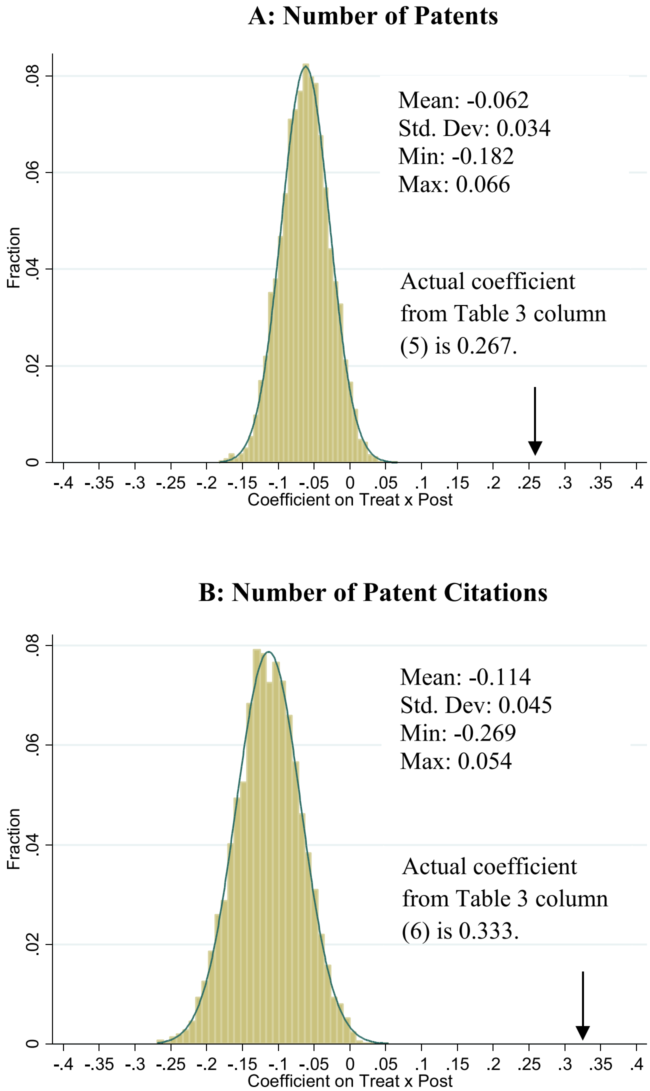


Fig. 3. Placebo test. This figure shows a histogram of the coefficients on *Treat* × *Post* from 5000 bootstrap simulations of the model in Table 3. For each iteration, we draw a random sample of 929 firms (the same number of the treated firms during the sample period and then treat the rest of the pool as "non-treated firms". Based on these "pseudo" treated and control groups, we re-estimate columns (5) and (6) of Table 3 and save the coefficients on *Treat* × *Post*. Fig. 3A reports the distribution of the coefficients when the dependent variable is *LnPat,* and Fig. 3B reports the distribution of the coefficients when the dependent variable is *LnCit*.

we calculate the difference between these two differences, which represents the incremental effect of PNTR on treated firms relative to control firms.

Table 3 presents the regression results. The coefficient estimates on *PNTR* are positive and statistically significant in all columns. The dependent variable in column (1) is *LnPat* (the natural logarithm of one plus the firm's total number of patents filed and subsequently granted) and we include *Treat* × *Post*, industry fixed effects and year fixed effects in the regression. We find that the coefficient estimate on *Treat* × *Post* is positive and significant at the 1% level, suggesting a positive effect of PNTR on the quantity of patents.

Examining *LnCit* (the natural logarithm of one plus the firm's total number of citations) as the dependent variable in column (2), we find that the coefficient on the *Treat* × *Post* indicator is also positive and is significant at the 1% level, which implies that PNTR leads to a significant increase in the quality of patents.

In columns (3) and (4), we additionally control for a long list of firm characteristics; in columns (5) and (6), we additionally control for time-varying industry characteristics. In all these columns, we find that PNTR continues to have a positive and significant impact on corporate innovation. The economic magnitude is also sizeable. For example, the coefficient on *Treat* × *Post* is 0.267 in column (5) and is significant at the 1% level, indicating that PNTR leads to an increase in the number of patents by approximately 31% ($= e^{0.267} - 1$). This number can be interpreted as an annual increase in the number of patents by approximately 3%, considering

Table 3
Baseline regression. This table reports the difference-in-differences tests that examine the impacts of granting PNTR to China on innovation in U.S. firms. The dependent variable *LnPat* is defined as the natural logarithm of one plus the number of patents. The dependent variable *LnCit* is defined as the natural logarithm of one plus number of citations. The indicator variable *Treat* takes the value of one if the firm belongs to an industry in the top tercile of NTR Gap values, and zero if it belongs to an industry in the bottom tercile of the NTR Gap. The indicator variable *Post* takes the value of one for the 2002–2005 period, and zero for the 1995–1998 period. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. T-statistics based on robust standard errors clustered by SIC 2-digit industries are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnPat	(4) LnCit	(5) LnPat	(6) LnCit
Treat × Post	0.230***	0.284***	0.326***	0.408***	0.267***	0.333***
	(0.079)	(0.081)	(0.087)	(0.084)	(3.475)	(4.159)
Ln (Firm size)			0.309***	0.403***	0.317***	0.413***
			(0.047)	(0.068)	(6.367)	(5.788)
Ln (Firm age)			0.189***	0.201**	0.175***	0.183**
			(0.052)	(0.078)	(3.286)	(2.271)
Cash			0.516***	0.952***	0.473**	0.899***
			(0.178)	(0.281)	(2.563)	(3.088)
R&D			0.942***	1.579***	0.562***	1.094***
			(0.295)	(0.376)	(3.158)	(5.218)
ROA			0.077	0.214*	0.019	0.141
			(0.093)	(0.126)	(0.189)	(1.101)
PPE			−0.399*	−0.546*	−0.176	−0.249
			(0.216)	(0.296)	(−0.792)	(−0.855)
Leverage			−0.348***	−0.376**	−0.305***	−0.314**
			(0.111)	(0.155)	(−2.980)	(−2.213)
Capex			1.447***	2.163***	1.419***	2.131***
			(0.375)	(0.670)	(3.681)	(3.075)
Tobin's Q			0.057***	0.075***	0.056***	0.074***
			(0.011)	(0.012)	(5.331)	(6.383)
H-index					−3.308	−2.164
					(−1.573)	(−0.685)
H-index^2					7.639	6.954
					(1.276)	(0.772)
Skill intensity					0.538	0.667*
					(1.623)	(1.758)
Capital intensity					−0.001	−0.001
					(−1.202)	(−1.386)
ADT					0.423***	0.528***
					(3.845)	(3.732)
Contract intensity					−0.224	−0.194
					(−0.840)	(−0.633)
NTR					−0.452	−0.940
					(−0.541)	(−0.781)
Union membership					−1.386***	−1.642**
					(−2.837)	(−2.331)
MFA exposure					0.721***	1.140***
					(6.086)	(6.148)
Constant	0.625***	0.898***	0.064	0.180	0.263	0.271
	(0.022)	(0.029)	(0.160)	(0.224)	(1.042)	(0.817)
Observations	6209	6209	6209	6209	6209	6209
R-squared	0.060	0.067	0.306	0.273	0.325	0.289
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

that our sample covers ten years of China's status as PNTR (1995 to 2005). When examining patent citations in column (6), the coefficient on *Treat* × *Post* is a significant 0.333, indicating that the number of patent citations increases by approximately 40% (= $e^{0.333} - 1$) following the implementation of PNTR (or equivalently, an annual increase in the number of patent citations by approximately 4%).

With regard to the control variables, the more innovative firms are larger firms, older firms, cash-richer firms, firms with higher R&D and capital expenditure, firms with more intangible assets, firms with lower leverage, firms with higher growth potential, and firms in industries with higher skill intensity and ADT. These results are broadly consistent with prior literature (e.g., Aghion et al. (2005)).

Taken together, these results indicate a positive effect of PNTR on innovation outputs in terms of both quantity and quality.

4.3. The pre-treatment trends

The validity of a difference-in-differences estimation depends on the parallel trends assumption: absent PNTR, treated firms' innovation would have evolved in the same way as that of control firms. We present the results that investigate the pre-trend

Table 4
Pre-treatment trend. This table investigates the pre-treatment trends between the treated group and control group. The indicator variable *Treat* takes the value of one if the firm belongs to an industry in the top tercile of NTR Gap values, and zero if it belongs to an industry in the bottom tercile of the NTR Gap. The indicator variables, Year1996–Year2005, flag years 1996–2005, respectively. Year 1995 is the baseline year. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. T-statistics based on robust standard errors clustered by a SIC 2-digit industry are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit
Treat × Year1996	−0.084	−0.069
	(−0.819)	(−0.507)
Treat × Year1997	−0.040	0.036
	(−0.323)	(0.203)
Treat × Year1998	−0.039	−0.015
	(−0.386)	(−0.103)
Treat × Year2002	0.258**	0.324**
	(2.353)	(2.461)
Treat × Year2003	0.237*	0.339**
	(1.952)	(2.253)
Treat × Year2004	0.275**	0.323**
	(2.209)	(2.480)
Treat × Year2005	0.244*	0.346***
	(1.910)	(2.935)
Control variables	Same as column (5) of Table 3	
R-squared	0.306	0.273

between the treated group and control group in Table 4. In particular, we estimate the following regression:

$$\begin{aligned}Innovation &= \alpha + \beta_1 Treat \times Year1996 + \beta_2 Treat \times Year1997 + \beta_3 Treat \times Year1998 \\ &+ \beta_4 Treat \times Year2002 + \beta_5 Treat \times Year2003 + \beta_6 Treat \times Year2004 + \beta_7 Treat \\ &\times Year2005 + Firm\ Characteristics + Industry\ Characteristics + Industry\ FE \\ &+ Year\ FE + \varepsilon. \end{aligned} \tag{2}$$

We define seven dummies, *Year1996, Year1997, Year1998, Year2002*, *Year2003*, *Year2004*, and *Year2005,* to indicate the corresponding years, respectively. Year 1995 is the baseline year.

The coefficients on $Treat \times Year1996$, $Treat \times Year1997$, and $Treat \times Year1998$ indicators are especially important because their significance and magnitude indicate whether there is any difference in the innovation trend between the treatment group and the control group prior to the passage of PNTR. The coefficients on all variables are small in magnitude and not statistically significant in both columns. These results suggest that the parallel trend assumption of the difference-in-differences approach is not violated.

In sum, Table 4 shows that the treated group and the control group share a similar trend in innovation prior to PNTR, thus supporting the parallel trends assumption associated with the difference-in-differences estimation. Moreover, Table 4 also indicates that most of the impact of PNTR on innovation occurs *after* it is implemented, which suggests a causal effect.

4.4. Cross-sectional variation of treatment effects

To provide further evidence that the effects of PNTR on innovation are indeed tied to reduced tariff uncertainty, in this subsection we examine the heterogeneous treatment effects. By doing so, we can further alleviate the concern that some omitted variables are driving our results, because such variables would also have to explain the cross-sectional variation of the treatment effects, which is less likely (Claessens and Laeven, 2003; Raddatz, 2006).

The real option literature indicates that when investments are irreversible, uncertainty will increase firms' incentives to delay investment until some of the uncertainty resolves (e.g. Bernanke (1983) and Dixit and Pindyck (1994)). Specifically, if PNTR enhances U.S. firms' innovation because the tariff uncertainty of Chinese imports increases the value of waiting for irreversible investment in innovation, we expect the treatment effect to be stronger for firms facing greater investment irreversibility. Following Kim and Kung (2016), we measure investment irreversibility by asset redeployability, considering that assets with lower redeployability have a lower liquidation value and thus higher investment irreversibility.[9]

In Table 5, we divide the sample based on the median value of asset redeployability (a lower value of asset redeployability indicates higher investment irreversibility), and re-estimate the baseline regression. In the subsample with low investment irreversibility, the coefficients on *Treat* × *Post* are small in magnitude and not significantly different from zero. In the subsample with

[9] Kim and Kung (2016) construct a firm-level asset redeployability score in three steps: (1) define an asset's redeployability score as the sum of weights of industries that use the asset among the 123 industries in the BEA table, (2) value-weight the asset-level redeployability scores across the 180 assets in the BEA table to obtain an industry-level redeployability index, and (3) construct a firm-level measure of redeployability as the value-weighted average of industry-level redeployability indices across business segments in which the firm operates. The redeployability score can be obtained at https://academic.oup.com/rfs/article/30/1/245/2669940#supplementary-data.

Table 5
Heterogeneous treatment effects based on investment irreversibility. This table reports the cross-sectional variation of the treatment effect based on firms' investment irreversibility. We measure irreversibility by asset redeployability as described in Kim and Kung (2016). Columns (1) and (2) represent the subsample of firms with low irreversibility (higher asset redeployability indicates low irreversibility) and columns (3) and (4) represent the subsample of firms with high irreversibility. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. T-statistics based on robust standard errors clustered by SIC 2-digit industries are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low investment irreversibility		High investment irreversibility	
	(1) LnPat	(2) LnCit	(3) LnPat	(4) LnCit
Treat × Post	0.110	0.089	0.609***	0.788***
	(0.817)	(0.712)	(3.597)	(4.441)
Control variables	Same as column (5) of Table 3			
R-squared	0.279	0.257	0.344	0.305

Table 6
Heterogeneous treatment effects based on Chinese imports. This table reports the cross-sectional variation of the treatment effect based on the increase of Chinese imports during our sample period. We compute the percentage increase in Chinese imports over the 1995–2005 period in a given industry (*PctImportChg*). Columns (1) and (2) represent the subsample of firms with smaller increase in Chinese imports (below-median value of *PctImportChg*) and columns (3) and (4) represent the subsample of firms with greater increase in Chinese imports (above-median value of *PctImportChg*). Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. T-statistics based on robust standard errors clustered by SIC 2-digit industries are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Small increase in Chinese imports		Great increase in Chinese imports	
	(1) LnPat	(2) LnCit	(3) LnPat	(4) LnCit
Treat × Post	−0.024	−0.049	0.340*	0.411**
	(−0.447)	(−0.701)	(2.153)	(2.574)
Control variables	Same as column (5) of Table 3			
R-squared	0.377	0.352	0.326	0.285

high investment irreversibility, the coefficients on *Treat* × *Post* are much larger in magnitude and significantly different from zero. When the dependent variable is *LnPat*, the coefficient on *Treat* × *Post* is 0.11 (insignificant) in the subsample of low investment irreversibility (see column (1)). The corresponding coefficient in the subsample of high investment irreversibility is 0.609 and is significant at the 1% level (see column (3)). Similarly, when the dependent variable is *LnCit*, the coefficient on *Treat* × *Post* is 0.089 (insignificant) in the subsample of low investment irreversibility (see column (2)). The corresponding coefficient in the subsample of high investment irreversibility is 0.788 and is significant at the 1% level (see column (4)).[10] In summary, the treatment effect for firms with high investment irreversibility is at least six times as large as that for firms with low investment irreversibility.

If U.S. firms' enhanced innovation after PNTR is truly related to Chinese imports, we expect this treatment effect to be stronger in industries that experience a greater increase in Chinese imports following PNTR. We compute the percentage increase in Chinese imports over the 1995–2005 period in a given industry (*PctImportChg*). We then divide the sample based on the median value of *PctImportChg* and re-estimate the baseline regression in Table 6. In the subsample with greater increase in Chinese imports, the coefficients on *Treat* × *Post* are large in magnitude and significantly different from zero. In the subsample with smaller increase in Chinese imports, the coefficients on *Treat* × *Post* are much smaller in magnitude and insignificantly different from zero. When the dependent variable is *LnPat*, the coefficient on *Treat* × *Post* is −0.024 and is insignificant in the subsample of industries with smaller increase in Chinese imports (see column (1)). The corresponding coefficient in the subsample of industries with greater increase in Chinese imports is 0.340 and is significant at the 10% level (see column (3)). Similarly, when the dependent variable is *LnCit*, the coefficient on *Treat* × *Post* is −0.049 and is insignificant in the subsample of industries with smaller increases in Chinese imports (see column (2)). The corresponding coefficient in the subsample of industries with greater increases in Chinese imports is 0.411 and is significant at the 1% level (see column (4)).[11] In summary, the treatment effect for firms in industries with a greater increase in Chinese imports is much larger than that for firms in industries with a smaller increase in Chinese imports. Overall, these results suggest that the impact of PNTR on corporate innovation is indeed tied to reduced uncertainty associated with Chinese imports' tariff rate and appears not to be spuriously driven by unobserved heterogeneity.

4.5. Placebo tests

In this section, we implement two placebo tests to investigate the possibility that our results are purely driven by chance. In the first placebo test, we draw a random sample of 929 firms (the same number of the treated firms) as the treated firms during the

[10] The Chow test on the equality of coefficients on *Treat* × *Post* between columns (1) and (3), and that between columns (2) and (4), indicates that these coefficients are significantly different at the 1% level.

[11] The Chow test on the equality of coefficients on *Treat* × *Post* between columns (1) and (3) and that between columns (2) and (4), indicates that these coefficients are significantly different at or below the 10% level.

Table 7

Placebo tests based on pseudo event year. This table reports the baseline regression based on two pseudo-treatment years: 1995 and 2010. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. T-statistics based on robust standard errors clustered by SIC 2-digit industries are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat	(2) LnCit	(3) LnPat	(4) LnCit
	Pseudo Year 1995		Pseudo Year 2010	
Treat × Post	−0.058	−0.108	−0.208	−0.506**
	(−0.707)	(−0.739)	(−1.321)	(−2.401)
Control variables	Same as column (5) of Table 3			
R-squared	0.421	0.398	0.426	0.396

Table 8

Alternative explanation: Outsourcing to China. This table investigates whether our main finding is driven by U.S. firms' outsourcing activities. In Panel A, we include the *Outsourcing* indicator in our baseline regression to control for the influence of outsourcing activities. In Panel B, we focus on the subsample of firms that do not have any outsourcing activities during our sample period. The indicator variable *Outsourcing* equals 1 if the firm engages in outsourcing activities through outside purchase contracts, and 0 otherwise. Details of purchase contracts are obtained from the MD&A section of firms' 10-K filings (Moon and Phillips, 2021). Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. Robust standard errors clustered by a SIC 2-digit industry are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline regressions additionally controlling for outsourcing		
	(1) LnPat	(2) LnCit
Treat × Post	0.227***	0.284***
	(2.800)	(3.433)
Outsourcing	0.469***	0.565***
	(6.411)	(6.369)
Control variables	Same as column (5) of Table 3	
R-squared	0.340	0.299
Panel B: Subsample of firms that do not outsource		
	(1) LnPat	(2) LnCit
Treat × Post	0.278***	0.279**
	(3.355)	(2.533)
Control variables	Same as column (5) of Table 3	
R-squared	0.256	0.230

sample period and then treat the rest of the pool as "non-treated firms". Consistent with our baseline regression, the dummy variable *Post* assumes the value of one for the 2002–2005 period (i.e., post-PNTR period), and zero for the 1995–1999 period (i.e., pre-PNTR period). Based on these "pseudo" treated and control groups, we re-estimate columns (5) and (6) of Table 3 and save the coefficients on *Treat* × *Post*. We repeat this procedure 5000 times.

Panel A of Fig. 1 plots the distribution of the coefficients on *Treat* × *Post* when the dependent variable is *LnPat*. The actual coefficient on *Treat* × *Post* of 0.267 (see column (5) of Table 3) is more than nine times the standard deviations (0.034) above the mean (−0.062) of the distribution and is even larger than the maximum coefficient estimate (0.066) from the placebo test. Panel B plots the distribution of the coefficients on *Treat* × *Post* when the dependent variable is *LnCit*. The actual coefficient on *Treat* × *Post* of 0.333 (see column (6) of Table 3) is about ten times the standard deviation (0.045) above the mean (−0.114) of the distribution and is much larger than the maximum coefficient estimate (0.054).

In the second placebo test, we re-estimate our baseline regression based on two pseudo-treatment years: 1995 (approximately five years before PNTR) and 2010 (approximately ten years after PNTR), respectively. This additional placebo test could help alleviate the concern of any misspecification in the difference-in-differences model. In particular, we treat 1995 (2010) as the pseudo-treatment year, and compare the change in firm innovation from four years before the pseudo-treatment year to four years afterward. Table 7 presents the results. We show that these pseudo-treatments have no positive effect on firms' innovation. Taking 1995 as an example (see columns (1) and (2)), the coefficients on *Treat* × *Post* are −0.058 (when the dependent variable is *LnPat*) and −0.108 (when the dependent variable is *LnCit*); both coefficients are not significantly different from zero. Overall, these results indicate that our results are unlikely to be driven by chance.

4.6. Alternative explanation of outsourcings

Our results are also consistent with the following alternative explanation: The admission of China into the WTO in 2000 eradicates the barriers to invest in China. As a result, U.S. firms have stronger incentives to outsource low-tech productions to China (or other low-income countries) and focus more on innovation, which leads to an increase in corporate innovation.

Table 9
Alternative innovation measures. This table examines the effects of PNTR on corporate innovation with alternative innovation measures. The regression specification is the same as that in Table 3. The dependent variables are the natural logarithm of one plus the value of a firm's number of patents and citations scaled by the number of the firm's employees in columns (1) and (2), respectively. The dependent variable in column (3) is the natural logarithm of the number of citations scaled by the number of patents. The dependent variable in column (4) is the natural logarithm of one plus the number of patent claims scaled by the number of patents. The dependent variable in column (5) is R&D expenditure normalized by total assets. The dependent variable in column (6) is the sum of R&D expenditure, capital expenditure, and SG&A expenses scaled by total assets. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. Robust standard errors clustered by a SIC 2-digit industry are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) LnPat/Emp	(2) LnCit/Emp	(3) LnCit/Pat	(4) LnClaim/Pat	(5) R&D	(6) R&D+Capex+SG&A
Treat × Post	0.129***	0.127**	0.093***	0.193**	−0.007	0.015**
	(5.105)	(2.643)	(2.706)	(2.417)	(−1.626)	(1.987)
Control variables	Same as column (5) of Table 3					
R-squared	0.212	0.205	0.197	0.198	0.561	0.465

We collect the firm outsourcing information from Moon and Phillips (2021), who construct a database of outsourcing activities based on outside purchase contracts extracted from firms' 10-K filings.[12] We implement two tests to investigate this alternative explanation. First, we define the *Outsourcing* indicator as taking the value of one if the firm has engaged in at least one outside contract manufacturing, and zero otherwise. We then re-estimate our baseline regression by additionally controlling for the *Outsourcing* indicator in Panel A of Table 8. We find that the positive effect of PNTR on U.S. firms' innovation remains significant even after controlling for firms' outsourcing activities: The coefficient on *Treat* × *Post* is 0.227 (significant at the 1% level) when the dependent variable is *LnPat*, and is 0.284 (also significant at the 1% level) when the dependent variable is *LnCit*. Moreover, the coefficient on the *Outsourcing* indicator is positive and significant, consistent with the view that outsourcing low-tech productions helps to promote U.S. corporate innovation.

In our second test, we focus on the subsample of firms that have no outsourcing during our sample period and re-estimate our baseline regression. If the above alternative explanation is the main driver of our findings, we would expect to find no significant effect in this subsample (because these firms do not outsource at all). Panel B of Table 8 presents the results. We still find that PNTR leads to a significant increase in U.S. firm innovation. Taking column (1) for example (where the dependent variable is *LnPat*), the coefficient on *Treat* × *Post* is 0.278 and significant at the 1% level. Overall, these results indicate that although outsourcing is likely to enhance U.S. firm innovation, it is unlikely to be the main driving force for our results.

4.7. Alternative measures of innovation

As a robustness check, we employ various alternative measures to examine the effect of PNTR on corporate innovation. Table 9 presents the results. In columns (1) and (2), we normalize the number of patents and citations by the number of employees. In columns (3) and (4), we use the number of citations and claims per patent to measure patent quality. A typical patent consists of several claims and each claim represents a separate inventive contribution. Thus, a larger number of claims per patent indicates a higher quality of the patent (Lerner, 1994; Hsu et al., 2020).

We show that PNTR has a positive and significant effect on these alternative innovation measures. For example, the dependent variable in column (1) is *LnPat/Emp*; the coefficient on *Treat* × *Post* is 0.129 and significant at 1% level, suggesting that PNTR leads to an approximate 14% ($= e^{0.129} - 1$) increase in the number of patents per employee. Similarly, the dependent variable in column (4) is *LnClaim/Pat*; the coefficient on *Treat* × *Post* is 0.193 and significant at 5% level, suggesting that PNTR leads to an approximate 21% ($= e^{0.193} - 1$) increase in the number of claims per patent.

In column (5), we use *R&D expenditure* as the dependent variable. Different from those patent-based variables that capture innovation outputs, R&D expenditure is likely an imperfect measure of innovation input. However, we do not find any significant effect for PNTR on a firm's R&D expenditure. This insignificant result is possibly because R&D expenditure does not measure a firm's innovation input in an accurate manner. As pointed out by Horwitz and Kolodny (1980), the notion of R&D expenditure is usually ambiguous to assess and often represents the manager's discretion. For example, if managers have incentive to limit their R&D information to competitors, they may tend to avoid classifying some research-related outlays as R&D expenses. Koh and Reeb (2015) show that many patenting-active companies report zero or missing R&D expenditure. Atanassov (2013) shows that many important innovation inputs may not be categorized as "R&D expenditure": For instance, purchasing experiment equipment may be classified as capital expenditure, while investment in human capital like employee benefits for scientists and engineers may be classified as SG&A expenses. To address such a possible inaccuracy of R&D expenditure, we follow Gao and Zhang (2019) and take the sum of R&D expenditure, capital expenditure, and SG&A expenses normalized by total assets to capture a firm's overall input that could be relevant to innovation. As reported in column (6), the coefficient on *Treat* × *Post* is positive and significant at the 5% level, suggesting that innovation input broadly increases following the PNTR.

Overall, Table 9 shows that the positive effect of PNTR on innovation is robust to various alternative innovation measures.

[12] In untabulated analysis, we show that PNTR indeed leads to more outsourcing activities of U.S. companies.

4.8. Other possible mechanisms

Although our paper focuses on the mechanism of reduced tariff uncertainty associated the PNTR, there are other possible mechanisms driving our findings, considering that many important events happened around the conferral of the PNTR to China. For example, China joined WTO in 2000. This event grants China access to the global markets and boosts Chinese firms' export, which in turn improves Chinese firms' production efficiency (Bloom et al., 2016; Brandt et al., 2017). The enhanced competitiveness of Chinese products makes U.S. products relatively less competitive and thus forces U.S. firms to differentiate themselves from Chinese firms through innovation. Our results that the treatment effect is stronger for firms experiencing a greater increase in Chinese goods following PNTR (see Table 6) is broadly consistent with this view.

For another example, the increase in innovation could be associated with the increasing competitiveness of U.S. technology-intensive industries, the abolishment of import quotas on textile and clothing imports under the global MFA, or the decline in unionization in the manufacturing sector during our sample period. In our baseline results, we have added a battery of corresponding variables to control for the potential impact of these events following Pierce and Schott (2016); but it might still be possible that these events could affect the impact of PNTR on innovation in a non-linear fashion. Although we do not find any evidence pointing to these implications, our current regression framework could not perfectly eliminate such possibilities. In summary, although we find evidence supporting the view that PNTR leads to an increase in U.S firm innovation through the mechanism of reducing tariff uncertainty, other factors discussed above could also play a role.

5. Conclusions

Does the tariff uncertainty associated with Chinese goods have any real effect on the U.S. economy? In this paper, we shed light on this question by examining the effect of United States' conferral of Permanent Normal Trade Relations (PNTR) status to China – a policy reducing the uncertainty of future tariff increases associated with Chinese goods – on U.S. firm innovation. Using a difference-in-differences approach, we find a significant increase in firms' patents and patent citations for firms affected by PNTR relative to firms that are unaffected by this policy. In support of a causal interpretation of our findings, our timing tests indicate that there is no difference in pre-treatment trends in innovation between the two groups of the firms, and that the increase in innovation occurs after PNTR is in effect. Finally, the cross-sectional variation of the treatment effects indicates that the treatment effect is larger for industries with more irreversible investments and for industries that experience a greater increase in Chinese goods following PNTR. Overall, our findings are consistent with the view that reducing the uncertainty associated with Chinese imports boosts the attractiveness for U.S. firms to make long-term irreversible investment (such as technological innovation).

Appendix. Variable definitions

Variable	Definition
Measures of innovation output	
Patent	Number of patents that are applied for (and subsequently granted) by a firm.
LnPat	Natural logarithm of one plus firm's total number of patents filed (and subsequently granted).
Citation	Total number of citations received on the firm's patents filed. To adjust the citation count, each patent's number of citations is divided by the average citation count of all patents applied in the same year.
LnCit	Natural logarithm of one plus firm's total number of citations received on the firm's patents filed.
LnPat/Emp	Natural logarithm of one plus firm's total number of patents filed (and subsequently granted), scaled by the number of the firm's employees.
LnCit/Pat	Natural logarithm of one plus firm's average number of citations received on the firm's patents filed. If the firm filed no patents in that year, the missing value of average citation counts is set to zero.
LnCit/Emp	Natural logarithm of one plus firm's total number of citations received on the firm's patents filed (and subsequently granted), scaled by the number of the firm's employees.
LnClaim/Pat	Natural logarithm of one plus the number of patent claims over number of patents.
Firm characteristics	
Treat	A dummy variable that equals 1 if the firm belongs to an industry in the top tercile of NTR Gap, and 0 if it is in the bottom tercile.
Post	A dummy variable that equals 1 for the 2002–2005 period, and 0 for the 1995–1998 period.
Total asset	Book value of total assets.
Firm size	Number of employees in thousands

Variable	Definition
Firm age	Number of years since a firm's first appearance in Compustat.
Cash	Cash and short-term investments normalized by total assets.
R&D	R&D expenditures normalized by total assets. If R&D expenditures variable is missing, we set the missing value to zero.
ROA	Return on assets, measured as EBITDA (earnings before interest, tax, depreciation and amortization) normalized by total assets.
PPE	Property, plant & equipment normalized by total assets.
Leverage	Long-term debt normalized by total assets.
Capex	Capital expenditures normalized by total assets. If capital expenditures variable is missing, we set the missing value to zero.
R&D+Capex+SG&A	The sum of R&D expenditure, capital expenditure, and selling, general and administrative (SG&A) expenses, normalized by total assets. If any one of R&D, Capex or SG&A variable is missing, we set the missing value to zero.
Tobin's Q	Market value of equity plus book value of total assets minus book value of equity minus balance sheet deferred taxes, normalize by total assets.
HighPctImportChg	A dummy variable that equals 1 if the percentage change in imports from China from 1995 to 2005 in the industry is above the sample median, and 0 otherwise.
Outsourcing	A dummy variable that equals 1 if the firm engages in outsourcing activities through outside purchase contracts, and 0 otherwise. Details of purchase contracts can be found in the MD&A section of firms' 10-K filings. The data is obtained from Moon and Phillips (2021).
Industry characteristics	
H-index	Herfindahl index, defined as sum of squared sales-based market shares of all firms in a two-digit SIC industry.
Skill intensity	The ratio of non-production workers to total employment in one industry. We use quinquennial data collected in the US Census of Manufactures.
Capital intensity	The ratio of capital to total employment in one industry. We use quinquennial data collected in the US Census of Manufactures.
ADT	A dummy variable that equals 1 if the industry produces advanced technology products. The definitions of advanced technology products are obtained from US Census Bureau's website.
Contract intensity	The proportion of intermediate inputs that require relationship-specific investments to capture the nature of contracting in the industry, as China's reduction of barriers to foreign investment may have affected industries differently (Nunn, 2007).
NTR	The NTR tariff rates are obtained from Feenstra et al. (2002), which are unavailable after 2001 and are assumed constant after that year.
Union membership	Industry-level unionization rate from Hirsch and MacPherson (2003).
MFA exposure	MFA exposure measures the exposure to the abortion of the global Multi-Fiber Arrangement (MFA) governing Chinese textile and clothing export quotas. It is defined in the Appendix of Pierce and Schott (2016).

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