Effects of Chinese Imports on U.S. Firm Innovation: Evidence from the US-China Permanent Normal Trade Relation[*]

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Abstract

We examine the effect of United States' conferral of Permanent Normal Trade Relations (PNTR) on China—a policy that eliminates the uncertainty of future tariff increases associated with Chinese goods— on U.S. firm innovation. We find a significant increase in the number of patents and patent citations for U.S. firms that are affected by PNTR relative to firms that are not affected. This result is stronger for industries that experience a greater increase in Chinese goods following PNTR. Overall, our evidence suggests that Chinese imports induce U.S firms to invest more in innovative technology.

Keywords: Permanent Normal Trade Relations; Innovation; Patents; Imports; China

JEL Classification: G38; O31

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1. Introduction

In October 2000, the U.S. Congress decided to grant Permanent Normal Trade Relations (PNTR) status to China, which became effective upon China's accession to the World Trade Organization (WTO) at the end of 2001. This conferral of PNTR was unique in that it did not change the import tariff rates the United States actually applied to Chinese goods over this period. U.S. imports from China had been subject to the relatively low NTR tariff rates reserved for WTO members since 1980.[1] But, for China these low rates required annual renewals that were uncertain and politically contentious. Without renewal, U.S. import tariff on Chinese goods would have jumped to the higher non-NTR tariff rates assigned to non-market economies, which were originally established under the Smoot-Hawley Tariff Act of 1930. PNTR removed the uncertainty associated with these annual renewals by permanently setting U.S. duties on Chinese imports at NTR levels.

We expect PNTR to foster innovation in U.S. firms, because it decreases the profitability of using low-skilled technology and boosts the attractiveness of new technologies that is more consistent with U.S. comparative advantage over China.

We empirically test the effect of PNTR on corporate innovation using a panel of 6,209 U.S. public firm years 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-

[1] 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.

However, it is possible that our results are likely to be driven by industry conditions that in turn increase firms' innovation. To mitigate this concern, we additionally control for industry characteristics such as: 1) industry skill intensity and capital intensity, to account for the 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; 2) contract intensity measured by the proportion of intermediate inputs that require relationship-specific investments, to control for China's barriers to foreign investment; and 3) advanced technology products, to control for the bursting of the U.S. tech "bubble" and the subsequent recovery. Furthermore, we explicitly control for industries' NTR rates. Our inferences are largely unchanged.

In further tests, we exploit the fact that Chinese goods arrive on the West Coast of the U.S. first, before they are shipped to other parts of the U.S. By comparing treated firms on the West Coast to their peers in the same industry but in other parts of the U.S., we can better identify how much of the observed change in innovation is due to Chinese imports rather than other shocks to industry business conditions. When we difference away changes in industry business conditions by focusing on treated firms on the West Coast and the same-industry peers outside the West Coast, we continue to find a significant increase in firms' innovation after PNTR. These results suggest that the observed increase in innovation following PNTR is not driven by industry economic shocks.

To provide further evidence that the effects of PNTR on innovation are indeed tied to Chinese goods in the U.S. market, we apply a triple difference-in-differences approach to examine heterogeneous treatment effects. We find that the treatment effects are stronger for 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 impact of PNTR on innovation is indeed related to Chinese imports.

Finally, we implement placebo tests to investigate the possibility that our results are purely driven by chance. In particular, 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. The results indicate that the effects of PNTR on innovation documented in our main tests are unlikely to be spurious: the maximum coefficient in magnitude estimated in the placebo test is substantially smaller than the actual coefficient estimate from the main test.

This paper provides at least two 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 political uncertainty and better integrating the U.S.-China economy have a significant impact on corporate innovation for U.S. firms.

Second, 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.

The remainder of the paper is organized as follows. Section 2 reviews the background on PNTR and Section 3 develops our hypothesis. Section 4 describes our sample and key variable construction. Section 5 presents the empirical results. We conclude in Section 6.

2. Background on PNTR

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.[2] According to Pierce and Schott (2016), the average House vote against an annual NTR renewal was 38%. 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. Pierce and Schott (2016) provided substantial anecdotal evidence in a Congressional testimony about this threat of uncertainty, and it was taken seriously by firms and government sources alike.

There is a large body of investment literature that mentions when uncertainty is high, firms derive more value in waiting to undertake irreversible investment, while when uncertainty is low firms are more likely to undertake such investments (e.g., McDonald and Siegel (1986); Pindyck (1993); Schwartz and Zozaya-Gorostiza (2003)). In particular,

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

Schwarts and Zozaya-Gorostiza (2003) find that uncertainty lowers incentives to invest in new technology.

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.

Conferral of PNTR status to China affects U.S. corporate innovation in at least three ways. First, it leads to a substantial reduction in expected U.S. import tariff rates on Chinese goods; second, it invites directed foreign competition from Chinese producers; and third, it reduces the profitability of using low-skilled technology and boosts the attractiveness of high-skilled technology that is more consistent with U.S. comparative advantage over China. Therefore, we expect that U.S. firms affected by the passage of PNTR invest more in innovative technologies.

To quantify the effect of PNTR, we define the "NTR gap" as the difference between the non-NTR rates to which tariff rates would have jumped if annual renewal had failed and the NTR 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.

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, pertinent in studies that use import tariff rate reductions as shocks to look at outcomes in real economy and changes in corporate polices. 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.

3. Hypothesis Development

Suppose that a U.S. firm has to choose between two types of technology to produce its goods: a low-skill technology to produce a conventional product or a high-skill technology to produce an innovative product. The profitability of these two technologies is P_L and P_H. The firm would choose to produce an innovative product if P_H is greater than P_L; otherwise, it would produce a conventional product. We expect PNTR to foster U.S. firms to innovate for the following two reasons.

First, compared to the U.S., Chinese manufacturing firms have significant wage advantages for low-skilled workers. According to Amiti and Freund (2010), despite a dramatic shift in its export composition over the last two decades, China continues to specialize in low-wage, labor-intensive goods once we account for processing trade (i.e. the activity of assembling intermediate inputs and re-exporting the finished products after processing). The comparative advantage of the U.S. lies in its industries using a high percentage of high-skilled labor and a low percentage of low-skilled labor (Keesing (1966)). It therefore follows from the prediction of the Heckscher–Ohlin comparative advantage model that the capital-abundant country (U.S.) will import labor-intensive goods from the labor-abundant country (China).

After PNTR eliminates the tariff uncertainty faced by Chinese manufacturing firms, a U.S. firm faces greater competition for conventional products in the U.S. domestic market, leading to a significant decrease in P_L. With the U.S. granting China with PNTR status and the ensuing elimination of trade policy uncertainty, Chinese exports have boomed significantly

(Berger and Martin (2011); Handley and Limão (2013)). Import competition from low-wage countries like China exerts downward pressure on the price and, therefore, the profitability of conventional products, $P_{L,}$ in the U.S. (Krugman (1979); Dollar (1986); Auer and Fischer (2010)). Given the high relative wages, it is unlikely that U.S. firms would continue to earn profit from labor-intensive low-skill-content products. As a consequence, they respond to the pressure from import competition by altering their product mix (Bernard, Jensen and Schott (2006)).

Second, 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 decreases (e.g., McDonald and Siegel (1986); Pindyck (1993); Dixit and Pindyck (1994); Schwartz and Zozaya-Gorostiza (2003)). The conferral of PNTR eliminates the tariff uncertainty for U.S. manufacturing firms, which boosts the attractiveness of investment in capital- or skill-intensive production innovations.

Based on the discussion above, we expect a positive effect of PNTR for innovation in U.S. manufacturing firms, because PNTR is likely to decrease the profitability of using low-skilled technology to produce conventional products while increasing the profitability of producing high-skilled innovative products.

4. 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). 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.

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)).[3]

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 for many years after a patent is created, patents created

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

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, Tobin's *Q*, and 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). 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 1 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.

5. Empirical Results

5.1 Univariate Tests

We examine the before-after effect of the change in innovation in firms that are affected by PNTR (the treatment group) compared to the before-after effect in firms that are unaffected by such a policy (the control group). Table 2 reports the univariate test. For each firm, we compute the change in the number of patents as:

$$\sum_{2002}^{2005} LnPat - \sum_{1995}^{1998} LnPat.$$

As shown in column (1), the change in the number of patents is 0.408 for treated firms, which is almost six times as that of control firms (0.073). This difference is significant at the 5% level.

In column (2), we define the change in the number of patent citations as:

$$\sum_{2002}^{2006} LnCit - \sum_{1995}^{1998} LnCit.$$

We find that the change in the number of patent citations is 0.494 for treated firms and is -0.037 for control firms. The difference is also significant at the 1% level.

Overall, the univariate test shows that treated firms become more innovative after PNTR, compared to the control firms. This result indicates that PNTR has a significantly positive effect on corporate innovation.

5.2 Baseline Regression

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

$$Innovation = \alpha + \beta_1 Treat \times Post + Firm\ Characteristics + Industry\ FE + Year\ FE + \varepsilon. \quad (1)$$

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 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. 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, and we continue to find a positive effect of PNTR on innovation. The economic magnitude is also sizeable. For example, the coefficient on *Treat*×*Post* is 0.32 in column (3) and is significant at the 1% level, indicating that PNTR leads to an increase in the number of patents by approximately 38% ($= e^{0.32} - 1$). This number can be interpreted as an annual increase in the number of patents by approximately 4%, considering that our sample covers ten years of China's status as PNTR (1995 to 2005). When examining patent citations in column (4), the coefficient on *Treat*×*Post* is a significant 0.403, indicating that the number of patent citations increases by 49% ($= e^{0.403} - 1$) following the implementation of PNTR (or equivalently an annual increase in the number of patent citations by approximately 5%).

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, and firms with higher growth potential. 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:

$Innovation = \alpha + \beta_1 Treat \times Year1996 + \beta_2 Treat \times Year1997 + \beta_3 Treat \times Year1998 + \beta_4 Treat \times Year2002 + \beta_5 Treat \times Year2003 + \beta_6 Treat \times Year2004 +$

$\beta_7 Treat \times Year2005 + Firm\ Characteristics + Industry\ FE + Year\ FE + \varepsilon.$

(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 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 Confounding Industry Conditions

It is possible that some omitted industry characteristics that are associated with both tariff rate and innovation are driving our results. In this section, we implement two tests to address this issue. In our first test, we additionally control for a set of observable industry characteristics in the regression. In our second test, we difference away unobservable industry characteristics by focusing on treatment firms located on the U.S. West Coast and firms in the same industry but located in other regions of the U.S. In both tests, we continue to find a significant increase in innovation after PNTR.

Table 5 presents our first test. In addition to our usual set of explanatory variables used in Table 3, we also account for various time-varying, industry-level variables in our regressions.

Specifically, we control for measures of industry capital and skill intensity, contract intensity, advanced technology products, and industries' NTR rates. 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. We collect the data from the Bureau of Economic Analysis. 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. The data is obtained from Nunn (2007). To 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. This variable is obtained from the U.S. Census Bureau. Furthermore, we also include industries' NTR rates.

We find that PNTR continues to have a positive and (statistically and economically) significant impact on corporate innovation. Compared to Table 3, the coefficient on the *Treat*×*Post* variable is largely unchanged. Also, we find that industry skill intensity and ADT have a positive effect on innovation.

Although the above test accounts for observable industry characteristics, some unobservable industry shocks may be associated with both tariff rate and corporate innovation. In our second test, we examine the change in innovation in treatment firms located on the West Coast of the U.S. and in firms in the same industry but located in other regions of the U.S. The logic is as follows. Suppose that the effect of PNTR on a given industry is driven by unobserved changes in industry-level business conditions, and that it is these changes, not PNTR, that spur corporate innovation. Both firms located on the U.S. West Coast and in other regions (but in the same industry) would spuriously appear to react to PNTR. In this case, the change in innovation in treated firms on the West Coast should be no different from the change in similar firms that are located in other regions of the U.S. However, if our documented effect is truly due to Chinese imports associated with PNTR, the firms on the West Coast should be affected more significantly relative to similar firms located in different regions of the U.S. This is because the majority of Chinese imports arrive on the West Coast of the U.S. first and then are distributed to other regions of the U.S. Thus, firms on the West Coast face greater pressure from Chinese imports. Since we are comparing a firm in treated industry on the West Coast to a firm in the same industry but different part of the U.S., we can difference away any unobservable industry characteristics.

Table 6 presents the results. In columns (1) and (2), we first select the treated firms on the West Coast (i.e., firms headquartered in California, Oregon, and Washington). We then match each of these firms to a firm located elsewhere in the U.S. that is in the same industry and that has the closest total asset value. The *WestCoast* indicator variable takes the value of one for each treated firm on the West Coast, and zero for their matched firms. Thus, we are comparing a firm in the treated industry (but close to China) with another firm in the same industry (but farther away from China). The coefficient on *WestCoast*×*Post* is 0.44 (significant at the 1% level) in column (1) when the dependent variable is *LnPat*, and is 0.685 (significant at the 1% level) in column (2) when the dependent variable is *LnCit*. This result indicates that, within the treated industries, firms that are physically closer to China experience a greater increase in innovation than the same-industry matched firms that are farther away from China. As a placebo test, we repeat the same analysis based on untreated industries in columns (3) and

(4), and we find no significant difference in innovation between firms on the West Coast and firms located in other regions of the U.S. in untreated industries. Overall, these results suggest that unobserved industry confounds seem unlikely to drive our results.

5.5 Triple Difference-in-differences Tests

To provide further evidence that the effects of PNTR on innovation are indeed tied to Chinese imports into the U.S. market, in this subsection we implement triple difference-in-differences tests to examine the heterogeneous treatment effects. Examining heterogeneous treatment effects can further help to alleviate the concern that some omitted variables are driving our results, because such variables would have to be uncorrelated with all the control variables included in the regression model. They would also have to explain the cross-sectional variation of the treatment effects, which is less likely (Claessens and Laeven (2003); Raddatz (2006)).

If U.S. firms' enhanced innovation after PNTR is truly due to Chinese imports, we expect this treatment effect to be stronger in industries that experience a greater increase of Chinese imports. We define the indicator variable *HighPctImportChg*, which takes the value of one if the percentage increase in Chinese imports over the 1995–2005 period in a given industry is above the sample median, and zero otherwise. We then re-estimate Equation (1) by adding the interaction *Treat* × *Post* × *HighPctImportChg*. Table 7 presents the results. In column (1), where the dependent variable is *LnPat*, the coefficient on *Treat* × *Post* is 0.265 (significant at the 5% level), and the coefficient on *Treat* × *Post* × *HighPctImportChg* is 0.177 (significant at the 5% level). For firms in industries with a greater increase in Chinese imports, their number of patents increase by 55% ($= \mathrm{e}^{(0.265+0.177)} - 1$), while the number of patents increases by 30% ($= \mathrm{e}^{0.265} - 1$) for firms in industries with a lower increase in Chinese imports. We find the same patterns in column (2), where the dependent variable is *LnCit*: The coefficient on *Treat* × *Post* × *HighPctImportChg* is positive and significant at the 1% level.

Overall, these results suggest that the impact of PNTR on corporate innovation is indeed tied to Chinese imports and appears not to be spuriously driven by unobserved heterogeneity.

5.6 Placebo Tests

In this section, we implement placebo tests to investigate the possibility that our results are purely driven by chance. In particular, 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 (3) and (4) 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 0.320 (see column (3) of Table 3) is more than seven times the standard deviations (0.043) above the mean (0.004) of the distribution and is even larger than the maximum coefficient estimate (0.141). Panel B plots the distribution of the coefficients on *Treat*×*Post* when the dependent variable is *LnCit*. The actual coefficient on *Treat*×*Post* of 0.403 (see column (4) of Table 3) is more than six times the standard deviations (0.060) below the mean (0.009) of the distribution and is much larger than the maximum coefficient estimate (0.201). These results indicate that our results are unlikely to be driven by chance.

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 8 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 normalize the number of patents and citations by R&D expenditure. In column (5), we use citations per patent to measure patent quality. We find that the coefficients on *Treat*×*Post* are positive and significant at or below the 5% level across all five columns.

Overall, Table 8 shows that the positive effect of PNTR on innovation is robust to various alternative innovation measures.

6. Conclusions

In this paper, we examine the effect of United States' conferral of Permanent Normal Trade Relations (PNTR) status to China—a policy eliminating 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 a greater increase in Chinese imports. Overall, our findings are consistent with the view that eliminating the possibility of sudden tariff spikes on Chinese imports boosts the attractiveness of technology innovation that is more consistent with U.S. comparative advantage over China.

Our paper provides important implications for public policies aimed at facilitating global trading. Our results suggest that such policies can promote corporate innovation—rather than cheap labor costs—in countries that have a comparative advantage in technological innovation. This effect is nontrivial considering that technological innovation has long been recognized as a key factor in economic growth, productivity increase, and competitive advantage of nations and that the U.S. economy is increasingly reliant on 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 in a given year.
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.
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.

WestCoast	A dummy variable that equals 1 if the firm is historically headquartered in one of the West Coast states (i.e., Washington, Oregon, and California), and 0 otherwise.
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.
Capital Intensity	The ratio of capital to total employment in one industry.
ADT	A dummy variable that equals 1 if the industry produces advanced technology products.
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.
NTR Gap	NTR Gap measures the intensity of industry-level PNTR shock, which is the difference of *ad valorem* equivalent tariff rates between Normal Trade Relation (NTR) country and non-NTR country.

Table 1: Summary Statistics

The sample 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.

	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

Table 2: Univariate Tests

This table reports the univariate tests that examine the impacts of granting Permanent Normal Trade Relations (PNTR) to China on corporate innovation in U.S. firms. Treated firms belong to industries in the top tercile of NTR Gap values, and control firms are those in the bottom tercile of the NTR Gap. Variable definitions are provided in the Appendix. All continuous variables are winsorized at the 0.5th and 99.5th percentiles. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$\sum_{2002}^{2005} LnPat - \sum_{1995}^{1998} LnPat$	$\sum_{2002}^{2005} LnCit - \sum_{1995}^{1998} LnCit$
Treat firms (1)	0.408	0.494
Control firms (2)	0.073	-0.037
Difference-in-differences test (*p*-value of t-test: (1)=(2))	0.020**	0.004***

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 in columns (1) and (3) is *LnPat*, defined as the natural logarithm of one plus the number of patents. The dependent variable in columns (2) and (4) 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 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)	(2)	(3)	(4)
	LnPat	LnCit	LnPat	LnCit
Treat × Post	0.230***	0.284***	0.320***	0.403***
	(2.897)	(3.516)	(3.740)	(4.650)
Ln(Firm Size)			0.309***	0.403***
			(6.560)	(5.886)
Ln(Firm Age)			0.189***	0.201**
			(3.640)	(2.572)
Cash			0.515***	0.951***
			(2.893)	(3.369)
R&D			0.941***	1.580***
			(3.213)	(4.198)
ROA			0.076	0.214*
			(0.815)	(1.706)
PPE			-0.401*	-0.547*
			(-1.855)	(-1.847)
Leverage			-0.348***	-0.376**
			(-3.130)	(-2.430)
Capex			1.441***	2.170***
			(3.827)	(3.222)
Tobin's Q			0.057***	0.075***
			(5.087)	(6.070)
H-index			-2.214	-0.807
			(-1.222)	(-0.271)
H-index^2			5.709	5.108
			(1.069)	(0.600)
Constant	0.625***	0.898***	0.161	0.201
	(28.683)	(30.740)	(1.009)	(0.922)
Observations	6,209	6,209	6,209	6,209
R-squared	0.060	0.067	0.306	0.273
Industry FE	Yes	Yes	Yes	Yes
Year FE	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 0.5^{th} 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	0.054	0.107
	(0.481)	(0.704)
Treat ×Year1997	0.069	0.180
	(0.531)	(0.987)
Treat ×Year1998	0.061	0.117
	(0.519)	(0.710)
Treat ×Year2002	0.316**	0.413***
	(2.640)	(2.870)
Treat ×Year2003	0.351**	0.485***
	(2.579)	(2.873)
Treat ×Year2004	0.357**	0.434***
	(2.555)	(2.938)
Treat ×Year2005	0.353**	0.494***
	(2.604)	(3.818)
Ln(Firm Size)	0.309***	0.403***
	(6.542)	(5.871)
Ln(Firm Age)	0.190***	0.203**
	(3.682)	(2.618)
Cash	0.515***	0.950***
	(2.899)	(3.361)
R&D	0.938***	1.571***
	(3.156)	(4.113)
ROA	0.074	0.211*
	(0.792)	(1.685)
PPE	-0.393*	-0.531*
	(-1.836)	(-1.822)
Leverage	-0.351***	-0.382**
	(-3.201)	(-2.499)
Capex	1.435***	2.156***
	(3.867)	(3.256)
Tobin's Q	0.057***	0.075***
	(5.050)	(6.052)
H-index	-2.314	-1.018
	(-1.289)	(-0.343)
H-index^2	6.057	5.902
	(1.156)	(0.699)
Constant	0.162	0.200
	(0.995)	(0.902)
Observations	6,209	6,209
R-squared	0.306	0.273
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 5: Controlling for Observable Industry Characteristics

This table reports the difference-in-differences tests that examine the impacts of granting PNTR to China on corporate innovation in U.S. firms, with additional controls for observable industry characteristics. 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 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
Treat × Post	0.328***	0.410***
	(3.367)	(4.043)
Skill Intensity	0.979**	1.142*
	(2.118)	(1.811)
Capital Intensity	-0.001	-0.001
	(-1.096)	(-1.251)
ADT	0.409***	0.522***
	(3.865)	(3.463)
Contract Intensity	-0.259	-0.218
	(-0.856)	(-0.640)
NTR	0.096	-0.248
	(0.106)	(-0.186)
Ln(Firm Size)	0.329***	0.430***
	(6.511)	(5.985)
Ln(Firm Age)	0.172***	0.179**
	(3.018)	(2.050)
Cash	0.535***	0.989***
	(3.112)	(3.588)
R&D	0.537***	1.094***
	(3.536)	(6.137)
ROA	0.015	0.141
	(0.152)	(1.084)
PPE	-0.047	-0.121
	(-0.217)	(-0.393)
Leverage	-0.206**	-0.190
	(-2.062)	(-1.286)
Capex	1.268***	1.990**
	(3.121)	(2.660)
Tobin's Q	0.059***	0.078***
	(4.770)	(5.489)
H-index	-2.762	-1.380
	(-1.089)	(-0.367)
H-index^2	9.175	8.697
	(1.179)	(0.753)
Constant	-0.161	-0.231
	(-0.502)	(-0.493)
Observations	5,542	5,542
R-squared	0.319	0.280
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 6: Controlling for Unobservable Industry Characteristics

This table examines whether the treatment effects are confounded unobservable industry characteristics. The dependent variables in columns (1) and (3) are *LnPat*, defined as the natural logarithm of one plus the number of patents. The dependent variables in columns (2) and (4) are *LnCit*, defined as the natural logarithm of one plus number of citations. The indicator variable *WestCoast* takes the value of one if the firm is headquartered in one of the West Coast states (Washington, Oregon, and California) and zero otherwise. The indicator variable *Post* takes the value of one for the 2002–2005 period, and zero for the 1995–1998 period. In columns (1) and (2), treated firms are firms that belong to industries in the top tercile of NTR Gap values. In columns (3) and (4), control firms are those in the bottom tercile of the NTR Gap. 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
	Treat Firm		*Control Firm*	
WestCoast × Post	0.440***	0.685***	0.123	0.182
	(3.211)	(4.753)	(1.296)	(1.522)
Ln(Firm Size)	0.527***	0.698***	0.185**	0.255*
	(26.313)	(30.010)	(2.251)	(2.129)
Ln(Firm Age)	-0.052	-0.202**	0.151*	0.165*
	(-0.888)	(-2.938)	(1.877)	(1.878)
Cash	0.932***	1.623***	-0.624**	-0.720**
	(8.282)	(7.389)	(-2.568)	(-2.398)
R&D	0.243	0.541	2.197	2.681
	(0.943)	(1.425)	(0.870)	(0.758)
ROA	-0.296***	-0.166	0.448	0.509
	(-3.861)	(-1.602)	(1.606)	(1.477)
PPE	-0.815***	-0.859**	0.130	0.266
	(-3.020)	(-2.651)	(0.463)	(0.646)
Leverage	-0.628***	-0.706**	-0.351	-0.431
	(-3.536)	(-2.849)	(-1.040)	(-0.991)
Capex	2.102***	3.468***	1.427	1.951
	(3.920)	(3.961)	(1.385)	(1.423)
Tobin's Q	0.021**	0.040***	0.110*	0.158*
	(2.345)	(3.223)	(2.045)	(1.958)
H-index	17.411	27.147*	107.835	129.168*
	(1.398)	(2.123)	(1.775)	(1.991)
H-index^2	-121.590	-189.588**	-1,066.525	-1,362.113*
	(-1.571)	(-2.386)	(-1.741)	(-2.144)
Constant	0.822	1.278**	-3.196**	-3.860**
	(1.544)	(2.472)	(-2.369)	(-2.373)
Observations	1,674	1,674	462	462
R-squared	0.379	0.314	0.492	0.507
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Table 7: Heterogeneous Treatment Effects based on China's Imports

This table reports the triple difference-in-differences tests to examine the relative impacts of PNTR on innovation in U.S. firms facing both a high and low increase in Chinese imports. 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 variable *Post* takes the value of one for the 2002–2005 period, and zero for the 1995–1998 period. The indicator variable *HighPctImportChg* takes the value of one if the percentage change in imports from China between 1995 and 2005 in the industry is above the sample median, and 0 otherwise. 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 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
Treat × Post	0.265**	0.285**
	(2.269)	(2.261)
Treat × Post × HighPctImportChg	0.177**	0.384***
	(2.362)	(4.117)
Ln(Firm Size)	0.308***	0.402***
	(6.545)	(5.873)
Ln(Firm Age)	0.189***	0.201**
	(3.660)	(2.591)
Cash	0.508***	0.935***
	(2.782)	(3.228)
R&D	0.938***	1.574***
	(3.157)	(4.071)
ROA	0.077	0.218*
	(0.827)	(1.722)
PPE	-0.414*	-0.576*
	(-1.895)	(-1.914)
Leverage	-0.349***	-0.377**
	(-3.147)	(-2.445)
Capex	1.473***	2.239***
	(3.913)	(3.301)
Tobin's Q	0.057***	0.075***
	(5.142)	(6.117)
H-index	-2.974*	-2.455
	(-1.687)	(-0.870)
H-index^2	5.997	5.734
	(1.173)	(0.721)
Constant	0.207	0.301
	(1.285)	(1.325)
Observations	6,209	6,209
R-squared	0.307	0.275
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 8: 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 a 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, by its R&D expenditure, and the firm's number of citations scaled by its number of patents in columns (1)-(5), respectively. 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) LnPat/R&D	(4) LnCit/R&D	(5) LnCit/Pat
Treat × Post	0.148***	0.162***	0.061**	0.114**	0.111***
	(4.545)	(3.054)	(2.595)	(2.726)	(3.110)
Ln(Firm Size)	0.081***	0.167***	0.015***	0.073***	0.129***
	(4.235)	(3.769)	(5.249)	(10.412)	(6.465)
Ln(Firm Age)	-0.021	-0.036	0.009	-0.021	0.055
	(-0.726)	(-0.616)	(0.678)	(-0.544)	(1.552)
Cash	0.941***	1.393***	0.102***	0.446***	0.504***
	(3.207)	(3.499)	(3.050)	(5.553)	(3.641)
R&D	1.407***	2.108***	-0.575***	-0.543**	0.802***
	(4.545)	(5.246)	(-4.502)	(-2.346)	(6.077)
ROA	0.235***	0.406***	-0.084***	-0.035	0.183***
	(3.207)	(4.282)	(-2.983)	(-0.724)	(3.779)
PPE	-0.048	-0.163	0.004	-0.106	-0.224**
	(-0.396)	(-0.890)	(0.041)	(-1.188)	(-2.041)
Leverage	-0.234**	-0.258**	-0.209***	-0.354***	-0.104
	(-2.523)	(-2.067)	(-7.099)	(-5.295)	(-1.510)
Capex	0.934	1.721*	0.339*	1.070**	0.956**
	(1.552)	(1.780)	(1.804)	(2.109)	(2.395)
Tobin's Q	0.031***	0.049***	0.015***	0.031***	0.028***
	(4.088)	(5.395)	(7.122)	(10.796)	(7.068)
H-index	1.101	3.770	3.001	4.351	0.920
	(0.856)	(1.495)	(1.602)	(1.345)	(0.660)
H-index^2	-4.328	-8.022	-9.179	-6.941	-1.577
	(-1.151)	(-1.167)	(-1.495)	(-0.656)	(-0.382)
Constant	0.261**	0.264*	0.098	0.249	0.116
	(2.622)	(1.936)	(1.183)	(1.624)	(1.297)
Observations	6,209	6,209	4,109	4,109	6,209
R-squared	0.205	0.198	0.065	0.090	0.192
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Figure 1 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 (3) and (4) of Table 3 and save the coefficients on *Treat*×*Post*. Figure 1A reports the distribution of the coefficients when the dependent variable is *LnPat*, and Figure 1B reports the distribution of the coefficients when the dependent variable is *LnCit*.

Figure 1A: Number of Patents

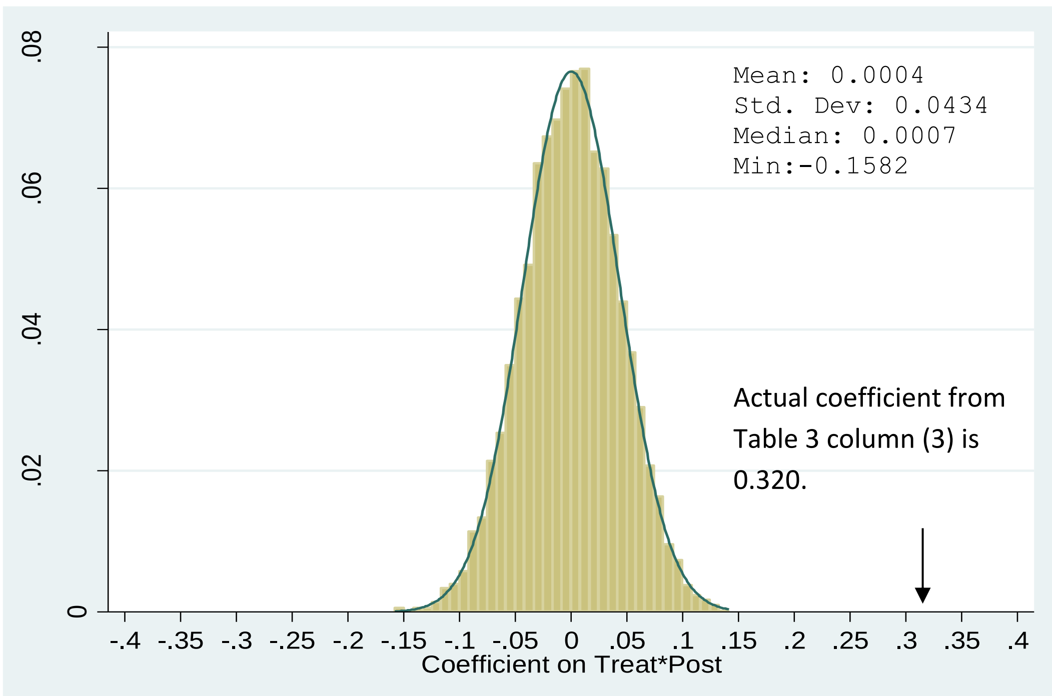

Figure 1B: Number of Patent Citations