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

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Accepted manuscript

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Please cite the published version:

Chen, T., Gao, H., & Wang, Y. (2021). Tariff uncertainty and firm innovation: Evidence from the U.S.–China Permanent Normal Trade Relation. *Journal of Empirical Finance*, 62, 12–27.

https://doi.org/10.1016/j.jempfin.2021.02.002

Posted by the author at https://taochen.org

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This version: November, 2020

Abstract

We examine the effect of the tariff uncertainty associated with Chinese imports on U.S. firm innovation. Our test exploits United States' 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 industries with more irreversible investments and for industries that experience a greater increase in Chinese goods following PNTR. Our evidence suggests that lowering the tariff uncertainty of Chinese imports induces U.S firms to innovate more.

Keywords: Permanent Normal Trade Relations; Tariff Uncertainty, Innovation; Patents; Imports; China

JEL Classification: G38; O31

1. Introduction

The recent 2018-present trade war between the world's largest economies escalates as U.S. and China continues to dispute tariffs placed on goods traded between them, and it has cost billions of dollars each in 2018.[1] For example, the U.S government started investigations on tariffs applied to Chinese products, and 11,207 products with a total value of $247 billion in Chinese imports were targeted in 2018. The uncertainty of further tariff increase has drawn global attention to rethinking the cost and benefit of globalization, with the recent wave particularly characterized by the impact from Chinese imports since China's entry to the World Trade Organization. Indeed, many U.S. firms have shifted investment and supply chains to elsewhere in Asia, with fears and uncertainty that the trade war would lead to a US-China economic "decoupling".[2] In academia, the recent papers have mostly cast various adverse effects of Chinese imports on U.S. society: for instance, a surge in manufacturing unemployment (e.g., Acemoglu et al. (2016); Pierce and Schott (2016)) and deterioration in worker health (e.g., McManus and Schaur (2016)). In this paper, we study the effects of Chinese imports on the real economy in the case of U.S. firm innovation by using 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 policy shock from the United States granting China PNTR in 2000 offers an ideal setting to study the effect of tariff uncertainty of Chinese imports on U.S. corporate innovation. The United States and China are two of the world's largest trading partners, and the tension between the two economies plays a crucial role in the world economy. The PNTR, which was finally

[1] See "A quick guide to the US-China trade war," BBC News (January 7, 2019); "Trade wars cost U.S., China billions of dollars each in 2018," Reuters (December 29, 2018); "US-China trade battle: Catch up here," *CNN Money* (April 8, 2018); "What's at stake in the looming US-China trade war: the full list," *Financial Times* (April 18, 2018). Financial Times also has a special topic on "US-China trade dispute" (https://www.ft.com/us-china-trade-dispute) and a collection on "The China-US trade war 2018" (https://www.ft.com/content/c36aacec-fc97-11e8-ac00-57a2a826423e).
[2] See "Fears rise that US-China economic 'decoupling' is irreversible: many American companies are shifting supply chains to elsewhere in Asia," Financial Times (January 21, 2020).

implemented on January 1, 2002, pushed the U.S. market to be more open to Chinese products by eliminating 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 reduces 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,[3] but these low rates had to be renewed every year by the U.S. Congress. The renewals were uncertain and politically contentious ((Pierce and Schott (2016))). If the Congress did not approve the renewal in any particular year, a much higher tariff rate (non-NTR rate) would be applied to China's imports. For example, in 1999, the average NTR rate was only 4 percent, but the average non-NTR rate was 37 percent. To sum, the passage of PNTR eliminated a great amount of the uncertainty in importing goods from China by permanently setting 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.

We empirically test the effect of PNTR on corporate innovation using a panel of 6,209 U.S. public firms 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 38% (or by 4% per year) and an increase in the number of patent citations by 49% (or by 5% 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-

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

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 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 reduced tariff uncertainty associated with Chinese goods.

Finally, 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 5,000 times. We find that the maximum coefficient in magnitude estimated in the placebo test is substantially smaller than the actual coefficient estimate 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.

This paper provides at least three major contributions to existing literature. First, 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.-China economy have a significant impact on corporate innovation for U.S. firms.

Second, our paper contributes to the literature studying on the effect of U.S. tariff rate policy. **Extant literature** has examined the effect of tariff rate reduction on 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 recently bourgeoning literature focuses on the consequences of Chinese import competition, such as the effects on manufacturing unemployment (e.g., Acemoglu et al., 2016; Pierce and Schott, 2016), public health (e.g., McManus and Schaur, 2016), relative decline of investment, operation profit and employment of small U.S. firms (Gutierrez and Philippon, 2017; Greenland et al., 2020), and the increased prices of inputs and consumer products in United States (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.

Third, our study sheds light on the real consequences of PNTR. As pointed out by (Pierce and Schott (2016)), PNTR has a significant impact on U.S. manufacturing firms, in that it leads to massive layoffs in these firms. They found that the number of workers in the U.S. manufacturing industry plunged by 18% from 2001 to 2007 and that this decline in employment was 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 innovation aimed at lowering production cost) than U.S. firms with a subsidiary in a low-wage Asian country but not China. Although both our study and theirs show the U.S.-China economics integration has significant effect 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 PNTR, which does not affect U.S. firms' access to Chinese labor but eliminates 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 X, we provide evidence that our results are unlikely driven by outsourcing activities to China."

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 Chinese imports on U.S. corporate innovation. Since the Smoot-Hawley Tariff Act of 1930, U.S. imports from non-market economies, including China, have been subject to high "non-NTR" tariff rates, which are 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] Figure 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 year 2001 (the year right before the PNTR became effective), the percentage of dis-approving vote is 40%. These facts indicate that there exists considerable uncertainty about China's NTR status.[5] This uncertainty left China's trade industry on edge, for 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 34%. More importantly, the NTR rate 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.

[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.

One paramount advantage of this natural experiment is its exogeneity to corporate innovation activities after PNTR. 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.

Uuncertainty 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 decreases (e.g., McDonald and Siegel (1986); Pindyck (1993) ; Dixit and Pindyck (1994); 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, Manso, and Silva (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 to make an irreversible investment in a new technology to produce an innovative product (to replace its conventional products that face competitions from China imports). The 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 can 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 eliminate 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 6,209 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 Normal Trade Relation (NTR) country and a non-NTR country, obtained from (Feenstra, Romalis and Schott (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, Jaffe and Trajtenberg (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, Lai, D'Amour, Doolin, Sun, Torvik, Amy and Fleming (2014))).[7]

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

[6] In unreported 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.

filed by the firm in a given year, which captures the significance of the patent outputs. Because citations are received for 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, Jaffe and Trajtenberg (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, Bloom, Blundell, Griffith and Howitt (2005)). These variables include firm size, firm age, asset tangibility, leverage, cash holding, R&D expenditures, capital expenditures, ROA, and Tobin's *Q*.

We control for several time-varying industry characteristics. We control for industry concentration (the Herfindahl index based on sales) and the squared Herfindahl index (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. Skill intensity is measured by the ratio of non-production workers to total employment in one industry, while 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. To control for the potential confounding effects of trends that overlap with the granting of PNTR to China, we control for the following events. First, we control for the U.S. tech "bubble" burst and the subsequent recovery in our study period, we further control for advanced technology products (ADT)—a dummy variable that equals one if the industry produces advanced technology products. Second, we control for the elimination of import quotas on some textile and clothing import in 2002 and 2005 under the global MFA. Third, we control for the steady decline in union membership in the US 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 variables at the 0.5th and 99.5th percentiles. Detailed variable definitions are provided in the 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 17 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 levered 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.

5. Empirical Results

5.1 Visual Illustration

Figure 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 assumption associated with the difference-in-differences estimation.[8] Second, although the treated industries are more innovative than the control industries in 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).

Overall, Figure 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.

5.2 Baseline Regression

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

. (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 firm-level 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

[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. Instead, this assumption requires a similar trend in corporate innovation in the pre-PNTR period for both groups.

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 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. However, economy-wide shocks may occur at the same time and affect corporate innovations. To difference away such factors, we calculate the same difference in innovations in firms that are unaffected by PNTR. Finally, 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 *Ln(1+patents)* 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 corporate innovations.

Examining *Ln(1+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 decrease 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 controls for time-varying industry characteristics described in Section 3. 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 30.6% (. This number can be interpreted as an annual increase in the number of patents by approximately 3%, considering 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 39.5% (following the implementation of PNTR (or equivalently an annual increase in the number of patent citations by approximately 4%).

With regards to control variables, the more innovative firms are larger firms, older firms, cash-rich firms, firms with higher R&D and capital expenditures, firms with more intangible assets, firms with low leverage, firms with higher growth potential, and firms in industries with high skill intensity and ADT. These results are broadly consistent with prior literature (e.g., (Aghion, Bloom, Blundell, Griffith and Howitt (2005))).

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

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

(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 and 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 PNTR. The coefficients on both 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.

5.4 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); 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 Gulen and Ion (2015) and Kim and Kung (2017), we measure investment irreversibility by asset redeployability, considering that assets with lower redeployability have a lower liquidation value, and thus have higher investment irreversibility.

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 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)). In summary, the treatment effect for firms with high investment irreversibility is about 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 0.340 and is significant at the 1% level (see column (1)) in the subsample of firms in industries with greater increase in Chinese imports. The corresponding coefficient in the subsample of firms in industries with smaller increase in Chinese imports is -0.024 and is insignificant (see column (3)). Similarly, when the dependent variable is *LnCit*, the coefficient on *Treat*×*Post* is 0.411 and is significant at the 1% level in the subsample of firms with a larger value of *PctImportChg* (see column (2)). The corresponding coefficient in the subsample of firms with a lower value of *PctImportChg* is -0.049 and is insignificant (see column (4)). 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.

5.5 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 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 5,000 times.

Panel A of Figure 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). 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 more than nine times the standard deviations (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 afterwards. Table 5 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. Taking 2010 as another example (see columns (3) and (4)), the coefficients on *Treat*×*Post* are also negative. Overall, these results indicate that our results are unlikely driven by chance.

5.6 Alternative Explanation of Outsourcings to China

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 and focus more on innovation, which leads to an increase in corporate innovation.

We collect the firm outsourcing information from Moon and Phillips (2020), who construct a database of outsourcing activities based on outside purchase contracts extracted from firms' 10-K filings. 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. Then we 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 remain 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 to China helps to promote U.S. corporate innovation.

In our second test, we focus on the subsample of firms that have no outsourcing to China during our sample period, and re-estimate our baseline regression. If the above alternative explanation is the main driver of our findings, then we expect to find no significant effect in this

subsample (because these firms donot 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 to China is likely to enhance U.S. firm innovation, it is unlikely to be the main driving force for our results.

5.7 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% (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% (increase in the number of claims per patent.

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

6. Conclusions

The on-going U.S.-China trade war has greatly increased the uncertainty of about the tariff rate of Chinese imports. Recent evidence shows that many U.S. firms have shifted investment and supply chains to elsewhere in Asia. In this paper, we shed light on this topic 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).

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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.
LnPat/R&D	Natural logarithm of one plus firm's total number of patents filed (and subsequently granted), scaled by its R&D expenditure.
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.
LnCit/R&D	Natural logarithm of one plus firm's total number of citations received on the firm's patents filed (and subsequently granted), scaled by its R&D expenditure.
LnClaim/Pat	Natural logarithm of one plus the number of patent claims over number of patents. Patent claims data is described in Hsu et. al. (2021) (Hsu, Hsu, Zhou and Ziedonis (2021))
R&D/Emp	R&D expenditure scaled by the number of the firm's employees.
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
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.
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.
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, Romalis, and Schott (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).

Table 1: NTR Gap by Industry

This table presents the NTR Gap by all manufacturing industries (SIC codes between 2000 and 3999).
The superscripts * and ** denote the treated industry and control industry, respectively.

Industry	SIC	NTRGAP
Rubber And Miscellaneous Plastics Products*	30	0.581
Apparel And Other Finished Products Made From Fabrics And Similar Materials*	23	0.578
Miscellaneous Manufacturing Industries*	39	0.507
Leather And Leather Products*	31	0.490
Textile Mill Products*	22	0.462
Electronic And Other Electrical Equipment And Components, Except Computer Equipment*	36	0.455
Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical* 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**	32	0.209
Primary Metal Industries**	33	0.209
Transportation Equipment**	37	0.185
Food And Kindred Products**	20	0.160
Paper And Allied Products**	26	0.130
Printing, Publishing, And Allied Industries**	27	0.055
Petroleum Refining And Related Industries**	29	0.052

Table 2: Summary Statistics

Panel A presents the summary statistics of the full sample, which consists of 6,209 firm-year observations from 1995–2005, 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 Asset (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)	Wilcoxon test (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 Asset (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

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	6,209	6,209	6,209	6,209	6,209	6,209
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

Table 4: Pre-treatment Trend

This table investigates the pre-treatment trends between the treated group and control group. The dependent variable in column (1) is *LnPat*, defined as the natural logarithm of one plus the number of patents. The dependent variable in column (2) is *LnCit*, 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 variables, Year1996-Year2005, flag year 1996–2005, respectively. Year 1995 is the baseline year. Variable definitions are elaborated 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

Table 5: Heterogeneous Treatment Effects based on Investment Irreversibility

Panel A 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 (2017). Columns (1) and (2) represent subsample of firms with low irreversibility (higher asset redeployability indicates low irreversibility) and Columns (3) and (4) represent subsample of firms with high irreversibility. Panel B 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 (2017). Columns (1) and (2) represent subsample of firms with low irreversibility (higher asset redeployability indicates low irreversibility) and Columns (3) and (4) represent subsample of firms with high irreversibility.Variable definitions are elaborated in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. We control for industry fixed effects and year fixed effects in all regressions. 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.

Panel A. Investment Irreversibility

	Low Asset Irreversibility		High Asset Irreversibility	
	(1)	(2)	(3)	(4)
	LnPat	LnCit	LnPat	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

Panel B. Chinese Imports

	High Reliance		Low Reliance	
	(1)	(2)	(3)	(4)
	LnPat	LnCit	LnPat	LnCit
Treat ×Post	0.340*	0.411**	-0.024	-0.049
	(2.153)	(2.574)	(-0.447)	(-0.701)
Control variables	Same as column (5) of Table 3			
R-squared	0.326	0.285	0.377	0.352

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 elaborated in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. We control for industry fixed effects and year fixed effects in all regressions. 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)	(2)	(3)	(4)
	LnPat	LnCit	LnPat	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 to China. 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 the our sample period. The indicator variable *Outsourcing* measures the outsourcing activities as described in Moon and Phillips (2020). Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. We control for industry fixed effects and year fixed effects in all regressions. 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 to China

	(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

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 column (1) and (2) respectively. The dependent variable in column (3) is the natural logarithm of the number of citations over number of patents. The dependent variable in column (4) is the natural logarithm of one plus the number of patent claims over number of patents. Patent claims data is described in Hsu *et. al.* (2021). 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. All the control variables used in Table 3 are also included in this regression. 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
Treat × Post	0.129***	0.127**	0.093***	0.193**
	(5.105)	(2.643)	(2.706)	(2.417)
Control variables	Same as column (3) of Table 3			
R-squared	0.212	0.205	0.197	0.198

Figure 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.

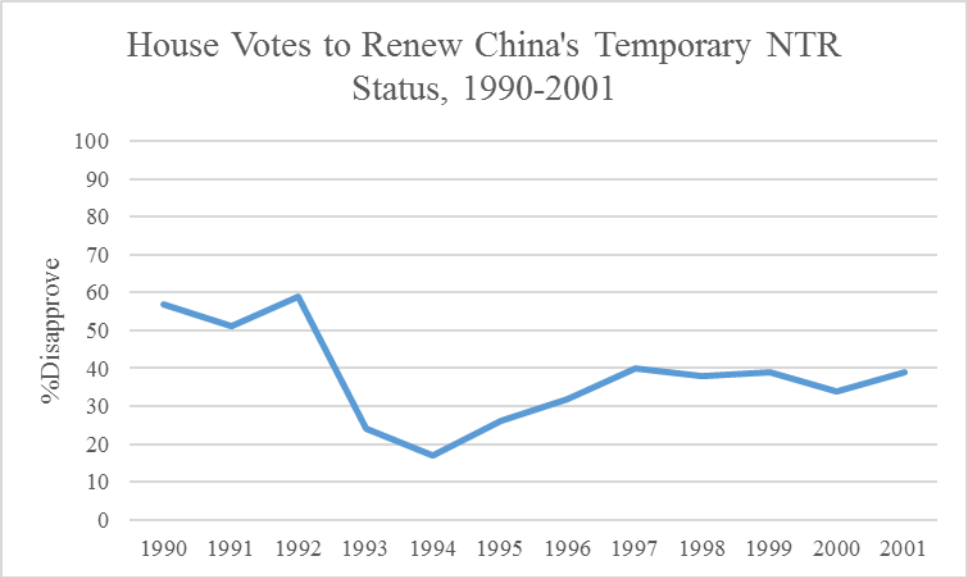


Figure 2. Visual Illustration

This figure shows corporate innovation during 1995-2005 for firms in the treated and control industries respectively.

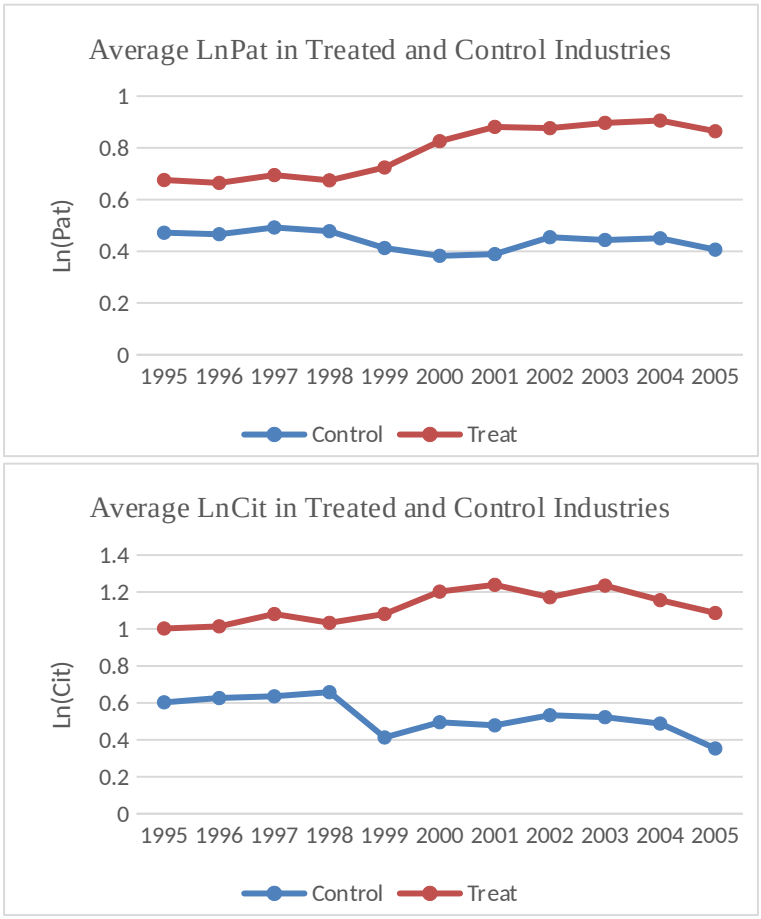


Figure 3. Placebo Test

This figure shows a histogram of the coefficients on *Treat×Post* from 5,000 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) as 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*. Figure 3A reports the distribution of the coefficients when the dependent variable is *LnPat*, and Figure 3B reports the distribution of the coefficients when the dependent variable is *LnCit*.

Figure 3A: Number of Patents

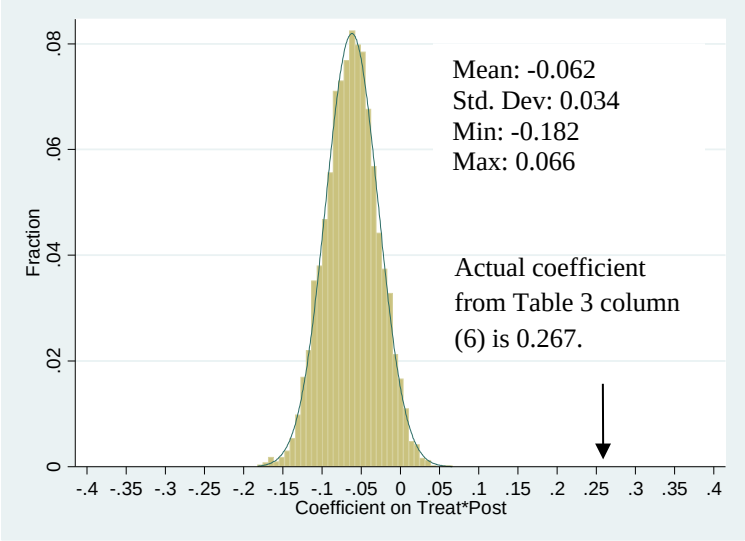


Figure 3B: Number of Patent Citations

