More Competition, Better Products

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Abstract

This paper examines how increased competition affects product and process innovation. I utilize plausibly exogenous variation in foreign competition induced by large tariff cuts with a difference-in-differences strategy and find that firms increase their product patenting in response to increased foreign competition, but, on average, foreign competition has no effect on process patenting. Firms operating in industries where patents are an effective means of protecting their competitive advantage increase their patenting more in response to competition. Initially large and productive firms engage in more process innovation in response to competitive pressure.

Keywords: Product and Process Innovation, Competition, Trade Liberalization, Tariffs, Corporate R&D Strategy

JEL: D22, F23, L1, O31, O32

1 Introduction

Firms engage in product innovation by introducing new product varieties. They also create process innovations by altering the assembly of their products. Prior work documents that one of the most salient differences between product and process innovation is that product innovations generate more knowledge spillovers (Mansfield 1985; Ornaghi 2006; Davison 2022). The rationale for this finding is that product innovations are easier to reverse engineer while process innovations are less visible to rivals (Kraft 1990). The importance of knowledge spillovers in generating positive externalities makes studying the determinants of product and process innovation particularly important as changes to product or process innovation will affect the flow of knowledge spillovers (Nelson 1959).

A key topic in the industrial organization literature is understanding the role that competition plays in incentivizing innovation. Despite a theoretical literature examining how product and process innovation respond to increased competition, the predictions are quite varied, in large part due to the lack of a "common framework" (Boone 2000; Marshall and Parra 2019). Further, empirical evidence on the topic is nonexistent, mainly because of the lack of large-scale, high quality data distinguishing product and process innovation.

To study how competition affects product and process innovation, I use the Economically Based Product Process Patent Dataset (EPP) which classifies the claims of all patents granted from 1980-2015 to publicly traded U.S. manufacturing firms as product or process innovations (Davison 2023). I combine this data with plausibly exogenous increases in import competition coming from sudden and large tariff reductions. This setting is particularly relevant for studying the effects of competition on product and process innovation since the U.S. and many other developed countries have experienced large increases in import competition over the last several decades (Autor et al. 2020).

In this setting, I employ a matched difference-in-differences strategy where firms experiencing large tariff cuts are matched to otherwise similar control firms who did not experience a large tariff cut. I find that firms exposed to large tariff cuts experience a 14% increase in industry import penetration[1] from mean levels, while there is no increase in industry exports

[1] Import penetration is defined as the ratio of imports to domestic expenditure at the industry level

as a share of output. The same firms who face higher import competition file for approximately 20% more product patents in the five years following the tariff reduction. Yet I do not observe any change in process patenting for treated firms. The results are robust to a wide variety of tests including weighting patents by their market value or the number of forward citations they receive, variations in the matching strategy, using alternative estimators, and using various definitions of treatment status.

Guided by predictions from economic theory, I test how the response of firms differ under various conditions. I find that the effect of import competition on both product and process innovation is greater for firms operating in industries where patenting is better able to protect the firm's competitive advantage. This is consistent with the idea that a necessary condition for firms to disclose their knowledge in patents is assurance that their knowledge will be protected (Cohen, Nelson, et al. 2000). Further, the finding sheds light on a potential reason why product patenting responds more to competition than process patenting. In my sample, process innovation is 33% less likely to be well protected by patents than product innovation. As firms have less confidence that patenting will protect their process innovations from being appropriated by their competitors, firms are less likely to use process innovation as a means of escaping their competition, relative to product innovation.

Motivated by models where the innovation choice in response to increased competitive pressure depends on the relative productivity of the firm, I test whether the responsiveness of product and process innovation to competition differs according to a firm's initial productivity and size. I find that initially larger and more productive firms engage in more innovation in response to increased competitive pressure. This result is consistent with the models of step-by-step innovation surveyed in Aghion, Blundell, et al. 2009 where frontier firms seek to escape the competition as their pre-innovation profits have been decreased, while laggard firms have smaller post-innovation profits to chase, lowering their innovation incentive. Further, I find that the increased innovation by initially more productive firms is entirely accounted for by an increase in process innovation. Since process innovation can be freely scaled in the production of a firm's output, the returns to process innovation are increasing in the size of a firm (Cohen and Klepper 1996). My finding that large and productive firms respond to increased competition with more process innovation is consistent with firms making a costly commitment to a product or process innovation strategy, similar to the model in Yang et al. 2021. Firms who are initially large and technically productive before the tariff cut, continue to pursue their process innovation strategy after the arrival of foreign competition while small and unproductive firms exclusively continue with their product innovation strategy.

Finally, I test whether firms differentially increase their product patenting in response to competition when the scope for product differentiation in a firm's industry is higher. Intuitively, some industries have more ability for firms to differentiate their products whereas in other industries the products are highly standardized. I hypothesize that for firms operating in industries where the product is homogenous, product innovation is less useful in escaping the competition (Chen and Wu 2019). On other hand, firms should be able to better shield themselves from the negative effects of competition through product innovation when there is greater scope for product differentiation. My findings are on this topic are statistically insignificant, and I am not able to provide definitive evidence on the importance of scope for product differentiation in driving the responsiveness of product and process innovation. Overall, my findings highlight that, for a broad sample of U.S. manufacturing firms, increased foreign competition leads them to not only increase their innovation, but it also alters the type of innovation they pursue.

2 Literature Review

My work most closely contributes to studies which have empirically examined how product and process innovation respond to increased foreign competition. In the context of developed countries, I am only aware of two studies which empirically test how foreign competition impacts product and process innovation. Using data on German manufacturing firms, Bertschek 1995 find that increased import competition leads to more product and process innovation. Yang et al. 2021 find that Canadian manufacturing firms engage in more product innovation and less process innovation in response to increased Chinese import competition. I contribute to these studies by providing another empirical test on this subject for U.S. manufacturing firms. My results generally support the findings of Yang et al. 2021.

While we both find a positive effect of foreign competition on product innovation, I find no average effect on process innovation, which stands in contrast with the negative effect found in Yang et al. 2021. My research also differs by using firm's patenting activity to measure product and process innovation as opposed to the self-reported measures of product and process innovation in Bertschek 1995 and Yang et al. 2021. Using patenting activity, along with various measures of each patent's value[2], I can more precisely quantify the total value of a firm's innovations as opposed to self-reported measures which only provide a count of the number of self-designated product and process innovations created in a year. Further, I explore heterogeneity in the effects of foreign competition by the ability of firms to protect their patents, initial firm size and productivity, along with the scope for product differentiation in a firm's industry. These heterogeneity tests contribute new insights into how firms differentially respond to foreign competition.

Other studies have examined how firms in developing countries change their product and process innovation in response to foreign competition. Teshima 2009 find, in the context of Mexican manufacturing plants, that a reduction in output tariffs lowers R&D with the effect entirely coming from a reduction in process R&D and no statistically significant change in product R&D. In the context of developing countries, Gorodnichenko et al. 2010 and Fernandes and Paunov 2013 find that increased foreign competition leads to more product innovation while the studies are not able to observe process innovation. Dang 2017 finds no effect of Chinese import competition on the product or process innovation of Vietnamese manufacturing firms. My research contributes to this literature by providing an empirical test of how the product and process innovation of firms in a developed country respond to increased foreign competition.

This paper also builds upon the theoretical literature which provides economic models explaining how product and process innovation respond to competition. Vives 2008 finds that competition increase the incentive for product innovation but decreases process innovation incentives. The intuition for the decline of process innovation comes from the insight that process innovation scales with output, in the sense that there is little to no cost of applying

[2] I measure patent value using both the Kogan et al. 2017 measure which utilizes excess stock returns around the publication of a patent to value the patent, and the number of citations a patent receives.

a process innovation to the production of more output (Cohen and Klepper 1996). Since the incentive to engage in process innovation is directly tied to a firm's output, and competition lowers a firm's output, then Vives 2008 gets the result that there is less incentive for process innovation in a competitive market, what Vives 2008 calls the "size effect." Yang et al. 2021 develop a model which arrives at the same prediction as Vives 2008; firms will increase their product innovation and lower their process innovation in response to more competition. In the model of Yang et al. 2021, firms have less incentive to invest in process innovation due to a "Schumpeterian effect" where firms who invest in process innovation have more to lose from competition due to their high pre-competition profits. On the other hand, product innovation can shield a firm from the negative effects of competition, making it a more valuable method of mitigating the negative effects of competition. I contribute to this literature by providing an empirical examination into the effect of competition on product and process innovation for a wide variety of U.S. manufacturing firms from 1980-2005. My findings are largely consistent with the models of Vives 2008 and Yang et al. 2021, as I find a large positive effect of competition on product innovation and no effect of competition on process innovation.

While the previously discussed models provide clear predictions on how product and process innovation will respond to increased competition, other models find that the effect will vary based on certain characteristics. For example, in the model of Boone 2000 the response to competition depends on the relative efficiency of the firm. Complacent firms, who are very productive relative to their competitors, engage in more product innovation and less process innovation in response to competition. Eager firms who are marginally more productive than their competitors complete more of both product and process innovation. Struggling firms who are marginally less productive than their competitors do less product innovation and more process innovation in response to competition, and faint firms do less product and process innovation. Intuitively, complacent and faint firms have little incentive to engage in process innovation since their level of productivity is relatively far from the nearest competitor. On the other hand, eager and struggling firms are incentivized to engage in process innovation as small changes to the firm's productivity are able to change their relative productivity standing. The story is different for product innovation. Struggling and faint firms who have relatively low productivity experience a "Schumpeterian effect" where increased competition lowers their profitability and thus reduces the returns from introducing a new product, as in Greenstein and Ramey 1998. On the other hand, complacent or eager firms who have relatively high productivity will see increased profitability at the expense of struggling and faint firms. This increases the returns to product innovation. While I do not find evidence consistent with the model of Boone 2000, my results are consistent with the step-by-step innovation models surveyed in Aghion, Blundell, et al. 2009 which predict that initially productive firms will increase their innovation in response to more competition while laggards will reduce their innovation.

This paper also adds to the empirical literature examining whether competition has a positive or negative effect on overall innovation. Using the rise of Chinese manufacturing as a shock to import competition for developed countries, the literature finds mixed results. Autor et al. 2020 find a negative effect of Chinese import competition on the innovative activity of U.S. firms while Hombert and Matray 2018 provide nuance to the finding, showing that firms which were sufficiently innovative before the rise of China increase their product differentiation in response to more Chinese competition. This is reminiscent of my finding that firms increase their product patenting in response to foreign competition. In Europe, Bloom, Draca, et al. 2016 and Bloom, Romer, et al. 2021 find unambiguously positive effects of Chinese import competition on innovation. My research aligns with the results in Bloom, Draca, et al. 2016 and Bloom, Romer, et al. 2021 as I find a positive effect of foreign competition on innovation. Further, Shu and Steinwender 2019 note that for firms in developing countries there is "overwhelming positive evidence" that foreign competition leads firms to increase their innovation (Iacovone 2012; Amiti and Khandelwal 2013; Bombardini et al. 2018; Ahn et al. 2018; Medina 2022). While this paper examines the effect of competition on U.S. manufacturing firms, my results are in agreement with the positive effect of competition on innovation found in studies of developing countries.

In addition, the empirical literature finds a positive correlation between a firm's initial productivity or size and the amount of innovation the firm undertakes in response to foreign competition (Iacovone 2012; Fernandes and Paunov 2013; Amiti and Khandelwal 2013; Gong 2017; Bombardini et al. 2018; Ahn et al. 2018; Autor et al. 2020; Medina 2022). This empirical finding is consistent with step-by-step models of innovation where neck-and-neck firms increase their innovation to escape their competition, while laggard firms fall further behind and lower their innovative effort (Aghion, Blundell, et al. 2009).[3] My findings support this view, as I find that initially productive or large firms increase both their product and process patenting in response to more import competition.

My results also contribute to a small set of empirical papers examining how other types of innovative activity respond to import competition. Morandi Stagni et al. 2021 find that firms limit their technological exploration in response to import competition, preferring to innovate in familiar areas. Liu and Rosell 2013 also uses import penetration and show that firms engage in less basic and more applied innovation in response to competitive pressure. My work adds to these papers by focusing on the distinction between product and process innovation and showing that competition increases product but not process innovation. Finally, my empirical work on how imports and exports respond to large tariff cuts contributes to the literature which has examined the effect of large tariff reductions on other firm decisions. Flammer 2015 finds that when firms face tariff reductions, they increase their corporate social responsibility activities while Frésard and Valta 2016 show that large tariff cuts lead firms to reduce their capital investments. I contribute to these papers by documenting the first stage effect of large tariff cuts on both imports and exports. While the prior literature assumes that large tariff cuts are accompanied by increased import competition, I empirically verify that tariff cuts lead to a large increase in import competition but no effect on exports.

3 Data

3.1 Firm Panel

To empirically test how the product and process innovation of firms respond to more competition, I assemble a firm $\times$ year panel. I rely on the EPP dataset to measure the amount of product and process innovation a firm engages in during a given year (Davison

[3] The step-by-step model of innovation finds empirical validation in the experimental findings of Aghion, Bechtold, et al. 2018.

2023). The EPP data captures the share of publication claims on each patent which are product innovations through machine learning text classification of patent publication claim text. Product and process innovations are defined to be consistent with the mainstream use of product and process innovation in economic theory. Specifically, the companion paper to the EPP dataset defines a product innovation as an innovation that "describes a physical object that a firm sells in the output market with no discussion about how the object is created" while process innovations make up all other innovations (Davison 2023). As Davison 2023 shows, process innovations in the EPP dataset correspond to innovations which are used internally, making them consistent with how economic theory conceives of process innovations as having increasing returns to scale since the cost savings from an improved process can be readily applied to the production of all a firm's output (Cohen and Klepper 1996). For each firm $\times$ year observation, I use the EPP to measure the number of product and process patents applied for by the firm in a given year where firms are assigned to patents using the crosswalk provided by the DISCERN dataset (Arora et al. 2020; Arora et al. 2021).[4] To get data on a firm's financials, I merge my data with COMPUSTAT. In order to focus on truly innovative firms, I require that firms must have filed for at least one product patent claim and one process patent claim in their lifetime. To align with the tariff data, I use all firm $\times$ year observations in the data from the years 1980-2005. This leaves me with an unbalanced panel of 16,007 firm $\times$ year observations and 1,438 unique firms.

3.2 Identifying Large Tariff Cuts

To measure imports and tariff rates at the industry level, I start with granular product (HS-10) level trade data from Feenstra 1996; Feenstra et al. 2002; Schott 2010. I then use the concordances provided by Feenstra et al. 2002 and Schott 2010 to map HS-10 products to 4-digit SIC codes. I match this data on the value of imports and tariff duties paid to the firm panel based on the firm's 4-digit SIC code. The tariff rate for an industry $\times$ year observation

[4] To arrive at the total number of product patents a firm applies for in a given year, I add up the total share of publication claims that are product innovations across all a firm's patents. For example, if a firm only applied for two patents in the year 2000 and Patent #1 had 25% of its publication claims as product innovations and Patent #2 had 75% of its publication claims as product innovations, then in the year 2000 this firm would have applied for $0.25 + 0.75 = 1$ product patent and $0.75 + 0.25 = 1$ process patent.

is calculated as the duties collected by U.S. customs divided by the free-on-board value of imports and import penetration is calculated as the value of imports divided by total U.S. expenditure on goods in the industry.[5] I also measure the export share of an industry which is defined as the share of U.S. gross output in the industry which is exported.

Tariffs are an important barrier to trade, protecting home country industries from foreign competition by raising the cost of foreign goods (Anderson and Wincoop 2004; Pierce and Schott 2016; Dix-Carneiro and Kovak 2017). Thus, reducing tariffs serves to lower the entry cost for potential foreign rivals into the domestic market and increase the competitive pressure faced by domestic firms. Despite the importance of tariffs in determining import competition, most changes in tariffs that a firm faces are small and insignificant. Figure A.1 plots the cumulative distribution function for the annual change in tariff rates for all firms in my sample and clearly shows that the mass of tariff changes is concentrated around zero.

Since small tariff cuts are unlikely to have much effect on the level of foreign competition a firm faces, I avoid using small variation in tariff rates and instead identify changes in tariffs that are large enough to have a meaningful impact on firms. This is similar to the empirical approach taken in the literature examining the effect of rainfall shocks on a host of outcomes. In this literature, the most common empirical specifications use a binary variable to capture whether rainfall is above or below some threshold (Jayachandran 2006; Dinkelman 2017). The reasoning for using this approach is that only large variation in rainfall that would cause droughts or floods is likely to affect the outcomes of interest in these studies. In a similar spirit, I follow a large literature that has identified sizeable tariff reductions that have a significant impact on the amount of foreign competition that firms in an industry face (Fresard 2010; Flammer 2015; Frésard and Valta 2016; Boubaker et al. 2018; Chen and Wu 2019; Morandi Stagni et al. 2021). I follow Frésard and Valta 2016 and use a threshold approach for finding large tariff cuts in the data. Specifically, I identify large tariff cuts as percentage point declines in the tariff rate that are greater than or equal to some multiple of the mean absolute value annual change in the tariff rate (Frésard and Valta 2016). In my baseline specifications, I use four as my multiple.

[5]Total U.S. expenditure is measured as U.S. gross output in the industry plus U.S. imports minus U.S. exports

To ensure that these cuts do not simply capture increased volatility in the tariff rate, I require that there is not an equally large increase in the tariff rate in any of the three years following the tariff cut. I follow Frésard and Valta 2016 in making the following additional restrictions. First, to ensure that I am capturing persistent tariff cuts, I exclude tariff cuts that are followed by equivalent increases in cumulative tariff changes over the following three years.[6] Next, I exclude all tariff cuts where the industry tariff rate is less than 1% in the year before the cut as tariffs are unlikely to be a significant barrier to entry at such a low baseline rate. Finally, I exclude tariff cuts that occur between 1988 and 1989 as the import data switched from data provided by Feenstra 1996 and Feenstra et al. 2002 to data provided by Schott 2010. I then match indicators for large tariff cuts to firms in my sample based on the primary 4-digit SIC industry of the firm.

Panel (a) of Figure 1 displays a histogram of the 24 unique tariff cuts that I identify distributed by year of occurrence where the tariff cuts meet the threshold of being weakly greater than 4x the mean absolute value annual change in the tariff rate.[7] The tariffs are distributed widely across time, insulating my results from being driven by spurious correlations with an unobserved shock occurring in a particular year. Panel (b) of Figure 1 visualizes the tariff cuts across broad manufacturing sectors (two-digit SIC industries). The cuts are dispersed across two-digit SIC codes 32-39 and SIC code 28. These sectors mainly comprise chemicals/pharmaceuticals, industrial machinery, electronics, transportation equipment, and measurement/sensing devices.[8] The concentration of tariff cuts in these sectors reflects the fact that innovative activity itself is concentrated amongst manufacturing sectors. Sectors which have at least one four-digit SIC industry experiencing a tariff cut apply for 93% of all patents in my sample. Detailed 4-digit SIC industries experiencing a large tariff cut

[6] For example, if a tariff cut of -.05 is a candidate for a 4x tariff cut, but is followed by tariff changes of .03, -.01, and .04 (a total increase of .06) over the next three years, then the tariff cut would be considered transitory and not marked as a 4x tariff cut.

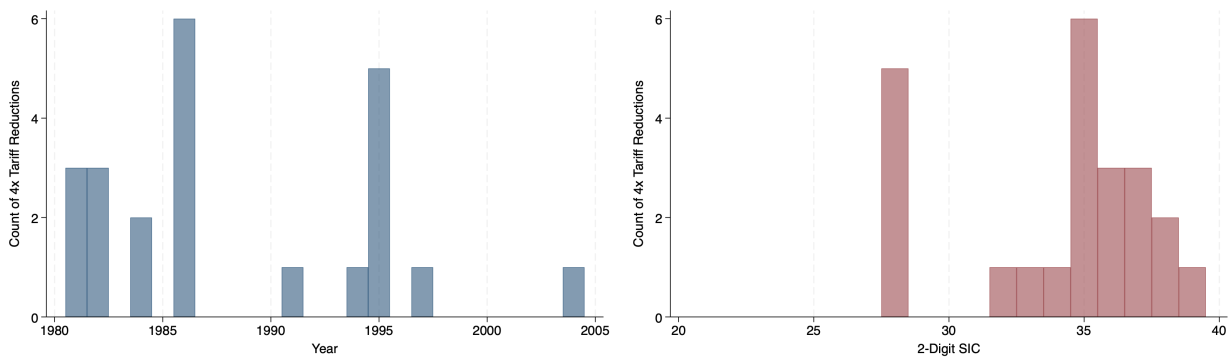
[7] I exclude tariff cut occurrences happening before 1981 as these occurrences cannot be used in my empirical strategy. This is because my panel starts in 1980, and I need at least one year of pre-treatment data for every treated firm.

[8] Specifically, the sectors are: (28) Chemicals and Allied Products (32) Stone, Clay, Glass, and Concrete Products (33) Primary Metal Industries (34) Fabricated Metal Products (except machinery and transport equipment) (35) Industrial and Commercial Machinery and Computer Equipment (36) Electronic, Electrical Equipment and Components (except computer equipment) (37) Transportation Equipment (38) Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks (39) Miscellaneous Manufacturing Industries

are highly innovative and represent aggregate innovative activity well. Of the ten 4-digit SIC industries with the most patenting over the 1980-2015 time period, six experienced a large tariff cut and industries that experience a large tariff cut created just under 50% of all patents.

Figure 1: Distribution of Large Tariff Cuts

(a) Annual Counts (b) Manufacturing Sector Counts



Notes: This figure presents histograms of the number of industry × year observations where the industry tariff reduction exceeds 4x the mean absolute value annual change. Panel (a) plots the histogram over time, identifying how many unique tariff cuts occurred in a given year. Panel (b) plots the histogram over two-digit SIC sectors, identifying how many unique tariff cuts occurred in a given sector.

On average, firms exposed to large tariff cuts saw their tariff rate fall by approximately 3.3 percentage points in the year of the tariff cut, relative to an average tariff rate of 5.2% in the year before the large tariff cut.[9] This decline of 3.3 percentage points is relative to all untreated firm × year observations which on average have a modest annual tariff decline of 0.15 percentage points. While a tariff decline of 3.3 percentage points may seem small in magnitude, it is comparable in size to the average tariff reductions on U.S. imports of Canadian goods resulting from the Canada-U.S. Free Trade Agreement (Trefler 2004) or the average reduction in tariffs on imports of Mexican goods resulting from the North American Free Trade Agreement (Hakobyan and McLaren 2016).

[9] Table A.1 displays the average tariff change in percentage points in firm × year observations where a 4x tariff cut occurs and the average tariff change in percentage points in firm × year observations where a 4x tariff cut does not occur.

3.3 Matching

My baseline empirical strategy involves matching firms who experience these large tariff cuts to otherwise similar control firms who do not experience large tariff cuts. I identify treated firms as firms who are operating in 4-digit SIC codes in the year of a 4x tariff cut.[10] Table A.1 shows that using a tariff cut which exceeds 4 times the mean annual change as my threshold of defining treatment, there are 172 treated firms operating across 20 different 4-digit SIC industries. The treated firms comprise around 11% of the firms in my entire sample. Table A.3 tests the equality of means across treated firm × year observations and all untreated firm × year observations and reveals that treated firms are significantly larger and more innovative than control firms. In order to be able to analyze the dynamic effects of a large tariff cut and to increase the similarity between treatment and control firms, I follow Frésard and Valta 2016 and pursue a matched difference-in-difference strategy as my baseline empirical specification.[11] To implement this, I match treated firms with control firms based on characteristics in the year before the tariff cut. Specifically, I match on: size, research intensity, cash position, profitability, and product/process patenting composition. There are many ways to measure each of these characteristics. In my baseline specification, I match on the IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural logarithm of revenue.[12] Matching on the IHS of product and process patenting controls for firm size, research intensity, and the product/process patenting composition, while matching on the net cash to asset ratio, and return on assets respectively controls for the firm's cash position and profitability. Matching on the R&D to asset ratio and the natural logarithm of revenue respectively provide another match on research intensity and firm size. I match each treated firm uniquely to one control firm using a matching algorithm which minimizes the Mahalanobis distance across all characteristics used for matching.[13] The matching algorithm is described in detail in

[10]In the case where the firm undergoes more than one treatment, I only consider the first instance of treatment

[11]Souza 2023 use a similar matching approach to examine the effects of receiving government R&D subsidies on innovation.

[12]Table A.2 provides detailed information on the definition of each of these variables.

[13]The Mahalanobis distance, δ between firm i amd for, j is $\delta = [(X_i - X_j)'\Omega^{-1}(X_i - X_j)]^{\frac{1}{2}}$ where X is a (n x 1) vector where n is the number of matching variables and Ω is the (n x n) covariance matrix of the n matching variables.

Appendix A.2. Table A.4 shows that after matching the statistically significant differences in means of the matching variables across treatment and control observations disappear.

To test the robustness of my findings to the specific set of matching characteristics used in my baseline specification, I replicate my results using 28 different combinations of these matching variables which are outlined in Appendix A.2. In all specifications, I match on the IHS of product and process patenting. This captures firm size and the product/process composition of the firm. I then include every combination of the variables used to measure research intensity, cash holdings, and profitability where at least two of the three characteristics are used. I measure research intensity using both the R&D to asset ratio and the R&D to sales ratio, and I measure a firm's cash position using the net cash to asset ratio and the cash to asset ratio. Finally, I measure profitability using both return on assets and a firm's profit margin. Also, in every combination where all five characteristics are used, I include a set of matching variables with and without the natural logarithm of revenue which provides a supplemental measurement of firm size.

Using all firm $\times$ year observations in my baseline matched sample of treatment and control firms, I present summary statistics in Table 1. The average firm $\times$ year observation faces 17% import penetration and has an average export share of 18%. The average firm $\times$ year observation applies for 29 product patents in a year, 7 process patents in a year, and has approximately 14,000 employees. Patenting activity and firm size are highly skewed. Some firms apply for no patents in a given year and others apply for a very large numbers of patents.

4 Empirical Strategy and Main Results

4.1 Tariff Cuts and Import Penetration

With the sample of matched treatment and control firms, I first test the effect of large tariff cuts on imports and exports. While the prior literature using these 1980-2005 U.S. tariff cuts has assumed that the cuts will increase import competition while having little to no impact on export demand, I provide an empirical test of this assumption. While it is

Table 1: Summary Statistics

	Mean	St. Dev.	Min	Max	Obs
Import Penetration	0.17	0.15	0.00	0.69	2,909
Export Share	0.18	0.13	0.01	0.56	2,909
Product Patents	29.40	98.44	0.00	1,258.14	2,909
Process Patents	7.33	24.72	0.00	323.30	2,909
$\frac{\text{R\&D}}{\text{Sales}}$	0.23	0.34	0.00	1.00	2,909
Product Protect	39.62	9.81	20.00	54.70	2,898
Process Protect	26.64	7.40	13.24	36.15	2,898
Employees (1,000)	14.03	48.74	0.00	876.80	2,909
Real Revenue (2009 Million $)	3,095.81	10,224.90	0.00	176,064.73	2,909
Quality Ladder	2.22	0.43	0.60	3.34	2,909
Share Differentiated	0.73	0.29	0.00	1.00	2,846

Notes: This table presents summary statistics for the sample used in the baseline specifications. Import penetration is measured as the ratio of imports to domestic expenditure at the industry level and export share is measured as the share of industry output that is exported. Both the "Product Protect" and "Process Protect" variables are taken from a 1994 survey of firms conducted by Cohen, Nelson, et al. 2000 which measures, for firms in an industry, the mean percentage of product or process innovations for which patenting is effective in protecting the firm's competitive advantage (see Section 5.1 for more details). The quality ladder measure is taken from Khandelwal 2010 and is used to measure the scope for product differentiation in an industry (see Section 5.3 for more details). The share differentiated measure is taken from Rauch 1999 and is used to measure the scope for product differentiation in an industry (see Section 5.3 for more details).

natural to assume that U.S. import tariff reductions will increase foreign competition since it becomes less costly for foreign firms to sell their products in the U.S., it may be the case that large tariff reductions in the U.S. are indicative of trade deals where other countries also agreed to reciprocally lower their tariffs on U.S. exports. If large reductions in U.S. import tariff rates are associated with increased export opportunities for U.S. firms, then my empirical strategy will capture a composite effect of import competition and export demand on patenting. Prior work has documented the positive effect that export demand has on both product and process innovation, making it especially important to know whether large tariff cuts are associated with increased exports for U.S. firms (Flach and Irlacher 2018; Coelli et al. 2022; Aghion, Bergeaud, et al. 2022).

To explore the dynamic impact of tariff cuts on the import penetration and export share of a firm f, operating in 4-digit SIC industry z, belonging to treatment-control pair m, and operating in year t, I estimate the following event study specification:

$$Y_{fzmt} = \beta \left(\mathbb{1}\{\text{Cut}_z\} \times \sum_{j \neq 0} \mathbb{1}\{t = j\} \right) + \phi_f + \delta_t + \varepsilon_{fzmt} \tag{1}$$

In all estimations, I follow Souza 2023 and include five years of data before and after the year before treatment. $\mathbb{1}\{\text{Cut}_z\}$ refers to an indicator variable that is one for treated firms. This indicator is interacted with dummies for each year relative to the treatment year, with the year before treatment (j=0) serving as the omitted category. Firm fixed effects are included to control for time-invariant differences between treated and control firms, while year fixed effects control for aggregate shocks across time. I cluster standard errors at the treatment-control pair level.

The left panel of Figure 2 shows the coefficients and 95% confidence intervals from estimating Equation (1) via OLS with import penetration as the dependent variable. Immediately after the identified tariff cuts, import penetration increases by a little less than two percentage points. In the fourth year after the tariff cut there is another sizeable increase in import penetration, with the gap in import penetration between treatment and control firms increasing to about four percentage points. This is consistent with foreign firms needing time to fully take advantage of lower U.S. tariff rates. The evidence indicates that the large tariff cuts I identified are followed by significant and persistent increases in import penetration. Consistent with Autor et al. 2020, I interpret increased import penetration in a firm's industry of output to indicate higher levels of foreign competition.

In order to identify the effect of large tariff cuts on import penetration, it must be the case that the difference in import penetration between treatment and control firms would have been constant over time in the absence of the large tariff cuts. While fundamentally untestable, the event study in the left panel of Figure 2 shows no significant pre-trend in differences between treatment and control firms before the arrival of the tariff cut.[14] This suggests that the gap in import penetration between treatment and control firms would have remained constant in the absence of the tariff cut.

The right panel of Figure 2 presents the results when export share is the dependent

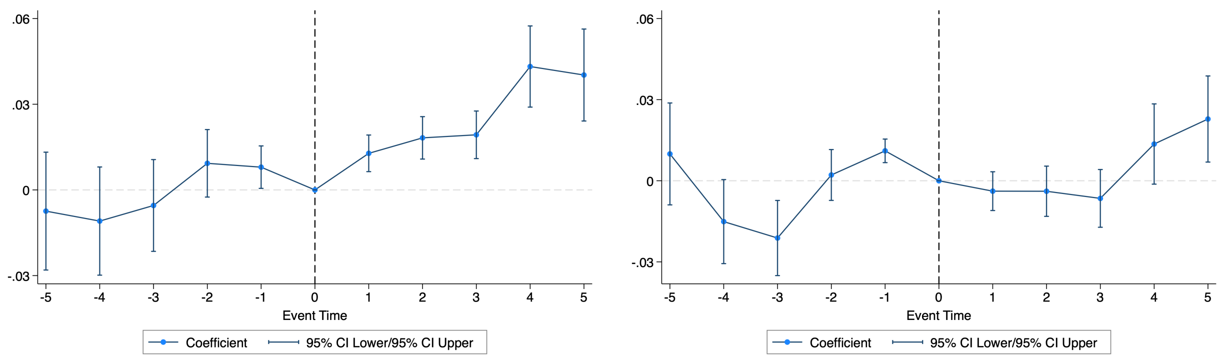
[14] While a Wald test of the joint significance of the five pre-tariff coefficients rejects the null hypothesis that all the coefficients are simultaneously zero with an F-statistic of 6.34 and a p-value of 0.00, the coefficients are small in magnitude and display no clear trend before the arrival of the tariff cut.

variable. In contrast to the large and clear increase in import penetration after the large tariff cut, there is no pre-trend in the export share before the tariff cut and no sizeable change in exporting activity after the arrival of the tariff cut. This indicates that large tariff cuts are not accompanied by increased exports for treated firms, ameliorating concerns that any effect of tariff cuts on innovation would be caused by increased export demand.

Figure 2: Imports/Exports Event Studies

(a) Import Penetration

(b) Export Share



Notes: This figure displays the point estimates and 95% confidence intervals from estimating Equation (1) via OLS using the baseline matched sample. In panel (a) the dependent variable is import penetration and in panel (b) the dependent variable is the export share. Details on the matching procedure can be found in Section 3.3 and Appendix A.2.

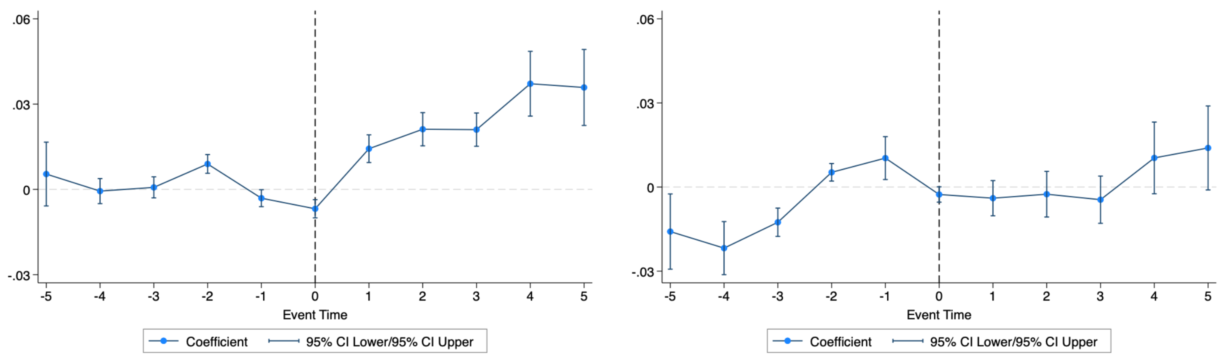
My baseline empirical strategy uses a traditional two-way fixed effects (TWFE) model estimated via OLS to generate event studies and treatment effects. A recent literature in econometrics points out potential pitfalls with using the TWFE model when treatment timing is staggered (Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Borusyak et al. 2023). In TWFE models with staggered treatment timing, the coefficient of interest is a weighted sum of the average treatment effects (ATEs) across the various treated groups. These weights from TWFE can even be negative, making it possible that the coefficient of interest from a TWFE model is negative even when all the ATEs are positive (Chaisemartin and D'Haultfœuille 2020).

To address these issues, I estimate event studies using the estimator of Callaway and Sant'Anna 2021. The Callaway and Sant'Anna 2021 estimator estimates a treatment effect for each treatment timing group, only comparing treated firms with firms who will never be treated and treated firms who have not yet been treated. Note that this strategy involves no matching procedure as all firms who do not face a large tariff cut are part of the control group. To get event study or difference-in-differences coefficients, the group level estimates are then aggregated. Figure 3 shows that when using the Callaway and Sant'Anna 2021 estimator, both the magnitude and the dynamic profile of the coefficients are similar to what is found when employing the matching strategy. Overall, these results indicate that the large tariff cuts I identified are followed by robust and significant increases in import penetration that are not driven by confounding pre-trends. In addition, there is no effect of large tariff cuts on the exporting intensity of U.S. firms.

Figure 3: Imports/Exports Event Studies (Callaway and Sant'Anna 2021 Estimator)

(a) Import Penetration

(b) Export Share



Notes: This figure displays the point estimates and 95% confidence intervals from estimating Equation (1) via the Callaway and Sant'Anna 2021 estimator. In panel (a) the dependent variable is import penetration and in panel (b) the dependent variable is the export share.

4.2 Tariff Cuts and Innovation

Now that I have documented that large tariff cuts have a meaningful impact on foreign competition, I turn to examining how these tariff cuts, and the subsequent import penetration they create, affect a firm's product and process patenting. With my baseline sample, I start by estimating event studies of the same form as in Equation (1) but replacing the dependent variable with measures of product and process patenting. As my baseline measures of innovation, I use the IHS of the number of product or process patents the firm applies for in a year.[15] Panel (a) of Figure 4 displays the coefficients and 95% confidence

[15]Only patents that are eventually granted are considered.

intervals from estimating Equation (1) with the IHS of product patents as the dependent variable. Before the arrival of the tariff cut, the coefficients are close to zero and display no significant pre-trend.[16] After the large tariff cut, treated firms display persistent increases in their product patenting relative to control firms. In Figure 2, import penetration increased immediately after the tariff cut and maintained at that level for three years, followed by another economically significant increase that persisted in the fourth and fifth years. Similarly, product patenting increases on impact and then experiences another increase in the fourth year after the tariff cut. Five years after the tariff cut occurs, the point estimate indicates that treated firms are applying for approximately 25% more product patents than control firms.

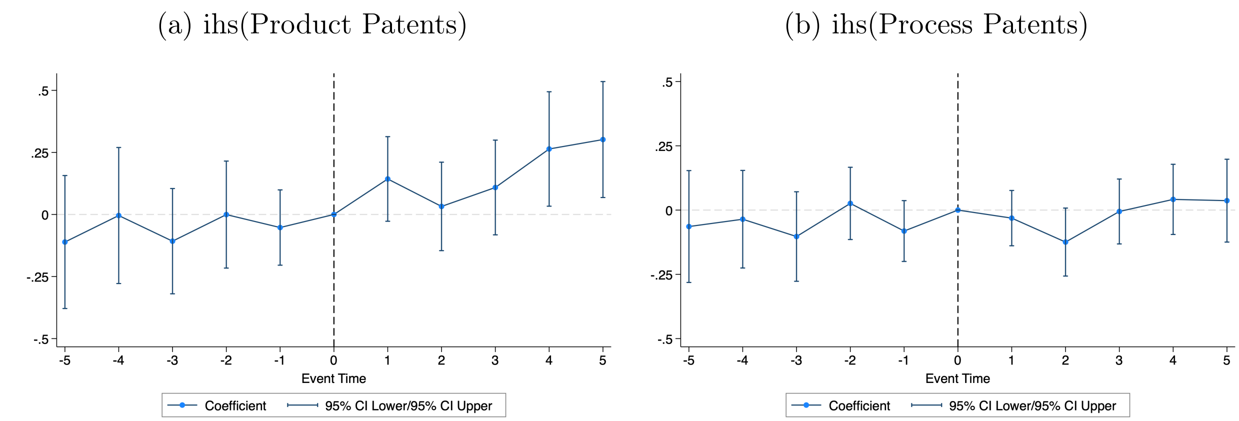
The right panel of Figure 4 displays the results when the IHS of process patents is the dependent variable. Similar to panel (a), there are no confounding pre-trends before the arrival of the tariff cut, with the coefficients being close to zero and not statistically significant.[17] After the tariff cut, the point estimates remain close to zero and none are statistically distinguishable from zero, indicating that there was no change in the process patenting of treated firms after the tariff cut. The results displayed in Figure 4 suggest that increased foreign competition causes firms to increase their product patenting but not their process patenting.

To address the issues associated with TWFE models and staggered treatment timing, I repeat my event study analysis using the Callaway and Sant'Anna 2021 estimator. As before, there is no matching procedure since all never treated and not-yet treated firms act as controls for treated firms. Figure 5 presents coefficients and 95% confidence intervals from event studies that implement the Callaway and Sant'Anna 2021 estimator. In the left panel when the IHS of product patents is the dependent variable, the coefficients are around zero before the arrival of the large tariff cut and there is no evidence of pre-trends. After the arrival of the tariff cut the coefficients jump, indicating that treated firms engage in more product innovation. The effects get larger over time, corresponding to the increase in

[16] A Wald test of the joint significance of the five pre-tariff coefficients cannot reject the null hypothesis that all the coefficients are simultaneously zero with an F-statistic of 1.48 and a p-value of 0.21

[17] A Wald test of the joint significance of the five pre-tariff coefficients cannot reject the null hypothesis that all the coefficients are simultaneously zero with an F-statistic of 1.47 and a p-value of 0.21

Figure 4: Innovation and Tariff Cuts Event Study



Notes: Both panels of this figure display the point estimates and 95% confidence intervals from estimating equation (1) via OLS using the baseline matched sample. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. In the left panel the dependent variable is the IHS of product patents. In the right panel the dependent variable is the IHS of process patents. Standard errors are clustered at the treatment-control pair level.

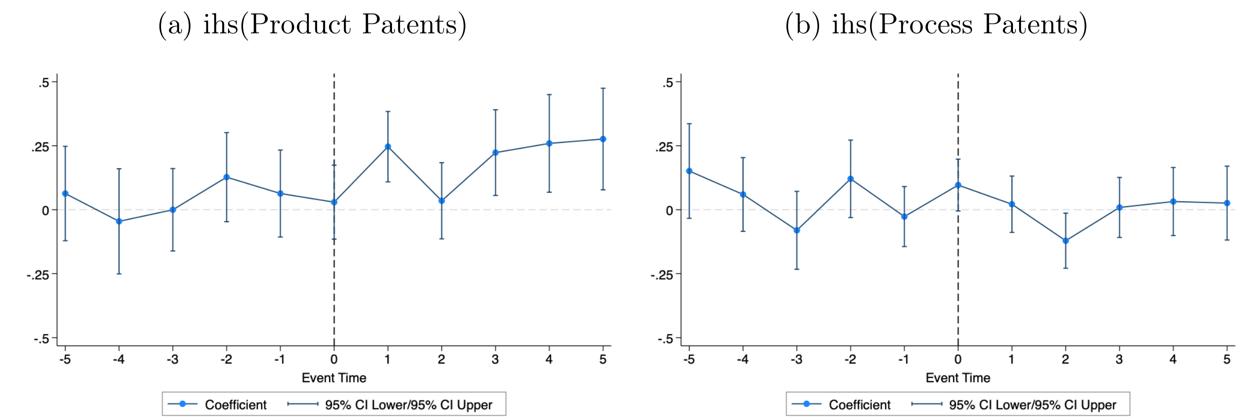
import penetration over time. On the other hand, when the IHS of process innovation is the dependent variable in the right panel, the coefficients remain close to zero both before and after the arrival of the tariff cut. Similar to my baseline event study, the results indicate that innovation increases after large tariff cuts, but the increase is entirely driven by product innovation with no change in process innovation. The result is not driven by confounding pre-trends and aligns with the contemporaneous increase in import penetration which occurs after a large tariff cut.

I now turn to estimating the average effect of large tariff cuts using the difference-in-differences specification outlined in Equation (2). This specification is similar to the event study specification in equation Equation (1) but does not allow the treatment effect to vary by year. $\mathbb{1}\{\text{Cut}_{zt}\}$ is an indicator variable that is one for treated firms after the arrival of a large tariff cut and zero otherwise. As before, standard errors are clustered at the treatment-control pair level.

$$\text{Y}_{fzmt} = \beta * \mathbb{1}\{\text{Cut}_{zt}\} + \phi_f + \delta_t + \varepsilon_{fzmt} \tag{2}$$

Column (1) of Table 2 uses the matched sample and shows the substantial effect that these large tariff cuts have on the amount of import penetration a firm faces. After the arrival

Figure 5: Innovation and Tariff Cuts Event Study (Callaway and Sant'Anna 2021 Estimator)



Notes: Panels (a) and (b) of this figure display the point estimates and 95% confidence intervals from estimating event studies via the Callaway and Sant'Anna 2021 estimator. Both never-treated and not-yet treated firms are used to comprise the control group. Standard errors are clustered at the firm level.

of a large tariff cut, import penetration increases by 2.3 percentage points which equates to approximately 14% off the mean level. In addition, the F-statistic is large, at 17. In column (2) when the export share is the dependent variable, the point estimate is small and statistically insignificant, indicating no effect of tariff cuts on exporting intensity. Columns (3) and (4) estimate Equation (2) using the Callaway and Sant'Anna 2021 estimator and show nearly identical results.

Having estimated how large tariff cuts impacted import penetration, I now turn to the effect on product and process innovation. In column (1) of Table 3 the IHS of product patenting is the dependent variable, and I find there is approximately a 20% increase in product patenting following a large tariff cut. This stands in contrast to the null effect estimated in column (2) when the IHS of process patenting is the dependent variable. Further, the two coefficients in columns (1) and (2) are statistically distinguishable from one another (p-value=0.00), indicating that product patenting responds more to foreign competition than process patenting. Many patents provide little value to firms and society (Kogan et al. 2017). To address whether the effect of import competition on product and process patenting can be thought of as a change to innovation and not simply an increase in the patenting of ideas that have little value, I estimate the effect of foreign competition on two

Table 2: Imports, Exports, and Tariff Cuts

	OLS		CS DiD	
	(1)	(2)	(3)	(4)
	Im Pen	Ex Share	Im Pen	Ex Share
Cut_{zt}	0.023***	0.003	0.025***	0.002
	(0.006)	(0.005)	(0.003)	(0.005)
$\overline{\text{Y}}$	0.17	0.18	.22	.23
F-stat	16.86	.46		
Observations	2,908	2,908	14,360	14,360

Notes: This table presents results from estimating Equation (2) via OLS and the Callaway and Sant'Anna 2021 (CS) DiD estimator with the baseline sample which includes data in the five years before and after the year before treatment. In columns 1 and 3 the dependent variable is industry import penetration. In columns 2 and 4 the dependent variable is the share of industry output that is exported. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). In the OLS specifications, firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

measures of value weighted patenting. First, I use market value weighted patenting[18], which captures the value of the patent to the firm. Second, I use citation weighted patenting which relates to the scientific value created by the patent as forward citations indicate that other firms are building upon the ideas in the patent.

Column (3) shows that large tariffs induce a 22% increase in market value weighted patenting, which is a similarly sized effect to what is found when looking at the unweighted count of patents in column (1). This indicates that firms are responding to increased foreign competition by engaging in product patenting that provides value to their firm. Further, column (5) shows that the result is similar when measuring the scientific value of a patent using the number of forward citations it receives. As in column (2), the results in column (4) and (6) continue to show no sizeable or statistically significant effect of large tariff cuts

[18]Estimates of patent market value are provided by Kogan et al. 2017 who rely on using abnormal stock returns around the issuance of a patent.

on value weighted process innovation. Further, the coefficients on the product and process specifications are statistically distinguishable from one other in the case of unweighted and citation weighted patenting. This indicates that product innovation responds more to import competition than process innovation. Overall, the results indicate that valuable product innovations are patented after the arrival of large tariff cuts, but there is no increase in process innovation.

Table 3: Innovation and Tariff Cuts

	ihs(Patents)		ihs(MVW Patents)		ihs(CW Patents)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Product	Process	Product	Process	Product	Process
Cut_{zt}	0.198***	0.002	0.221**	0.101	0.246*	-0.011
	(0.072)	(0.050)	(0.093)	(0.075)	(0.145)	(0.117)
$\beta_{\text{pdt}} = \beta_{\text{prs}}$ (p)	0***		.13		.08*	
Observations	2,908	2,908	2,908	2,908	2,908	2,908

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1) and (2) the dependent variables are the IHS of product and process patents applied for by the firm in a given year. In columns (3) and (4) the dependent variables are the IHS of market value weighted (Kogan et al. 2017) product and process patents applied for by the firm in a given year. In columns (5) and (6) the dependent variables are the IHS of citation weighted product and process patents applied for by the firm in a given year. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

To address concerns with TWFE models, I repeat my difference-in-differences analysis using the Callaway and Sant'Anna 2021 estimator and present the results in Table 4. Although the strategy involves no matching and uses a different estimation technique relative to my OLS estimation, the results are similar. Across the different measures, Table 4 reveals that tariff cuts increase the various measures of product innovation by around 20% while there is no effect on process innovation as the coefficients hover around zero.

Table 4: Innovation and Tariff Cuts ((Callaway and Sant'Anna 2021) Estimator)

	ihs(Patents)		ihs(MVW Patents)		ihs(CW Patents)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Product	Process	Product	Process	Product	Process
Cut$_{zt}$	0.205***	-0.009	0.231***	-0.013	0.245	0.019
	(0.066)	(0.049)	(0.083)	(0.074)	(0.150)	(0.128)
$\overline{\text{Y}}$						
Observations	14,360	14,360	14,360	14,360	14,360	14,360

Notes: This table presents results from estimating Equation (2) via the Callaway and Sant'Anna 2021 (CS) DiD estimator with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1) and (2) the dependent variables are the IHS of product and process patents applied for by the firm in a given year. In columns (3) and (4) the dependent variables are the IHS of market value weighted (Kogan et al. 2017) product and process patents applied for by the firm in a given year. In columns (5) and (6) the dependent variables are the IHS of citation weighted product and process patents applied for by the firm in a given year. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Standard errors are clustered at the firm level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

4.3 Robustness of Main Results

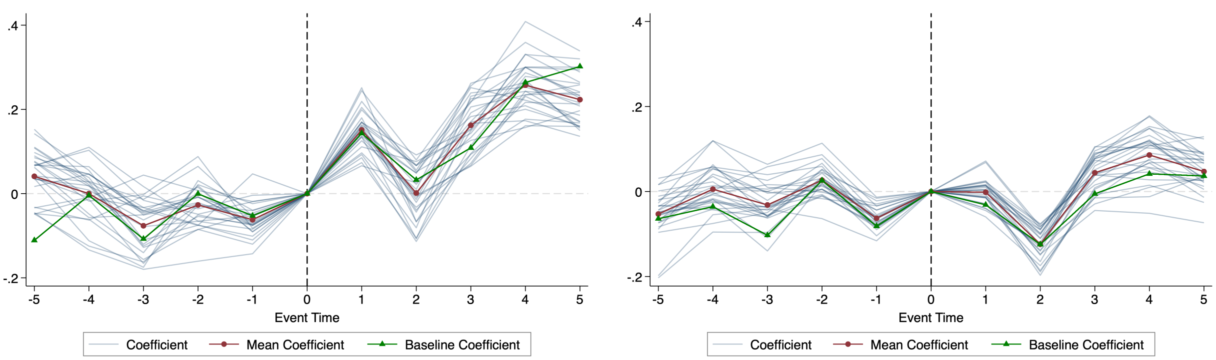
4.3.1 Alternative Matching Strategies

To ensure that my results are not sensitive to choosing a particular set of matching variables, I repeat my analysis 27 additional times, each time using a different set of matching variables. While each of these 27 matches between treatment and control firms preserves the intent of matching on firm size, research intensity, cash holdings, profitability, and product/process composition, I achieve the goal using a different set of matching variables in order to pair firms operating in treated industries with control firms. The results of this exercise would not be very interesting if these matches retrieved a similar set of control firms each time. Fortunately, this is not the case. Table A.5 summarizes the distribution of the share of control firms found in the 27 matches which are also found in the list of baseline control firms. On average, 47% of controls firms are found in both the baseline set of control firms and one of the other 27 matches. This provides evidence that the exercise is accomplishing its stated purpose: perturbing the set of control firms in a meaningful way while still matching on relevant characteristics.

In Figure 6, I plot the event study coefficients from the baseline specification, the 27 additional specifications, and the mean coefficient across all 28 specifications. For both product and process patenting, the 28 specifications follow a similar pattern after the arrival of a large tariff cut. There is an increase in product patenting in the five years after a large tariff cut. On the other hand, process patenting immediately falls. Three to five years after the tariff cut, process patenting recovers and the point estimates are generally positive, but the coefficients are much smaller than those found in the product patenting specifications. In addition, the results in my baseline specification follow the mean outcome assuring us that the baseline results are not an artifact of a particularly chosen control group. Figure A.2 plots the density of the difference-in-differences coefficients from the 28 specifications. The mean coefficient when the IHS of product (process) patenting is the dependent variable is around 0.2 (0.0), right in line with my baseline specification. In addition, the density of the estimates is fairly tight, further suggesting that the results obtained are robust to using various matching specifications.

Figure 6: Innovation and Tariff Cuts Event Studies (28 Matches)

(a) ihs(Product Patents) (b) ihs(Process Patents)



Notes: Both panels of this figure display the point estimates from estimating Equation (1) via OLS for the 28 different treatment-control matches. Details on the exact variables which are matched on are available in Appendix A.2. In panel (a) the dependent variable is the IHS of product patents. In panel (b) the dependent variable is the IHS of process patents.

4.3.2 Negative Binomial Estimation

In my baseline empirical specifications I apply the inverse hyperbolic sine transformation to my firm × year patent count variables. The IHS transformation is commonly used as it is similar to applying a natural logarithm transformation, but allows researchers to retain zero values. Despite common use of this transformation, research has documented that when using the IHS transformation, regression results can depend on the scale of the transformed variable (Aihounton and Henningsen 2021). In addition, there are concerns with interpretation of regression results when there are "too many" zeros in the data (Bellemare and Wichman 2020). To address these concerns, I estimate Equation (3) with Negative Binomial regression where the dependent variable is now the count of either product or process patents that firm f, belonging to industry z, and treatment-control pair m applies for in year t. I use a Negative Binomial regression as opposed to a Poisson regression as the count of product and process patents displays significant overdispersion[19], and I cluster standard errors at the treatment-control pair level.[20] Columns (1) and (2) of Table 5 display the results, showing that product patenting increases by 22% in the five years after a large tariff cut while there is no effect of large tariff cuts on process patenting. The magnitude of these results is similar to my baseline findings in Table 3.

$$\mathbb{E}[\text{Patent Count}_{fzmt} \mid \phi_f, \delta_t] = \exp(\beta * \mathbb{1}\{\text{Cut}_{zt}\} + \phi_f + \delta_t) \tag{3}$$

Columns (3) and (4) similarly estimate Equation (3), but employ a Zero-Inflated Negative Binomial model which is useful for modeling count data when there are a sizeable number of zeros and the observations taking on the value of zero should be modeled separately. My data fits this case well as the likelihood that an observation is zero is related to firm size since smaller firms are much less likely to patent in a given year. In the model, I separately estimate the likelihood of an observation taking on a zero value using a Logistic regression with log employment in a given year as the independent variable. When the zeros are modelled separately in columns (3) and (4), the results are nearly identical to the baseline Negative Binomial model. The results in Table 5 indicate that my findings are not being driven by the IHS transformation and are robust to estimation strategies intended to model count variables with an inflated number of zeros and overdispersion.

[19] A Negative Binomial regression is a generalized version of a Poisson regression which additionally models the overdispersion in the data. Overdispersion occurs when the variance is greater than the mean. In the case of product patents, the mean is 31 but the variance is 7,081. In the case of process patents, the mean is 8 but the variance is 482.

[20] The approach of using Negative Binomial estimation to examine how firm patenting responds to trade shocks has been used in Aghion, Bergeaud, et al. 2022.

Table 5: Innovation and Tariff Cuts (Negative Binomial Estimation)

	NB		ZINB	
	(1)	(2)	(3)	(4)
	Product	Process	Product	Process
Cut_{zt}	0.222**	-0.000	0.223***	-0.012
	(0.088)	(0.115)	(0.086)	(0.114)
Observations	2,579	2,579	2,579	2,579

Notes: This table presents results from estimating Equation (3) via Negative Binomial (NB) regression in columns (1) and (2) and Zero-Inflated Negative Binomial (ZINB) regression in columns (3) and (4). In the ZINB specification, excess zeros are modeled using Logistic regression with log employment as the independent variable. The sample which includes data in the five years before and after the year before treatment. In columns (1) and (3) the dependent variable is the count of product patents applied for in the year. In columns (2) and (4) the dependent variable is the count of process patents applied for in the year. The dependent variables are winsorized at the 1st and 99th percentiles. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

4.3.3 Alternative Definition of Treatment

Up until now, my definition of a large tariff cut has focused on relative changes in tariff rates within an industry. This means that the size of the large tariff cuts can vary by industry. Industries with relatively low tariff rates and low volatility in the rate could see small changes in their tariff rates lead to a 4x tariff cut. To probe the sensitivity of my results to using this definition of treatment, I create an invariant measure of what constitutes a large tariff cut. In this formulation of treatment, an annual decline in the tariff rate of 1.5 percentage points or greater constitutes a large tariff cut.

Using my baseline matching strategy, Table A.6 shows that the effect of these tariff cuts on imports and exports is similar to the effect I find in my baseline definition of treatment. Table 6 shows the effect of these 1.5 percentage point tariff cuts on patenting outcomes.

While the results are attenuated compared to my baseline results in Table 3, I continue to observe that the coefficients are larger when the IHS of various measures of product patenting is the dependent variable relative to process patenting.

Table 6: Innovation and 1.5 Percentage Point Tariff Cuts

	ihs(Patents)		ihs(MVW Patents)		ihs(CW Patents)	
	(1) Product	(2) Process	(3) Product	(4) Process	(5) Product	(6) Process
Cut_{zt}	0.148**	0.024	0.097	0.061	0.153	0.077
	(0.066)	(0.051)	(0.084)	(0.071)	(0.134)	(0.120)
$\beta_{\text{pdt}} = \beta_{\text{prs}}$ (p)	.03**		.63		.6	
Observations	3,095	3,095	3,095	3,095	3,095	3,095

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In column (1) the dependent variable is import penetration. In columns (2) and (3) the dependent variables are the IHS of product and process patents applied for by the firm in a given year. In columns (4) and (5) the dependent variables are the IHS of market value weighted (Kogan et al. 2017) product and process patents applied for by the firm in a given year. In columns (6) and (7) the dependent variables are the IHS of citation weighted product and process patents applied for by the firm in a given year. Treated firms are those with a primary industry that experiences a tariff cut of 1.5 percentage points. Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

5 Heterogeneous Effects

5.1 Patent Protection

A potential factor impacting a firm's decision to patent in response to increased competition is the firm's ability to protect the intellectual property contained in their patents. If a firm is unable to protect the intellectual property contained in their patents, then presumably they would be less likely to patent their innovations as a means of dealing with competition since their competitors could more easily appropriate the value present in their patent. To test if this is the case, I use a survey from Cohen, Nelson, et al. 2000 which asked firms to report the percentage of their product and process innovations for which patenting had been effective in protecting the firm's competitive advantage from those innovations during the prior three years. The population for the survey was all R&D labs of manufacturing firms in the U.S. with 3,240 labs being sampled in 1994. Cohen, Nelson, et al. 2000, aggregate statistics about the protection of patents at the 3-digit SIC level, with some 3-digit SIC industries sharing a common statistic. While the firms in my baseline sample represent 91 unique 4-digit SIC industries, they only represent 27 unique measures of patent protection. Despite having only 27 different values of the patent protection score, there is significant variation across 3-digit SIC industries. The industry with the lowest effectiveness of patents being able to protect their product innovations is the food industry with an average of only 18.3% effectiveness while the highest is medical equipment at 54.7%. For process innovations, the industry with the lowest effectiveness of patenting is the search/navigational equipment industry at 13.2% while the industry with the highest effectiveness is the petroleum industry at 36.7%.

I create an indicator variable which is one when the value of the patenting protection measure is above the median and zero otherwise. I then interact these measures of patenting effectiveness with the tariff cut indicator in Equation (2) to compare the effects of large tariff cuts on innovation for firms in industries with high patent effectiveness as compared to firms in industries with low patent effectiveness. Since the data from Cohen, Nelson, et al. 2000 asks about the effectiveness of patents in protecting product and process innovations separately, I use the measure relating to patent protection of product innovations when product patenting is the outcome of interest, and I use the measure relating to patent protection of process innovations when process patenting is the outcome of interest.

Across the columns of Table 7, the main effect of a tariff cut is negative and imprecisely estimated, suggesting that tariff cuts only lead to patenting when firms perceive patenting as an effective means of protecting their competitive advantage. Indeed, across the various measures of product innovation in columns (1), (3), (5), the interaction term is positive and statistically distinguishable from zero, indicating that firms who are above the median level of product patenting protection engage in more product innovation than those below the median. Further, the finding that value weighted product patenting is more responsive to patent protection than unweighted counts of product patenting is consistent with the notion

Table 7: Heterogeneous Effects by Scope for Patent Protection

	ihs(Patents)		ihs(MVW Patents)		ihs(CW Patents)	
	(1) Product	(2) Process	(3) Product	(4) Process	(5) Product	(6) Process
Cut_{zt}	-0.065	-0.100	-0.170	-0.062	-0.197	-0.280
	(0.117)	(0.098)	(0.114)	(0.113)	(0.225)	(0.200)
$\text{Cut}_{zt} \times$ Product Protect $>$ p50	0.334**		0.509***		0.567**	
	(0.138)		(0.143)		(0.258)	
$\text{Cut}_{zt} \times$ Process Protect $>$ p50		0.138		0.237*		0.371
		(0.113)		(0.138)		(0.231)
Observations	2,897	2,897	2,897	2,897	2,897	2,897

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In column (1) [(2)] the dependent variable is the IHS of product [process] patents applied for in a given year. In columns (3) and (4), patents are scaled by their market value as calculated in Kogan et al. 2017. In columns (5) and (6), patents are scaled by the number of forward citations they receive. Both the "Product Protect" and "Process Protect" variables are taken from a 1994 survey of firms conducted by Cohen, Nelson, et al. 2000 which measures, for firms in an industry, the mean percentage of product or process innovations for which patenting is effective in protecting the firm's competitive advantage. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

that increased patent protection incentivizes firms to patent innovations which are of high value. While the interaction terms are all positive when the dependent variable measures process innovation in columns (2), (4), and (6), the interaction term is only statistically significant at the 10% level for measures of process patenting when market value weighted process patenting is the dependent variable.

The results in Table 7 indicate that the ability of a firm to protect their knowledge through patenting is an important factor in determining whether a firm will patent their valuable innovation in response to increased competition. The results also provide a possible explanation for why product patenting responds to competition but process patenting does not. Table 1 shows that the mean percentage of product innovations for which patenting is an effective means of protecting the firm's competitive advantage is 40%. For the protection of process innovations, this number drops to 27%. Since, on average, process innovations are less able to be protected through patenting, firms will be less incentivized to increase their process patenting in response to increased competition. But as column (4) of Table 7 shows, for firms operating in industries where process patenting is sufficiently protected, an increase in foreign competition leads to an increase in valuable process patenting. This finding suggests that policies which provide sufficient protection for process patents would close the gap between the responsiveness of product innovation and process innovation to increased competition. Given that disclosure of new knowledge in a patent generates socially beneficial knowledge spillovers as it allows for other inventors to engage in cumulative innovation, offering patent protection is crucial for fostering the pro-competitive effect of increased knowledge disclosure (Furman et al. 2021).

5.2 Productivity & Firm Size

Models of competition and innovation often predict that the relative productivity of a firm plays a key role in determining how the firm will alter its innovation in response to increased competition. For example, the step-by-step innovation models predict that firms with high productivity will increase their innovation effort to escape the competition while firms with low productivity will lower their innovation effort as they anticipate smaller post-innovation profits (Aghion, Blundell, et al. 2009).

To measure the productivity of a firm, I use the measure of total factor productivity (TFP) for COMPUSTAT firms, provided by İmrohoroğlu and Tüzel 2014.[21] Since TFP varies for firms over time, I measure TFP in the year before a large tariff cut for both treatment and control firms and then indicate "high productivity" firms if they fall above the median level of TFP. As an alternative measure of productivity, I use firm size which I measure both through real revenue and employment. In the model of Aghion, Bergeaud, et al. 2022, which examines the effect of trade liberalization on patenting, large firms have higher productivity. A potential reason that large firms would be more productive is that

[21] İmrohoroğlu and Tüzel 2014 estimate TFP using the semi-parametric method of Olley and Pakes 1996. Industry and time dummies were included in the estimation, so all industry and year effects are already removed.

the incentive for firms to engage in process innovation increases with the amount of output a firm produces (Cohen and Klepper 1996). Since process innovations can be applied to the production of more output with relatively little increased cost, as firms increase their production the returns to any given process innovation increase.

Table 8: Heterogeneous Effects by Productivity

	ihs(MVW Patents)					
	(1) Product	(2) Product	(3) Product	(4) Process	(5) Process	(6) Process
Cut_{zt}	0.156	0.129	0.176	-0.057	-0.066	-0.028
	(0.102)	(0.105)	(0.155)	(0.073)	(0.073)	(0.119)
$\text{Cut}_{zt} \times \text{Revenue} > \text{p50}$	0.203			0.423^{***}		
	(0.180)			(0.152)		
$\text{Cut}_{zt} \times \text{Employees} > \text{p50}$		0.259			0.428^{***}	
		(0.178)			(0.150)	
$\text{Cut}_{zt} \times \text{TFP} > \text{p50}$			0.127			0.418^{**}
			(0.210)			(0.191)
Observations	2,845	2,845	1,886	2,845	2,845	1,886

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1)-(3) the dependent variable is the IHS of market value weighted Kogan et al. 2017 product patents applied for in a given year. In columns (4)-(6) the dependent variable is the IHS of market value weighted Kogan et al. 2017 process patents applied for in a given year. Firm size and productivity are measured in the year before the firm experiences the tariff cut. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table 8 displays the results when the IHS of market value weighted product and process patenting is the dependent variable. All the indicators for large and productive firms have positive point estimates, indicating that large and productive firms increase their innovation more when confronted with increased foreign competition. This finding is consistent with the models of step-by-step innovation (Aghion, Blundell, et al. 2009). Table 8 also shows that the coefficients are larger and statistically significant when market value weighted process patenting is the dependent variable. As discussed previously, large firms have an increased incentive to engage in process innovation since they can apply any cost saving process innovation to the production of more output. If firms make a costly commitment to focus on product or process innovation, as in (Yang et al. 2021), then the insight of Cohen and Klepper 1996 suggests that large firms are more likely to focus their innovation strategy on process innovation before the tariff cut. Since commitment to a product or process innovation is costly, large and productive firms would continue with their process innovation strategy to combat increased foreign competition. Table 8 provides evidence for this view as large and productive firms respond to increased foreign competition with substantial increases in their process innovation but no statistically different response in their product innovation. Table A.7 and Table A.8 display the results when the IHS of unweighted patent counts and citation weighted patent counts are the dependent variables. While the magnitude and precision of the estimates declines, the results are consistent with the findings in Table 8 where patents are weighted by their market value.

While the models of step-by-step innovation examine the differential effect of competition on the innovation of neck-in-neck and laggard firms, Boone 2000 segments firms into four groups based on their relative productivity and derives predictions regarding how product and process innovation will respond to competition for all four groups.[22] In Appendix A.4, I test the model of Boone 2000 and do not find support for the predictions of their model. Interestingly, though, the results in Table A.9 indicate that the increase in process innovation for large and productive firms is driven by the largest and most productive quartile of firms, suggesting that only the most productive firms respond to foreign competition with increased process innovation.

5.3 Product Differentiation

In response to foreign competition, firms can compete directly with foreign competitors on cost by lowering their cost of production through process innovation. Another strategy that firms could take is "escaping the competition" though product innovation by differentiating themselves from their competition (Yang et al. 2021). Using product innovation as

[22] From highest to lowest relative productivity are complacent, eager, struggling, and faint firms.

a means of product differentiation is only useful in industries where there exists the ability to differentiate your product. For example, the 4-digit SIC industry 3452 that makes bolts, nuts, screws, rivets, and washers, has relatively little scope for product differentiation. The homogeneous nature of the bolt industry's products makes it difficult to escape the competition through product innovation, making process innovation a more attractive strategy for mitigating the effects of increased competition. On the other hand, an industry like the electronic computer industry (4-digit SIC 3571) should find product innovation a more profitable strategy to use when coping with foreign competition since there are many ways to differentiate one's product and increase demand in that industry. To test whether this theory is supported in the data, I use two measures of a firm's scope for product differentiation, both measured at the industry level. First, is the quality ladder measure of Khandelwal 2010 and second is the share of differentiated products from Rauch 1999. I measure each of these variables in the year before the tariff cut occurs and standardize them to have mean zero and standard deviation one.

Khandelwal 2010 uses nested logit models to infer product quality from price and quantity information that is available in US product-level import data from 1989 to 2001. A product is said to have high quality if conditional on its price it has a high market share. Products are highly disaggregated and available at the HS-10 level. For each HS-10 product p, the quality ladder length is defined as: $\text{Quality Ladder}_p = \ln(\max\{\text{Quality}_p\} - \min\{\text{Quality}_p\})$, where quality is measured in the first year the product is observed in the data[23] and $\max\{\text{Quality}_p\}$ ($\min\{\text{Quality}_p\}$) is the product quality of the country with the highest (lowest) quality in the product category. Products with high ranges in quality across countries will have longer quality ladders. Quality ladders are then aggregated to the 4-digit SIC level by taking a weighted average of product quality ladders where the weights are the import share of the product in the industry. Intuitively, industries with short quality ladders will have little scope for product differentiation due to the nature of the products in their industry while industries with long quality ladders will have greater scope for product differentiation. Of the industries experiencing a large tariff cut, the bolt industry had the shortest quality ladder while the electronic computer has the longest ladder length.

[23] For most products, this is 1989.

As an alternative measure of the scope for product differentiation, I use the share of differentiated products measure from Rauch 1999. Rauch 1999 assigns each Standard International Trade Classification (SITC) product to one of three groups: homogeneous, reference-priced, and differentiated. Homogeneous products are traded in organized exchanges. For example, Lead and Lead Alloys, Unwrought (SITC 6851) is a homogeneous product and is traded on the London Metal Exchange (Rauch 1999). Reference-priced products have a quoted reference price, that is irrespective of brand. For example, within Polymerization and Copolymerization Products (SITC 583) a price per pound of Polyoxyethylene Sorbitan Monostearate is quoted weekly in *Chemical Marketing* on the basis of surveys of suppliers (Rauch 1999). In contrast, differentiated products have no reference price and can be thought of as "branded" products. I use data from Liao et al. 2020, who calculate the share of differentiated products at the North American Industry Classification System (NAICS) level by concording SITC products to NAICS codes and using the Rauch 1999 measure. I match the share of differentiated products to firms based on the firm's NAICS affiliation. Industries that have higher shares of differentiated products have higher scope for product differentiation.

For each measure of scope for product differentiation, I indicate whether firms have a high or low scope for product differentiation by cutting at the median level and interact this indicator with the tariff cut treatment indicator in Equation (2). Table 9 displays the results when IHS of market value weighted patenting is the dependent variable. Using both measures of scope for product differentiation, I find positive, but statistically insignificant point estimates when product innovation is the dependent variable and negative but statistically insignificant point estimates when process innovation is the dependent variable. Given the imprecision of the estimates, I am unable to conclude that scope for product differentiation increases the incentive for firms to respond to competition with product innovation and decreases their incentive to engage in process innovation. Despite this, the positive coefficients when product innovation is the dependent variable and negative coefficients when process innovation is the dependent variable are suggestive that the desire to differentiate their products could be a reason why firms engage in product innovation in response to increased import competition. Table A.10 and Table A.11 report similar results when the IHS of patent counts and the IHS of citation weighted patent counts are the dependent variables.

Table 9: Heterogeneous Effects by Scope for Product Differentiation

	ihs(MVW Patents)			
	(1)	(2)	(3)	(4)
	Product	Process	Product	Process
Cut_{zt}	0.195*	0.124	0.152	0.162*
	(0.100)	(0.077)	(0.106)	(0.091)
Cut_{zt} × Quality Ladder > p50	0.166	-0.014		
	(0.206)	(0.172)		
Cut_{zt} × Share Diff > p50			0.199	-0.093
			(0.182)	(0.141)
Observations	2,845	2,845	2,845	2,845

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1) and (3) [(2) and (4)] the dependent variables are the IHS of product [process] patents applied for by the firm in a given year, weighted by the market value of the patent as calculated in Kogan et al. 2017. In columns (1) and (2), the quality ladder measure from Khandelwal 2010 is used to measure product differentiation. In columns (3) and (4), the share differentiated measure from Rauch 1999 is used to measure product differentiation. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

6 Conclusion

This paper addresses the question of how foreign competition affects a firm's decision to engage in product and process patenting. I find that in response to large tariff cuts, firms face more import competition but see no increase in their exports. In response to this increased import competition, firms increase their innovation as measured by an increase in their value weighted patenting. This is entirely driven by an increase in product innovation; process innovation does not respond. I find evidence that the ability of firms to protect their innovations with patenting is an important condition for them to engage in valuable patenting activity as a strategic response to increased competition. While the ability of a firm to protect their innovation through patenting is a necessary condition for a firm to patent, initial productivity and firm size also plays a key role in determining whether a firm will focus on product or process innovation in response to foreign competition. Large and productive firms engage in process innovation as a strategic response to competition, consistent with the fact that the payoffs to process innovation scale with firm size and firms make a costly commitment to focus on product or process innovation (Yang et al. 2021).

An important difference between product and process innovation is that the information in product innovations is more likely to "spill over" to other economic actors as product innovations are more visible to competitors (Mansfield 1985; Ornaghi 2006; Davison 2022). This insight, combined with the results in this paper, suggest that foreign competition has the potential to create more socially beneficial knowledge spillovers through two channels. First, is the direct effect that foreign competition has in increasing the total amount of innovation, as evidenced by the increase in valuable product patenting which occurs after large tariff cuts. Second, is the indirect effect resulting from the fact that the increase in innovation is product innovation, not process innovation. While this paper only examines partial equilibrium effects resulting from a particular set of tariff reductions, the results suggest that there may be potential welfare gains from import competition that have, up until this point, gone unexplored. Being able to quantify any welfare gains or losses that come through this channel of increased product innovation would be a natural next step in quantifying the implications of this paper.

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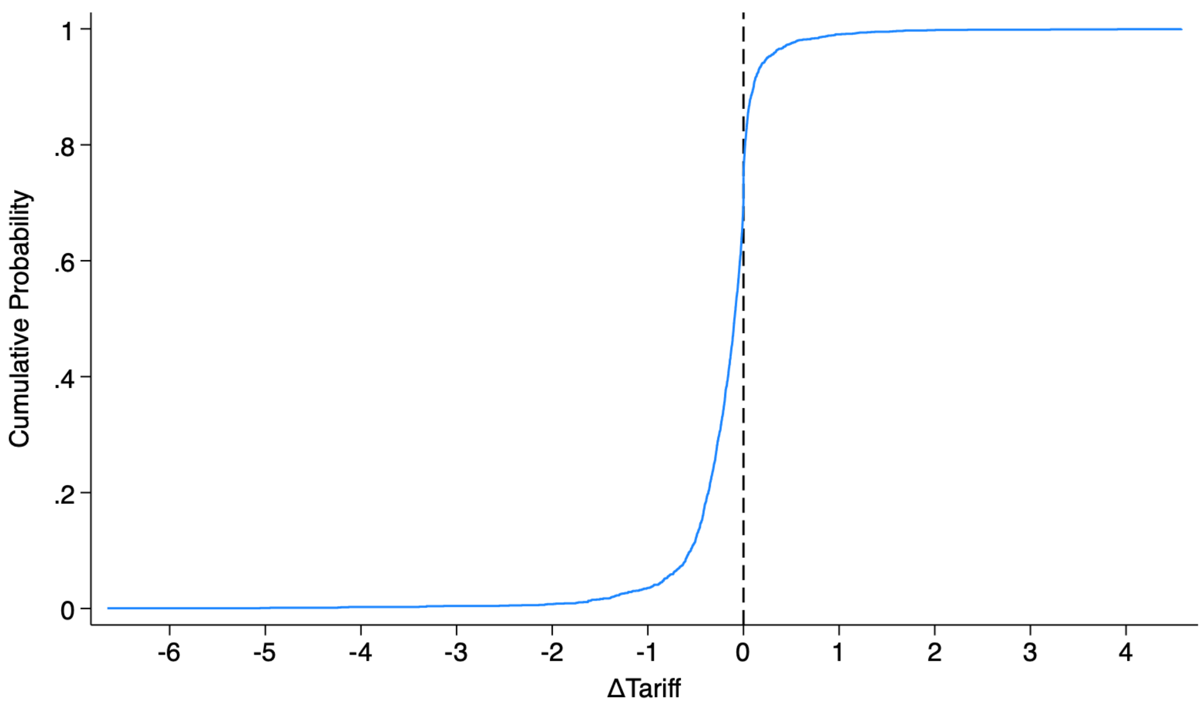
A Appendix

A.1 Tariff Cuts

Figure A.1: Distribution of Large Tariff Cuts



Notes: This figure presents the cumulative distribution function over the size of all annual tariff cuts. I use industry level data from 1980-2005 for all industries associated with firms in my unrestricted sample of firms.

Table A.1: Tariff Cut Summary Statistics

	Mean	St. Dev.	25%	50%	75%	Obs
ΔTariff Rate ($\mathbb{1}\{4x \text{ Cut} = 1\}$)	-3.3	1.73	-5.05	-3.22	-1.62	172
ΔTariff Rate ($\mathbb{1}\{4x \text{ Cut} = 0\}$)	-.15	.35	-.27	-.04	0	13,042

Notes: The row labeled ΔTariff Rate ($\mathbb{1}\{4x \text{ Cut} = 0\}$) presents summary statistics on the annual percentage point change in the tariff rate for the 172 treated firms in the year the tariff cut occurs. The row labeled ΔTariff Rate ($\mathbb{1}\{4x \text{ Cut} = 1\}$) presents summary statistics on the annual percentage point change in the tariff rate for all untreated firm $\times$ year observations.

A.2 Matching Procedure

In order to uniquely match each treated firm to one control firm, I first eliminate any treated firms who do not have observations for at least one year before and after the tariff cut. In addition, all firms in the sample must have non-missing matching variables. In the first iteration of the algorithm I match each treated firm without replacement to its nearest untreated neighbor firm based on an exact match between the year before treatment and minimum Mahalanobis distance across the matching characteristics. In this matching, control firms can be used more than once since matching is occurring at the firm-year observation level. For example, a firm treated in 1985 may match to control firm #1 based on characteristics in 1984. A different treated firm that experienced a tariff cut in 1996 may also match to control firm #1 based on characteristics in 1995. When this situation occurs, I randomly select one treated × control observation and discard the other matches which include the same control firm. In the second iteration, I remove all treated and control firms that were successfully matched in the first iteration. Next, I remove any treated firms who do not have a potential control to choose from, a rare occurrence. This can occur when all potential control firms with data in a given year before a tariff cut have been used in previous iterations, but there are still treated firms left unmatched. After these treated firms have been removed, if there are any treated firms left to match, I then match them to their nearest control firms, breaking any ties randomly in the same way as the first iteration. I continue iterating, removing all successfully matched treated and control firms from all previous iterations, until every treatment firm has found a control firm or there does not exist a potential control firm for them to match to.

28 Sets of Variables to Match On

1. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
2. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA
3. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
4. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA

5. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
6. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA
7. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
8. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA
9. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)
10. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA, ln(Sales)
11. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)
12. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA, ln(Sales)
13. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)
14. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA, ln(Sales)
15. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)
16. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA, ln(Sales)
17. ihs(Product Patents), ihs(Process Patents), $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
18. ihs(Product Patents), ihs(Process Patents), $\frac{\text{Net Cash}}{\text{Assets}}$, ROA
19. ihs(Product Patents), ihs(Process Patents), $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
20. ihs(Product Patents), ihs(Process Patents), $\frac{\text{Cash}}{\text{Assets}}$, ROA
21. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
22. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, ROA
23. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
24. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, ROA
25. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$

26. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$

27. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$

28. ihs(Product Patents), ihs(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$

Table A.2: Matching Variable Definitions

Variable	Definition
ihs(Product Patents)	The inverse hyperbolic sine of the number of product patents the firm applies for in year t
ihs(Process Patents)	The inverse hyperbolic sine of the number of process patents the firm applies for in year t
ln(Sales)	The natural log of SALE (sales)
$\frac{\text{R\&D}}{\text{Assets}}$	XRD (R&D expenditures) divided by AT (total assets) in year t winsorized at zero and one
$\frac{\text{R\&D}}{\text{Sales}}$	XRD (R&D expenditures) divided by SALE (sales) in year t winsorized at zero and one
$\frac{\text{Cash}}{\text{Assets}}$	CH (cash holdings) divided by AT (total assets) in year t winsorized at zero and one
$\frac{\text{Net Cash}}{\text{Assets}}$	CH (cash holdings) less DLC (debt in current liabilities) and DLTT (long-term debt), all divided by AT (total assets) in year t winsorized at zero and one
$1 - \frac{\text{COGS}}{\text{Sales}}$	One minus COGS (Cost of Goods Sold) divided by SALE (sales) in year t, winsorized at one and negative one
$\frac{\text{Income}}{\text{Assets}}$	IB (Income before extraordinary items) divided by AT (total assets) in year t, winsorized at one and negative one

Table A.3: Treatment and Untreated Balance Test

	Diff.	Treat	Control	p-value	Treat N	Control N
ihs(Product Patents)	0.52	2.56	2.04	0.00	2,920	13,087
ihs(Process Patents)	0.50	1.31	0.82	0.00	2,920	13,087
ln(Sales)	0.35	5.71	5.36	0.00	2,920	13,087
$\frac{\text{R\&D}}{\text{Assets}}$	0.02	0.13	0.11	0.00	2,920	13,087
$\frac{\text{R\&D}}{\text{Sales}}$	0.04	0.23	0.19	0.00	2,920	13,087
$\frac{\text{Cash}}{\text{Assets}}$	0.02	0.15	0.13	0.00	2,607	12,127
$\frac{\text{Net Cash}}{\text{Assets}}$	0.00	0.09	0.09	0.95	2,602	12,113
$1 - \frac{\text{COGS}}{\text{Sales}}$	-0.00	0.28	0.28	0.97	2,920	13,087
$\frac{\text{Income}}{\text{Assets}}$	-0.00	-0.05	-0.05	0.74	2,920	13,087

Notes: This table presents results from testing the equality of means across treated and untreated firm $\times$ year observations. All firm $\times$ year observations available in the panel are used in the comparison and no matching has been done between treated and untreated firms.

Table A.4: Treatment and Matched Control Balance Test

	Diff.	Treat	Control	p-value	Treat N	Control N
ihs(Product Patents)	0.10	1.97	1.87	0.59	172	172
ihs(Process Patents)	0.10	0.99	0.90	0.54	172	172
ln(Sales)	-0.14	4.30	4.43	0.67	172	172
$\frac{\text{R\&D}}{\text{Assets}}$	0.02	0.17	0.15	0.40	172	172
$\frac{\text{R\&D}}{\text{Sales}}$	0.07	0.29	0.21	0.06	172	172
$\frac{\text{Cash}}{\text{Assets}}$	0.02	0.11	0.09	0.16	172	172
$\frac{\text{Net Cash}}{\text{Assets}}$	0.01	-0.06	-0.07	0.71	172	172
$1 - \frac{\text{COGS}}{\text{Sales}}$	-0.00	0.19	0.19	0.94	172	172
$\frac{\text{Income}}{\text{Assets}}$	-0.02	-0.10	-0.08	0.58	172	172

Notes: This table presents results from testing the equality of means using the baseline matched sample in the year before treatment occurs.

A.3 Robustness of Main Results

A.3.1 Alternative Matches

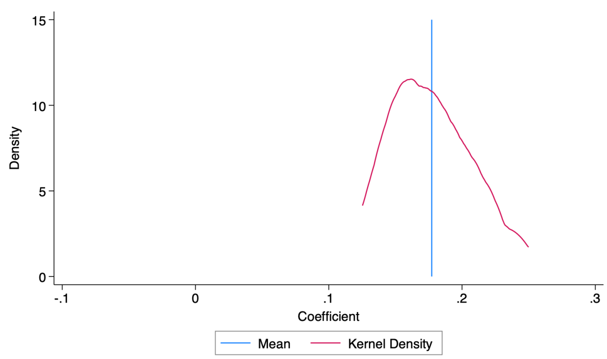
Table A.5: Share of Control Firms Repeated Relative to Baseline Specification

	Mean	St. Dev.	Min	25%	50%	75%	Max	Obs
Share Repeat	0.47	0.09	0.37	0.41	0.46	0.51	0.67	27

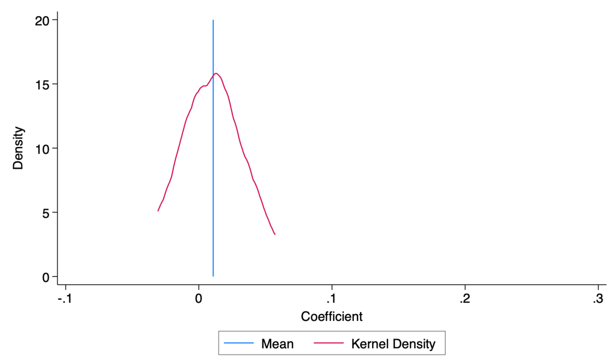
Notes: This table presents summary statistics on the share of control firms which are found in the baseline specification and the 27 other non-baseline matches.

Figure A.2: Distribution of Difference-in-Differences Coefficients

(a) ihs(Product Patents)



(b) ihs(Process Patents)



Notes: Both panels of this figure display the kernel density of the point estimates resulting from estimating Equation (2) via OLS for the 28 different treatment-control matches. The Epanechnikov kernel is used to calculate the kernel density. The mean across all 28 coefficients is also displayed via the vertical line. In panel (a) the dependent variable is the IHS of product patents. In panel (b) the dependent variable is the IHS of process patents.

A.3.2 Alternative Definition of Treatment

Table A.6: Imports/Exports and 1.5 Percentage Point Tariff Cuts

	OLS		CS DiD	
	(1)	(2)	(3)	(4)
	Im Pen	ihs(Exports)	Im Pen	ihs(Exports)
Cut_{zt}	0.019***	0.007	0.025***	0.005
	(0.005)	(0.005)	(0.004)	(0.005)
$\overline{\text{Y}}$	0.15	0.18	.22	.23
F-stat	12.14	2.29		
Observations	3,095	3,095	14,359	14,359

Notes: This table presents results from estimating Equation (2) via OLS and the Callaway and Sant'Anna 2021 (CS) DiD estimator with the baseline sample which includes data in the five years before and after the year before treatment. In columns 1 and 3 the dependent variable is import penetration. In columns 2 and 4 the dependent variable is the IHS of exports. Treated firms are those with a primary industry that experiences a tariff cut of 1.5 percentage points. In the OLS specifications, firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

A.4 Heterogeneous Effects

Table A.7: Heterogeneous Effects by Productivity (Unweighted)

	ihs(Patents)					
	(1) Product	(2) Product	(3) Product	(4) Process	(5) Process	(6) Process
Cut_{zt}	0.203***	0.184**	0.176	-0.048	-0.048	-0.061
	(0.077)	(0.078)	(0.128)	(0.052)	(0.051)	(0.087)
$\text{Cut}_{zt} \times$ Revenue > p50	0.027			0.152		
	(0.137)			(0.100)		
$\text{Cut}_{zt} \times$ Employees > p50		0.069			0.147	
		(0.134)			(0.097)	
$\text{Cut}_{zt} \times$ TFP > p50			0.021			0.147
			(0.168)			(0.131)
Observations	2,845	2,845	1,886	2,845	2,845	1,886

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1)-(3) the dependent variable is the IHS of market value weighted Kogan et al. 2017 product patents applied for in a given year. In columns (4)-(6) the dependent variable is the IHS of market value weighted Kogan et al. 2017 process patents applied for in a given year. Firm size and productivity are measured in the year before the firm experiences the tariff cut. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table A.8: Heterogeneous Effects by Productivity (Citation Weighted)

	ihs(CW Patents)					
	(1) Product	(2) Product	(3) Product	(4) Process	(5) Process	(6) Process
Cut_{zt}	0.196	0.162	0.290	-0.107	-0.135	-0.312
	(0.182)	(0.183)	(0.243)	(0.144)	(0.141)	(0.190)
$\text{Cut}_{zt} \times \text{Revenue} > \text{p50}$	0.153			0.279		
	(0.246)			(0.212)		
$\text{Cut}_{zt} \times \text{Employees} > \text{p50}$		0.226			0.333	
		(0.246)			(0.206)	
$\text{Cut}_{zt} \times \text{TFP} > \text{p50}$			-0.164			0.413
			(0.286)			(0.268)
Observations	2,845	2,845	1,886	2,845	2,845	1,886

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1)-(3) the dependent variable is the IHS of market value weighted Kogan et al. 2017 product patents applied for in a given year. In columns (4)-(6) the dependent variable is the IHS of market value weighted Kogan et al. 2017 process patents applied for in a given year. Firm size and productivity are measured in the year before the firm experiences the tariff cut. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

Table A.9: Test of Boone 2000 Model

	ihs(MVW Patents)					
	(1) Product	(2) Process	(3) Product	(4) Process	(5) Product	(6) Process
Cut_{zt}	-0.008	0.130	0.045	-0.102	-0.003	-0.167
	(0.133)	(0.144)	(0.209)	(0.091)	(0.097)	(0.162)
Cut_{zt} × Hi Revenue	0.347*			0.638***		
	(0.202)			(0.199)		
Cut_{zt} × Mid Revenue	0.388*			0.202		
	(0.198)			(0.147)		
Cut_{zt} × Hi Employees		0.104			0.554**	
		(0.242)			(0.230)	
Cut_{zt} × Mid Employees		0.199			0.032	
		(0.194)			(0.140)	
Cut_{zt} × Hi TFP			0.397			0.703***
			(0.241)			(0.249)
Cut_{zt} × Mid TFP			0.168			0.310
			(0.277)			(0.210)
Observations	2,845	2,845	1,886	2,845	2,845	1,886

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1)-(3) the dependent variable is the IHS of market value weighted Kogan et al. 2017 product patents applied for in a given year. In columns (4)-(6) the dependent variable is the IHS of market value weighted Kogan et al. 2017 process patents applied for in a given year. Firm size and productivity are measured in the year before the firm experiences the tariff cut. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table A.10: Heterogeneous Effects by Scope for Product Differentiation (Unweighted)

	ihs(Patents)			
	(1) Product	(2) Process	(3) Product	(4) Process
Cut_{zt}	0.169**	0.016	0.125	0.015
	(0.075)	(0.054)	(0.081)	(0.067)
$\text{Cut}_{zt} \times$ Quality Ladder > p50	0.163	-0.003		
	(0.178)	(0.123)		
$\text{Cut}_{zt} \times$ Share Diff > p50			0.197	0.001
			(0.142)	(0.093)
Observations	2,845	2,845	2,845	2,845

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1) and (3) [(2) and (4)] the dependent variables are the IHS of product [process] patents applied for by the firm in a given year. In columns (1) and (2), the quality ladder measure from Khandelwal 2010 is used to measure product differentiation. In columns (3) and (4), the share differentiated measure from Rauch 1999 is used to measure product differentiation. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

Table A.11: Heterogeneous Effects by Scope for Product Differentiation (Citation Weighted)

	ihs(CW Patents)			
	(1) Product	(2) Process	(3) Product	(4) Process
Cut_{zt}	0.125	0.003	0.074	-0.078
	(0.162)	(0.130)	(0.175)	(0.146)
Cut_{zt} × Quality Ladder > p50	0.486	0.023		
	(0.300)	(0.254)		
Cut_{zt} × Share Diff > p50			0.411	0.193
			(0.276)	(0.216)
Observations	2,845	2,845	2,845	2,845

Notes: This table presents results from estimating Equation (2) via OLS with the baseline sample which includes data in the five years before and after the year before treatment. In columns (1) and (3) [(2) and (4)] the dependent variables are the IHS of product [process] patents applied for by the firm in a given year, weighted by the number of forward citations the patent has received. In columns (1) and (2), the quality ladder measure from Khandelwal 2010 is used to measure product differentiation. In columns (3) and (4), the share differentiated measure from Rauch 1999 is used to measure product differentiation. Treated firms are those with a primary industry that experiences a tariff cut of 4 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.3). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics in the year before the tariff cut occurs: IHS of product patenting, the IHS of process patenting, the R&D to asset ratio, the net cash to asset ratio, return on assets, and the natural log of revenue. Details on the matching procedure can be found in Section 3.3 and Appendix A.2. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).