More Competition, Better Products: Evidence from a Novel Classification of Patents

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October 5, 2022

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Abstract

This paper uses the text of patents and machine learning techniques to classify patents as product or process innovations. I combine this newly created data with plausibly exogenous variation in import penetration induced by large tariff cuts and find that firms increase their product innovation in response to increased import competition. In contrast, I find that import competition has no effect on process innovation. Heterogeneity analysis provides evidence that the effect on product innovation is stronger for firms operating in industries with wider scope for product differentiation.

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1 Introduction

Innovation is often thought of as a single object, but in reality there are many different types of innovation. Firms engage in product innovation by introducing new product varieties, and they also introduce process innovations by altering the assembly of their products. Prior work has documented that one of the most salient differences between product and process innovation is that they have different information properties (Mansfield 1985; Ornaghi 2006; Davison 2022). The information contained in product innovations is more likely to be reused by other firms, relative to the information in process innovations. Therefore, changes in the product and process composition of innovation have the potential to alter the amount of knowledge spillovers occurring in the economy.

Despite the implications that product and process innovation have for knowledge spillovers and the central role of competition in shaping a firm's incentive to innovate, we still know relatively little about how and why changes in a firm's competitive environment shape their product and process innovation. This is surprising, since over the last several decades, the United States and many other high-income countries have experienced large increases in foreign import competition. Progress on this topic has remained elusive, mainly because of the lack of large-scale, high quality data distinguishing product and process innovation.

This paper addresses the lack of data by combining the text of United States Patent and Trademark Office (USPTO) patents with machine learning methodologies to measure the amount of product and process innovation at the firm-year level. The data covers all patents granted from 1980-2015 to publicly traded U.S. manufacturing firms. With this data, I provide the first empirical estimates of how increased foreign import competition affects the amount of product and process innovation a firm engages in.

In order to explore the topic of foreign import competition, I match this innovation data with industry level data on import penetration (ratio of imports to domestic expenditure) and import tariff rates. I use sudden and large industry tariff reductions to generate plausibly exogenous increases in the amount of foreign import competition a firm faces (Frésard 2010; Frésard and Valta 2016). Indeed, using a matched difference-in-differences strategy, I find that firms exposed to large tariff cuts see a 13% increase in import penetration off of mean levels, relative to control firms. Using the same empirical strategy, I find that the same firms who face higher foreign import competition increase their product patenting by approximately 21% 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 variations in the matching strategy, using alternative estimators, only utilizing variation from multilateral tariff cuts, and various definitions of treatment status. When examining heterogeneity in the effect, I find results that are consistent with a story where firms differentiate their products in order to "escape the competition."

My results contribute to several literatures. First, is the literature concerned with measuring product and process innovation. Scherer 1982 creates data on industry-level product and process innovation by hand classifying the industry of origin and industry of use for 15,112 patents. This classification is cross-sectional and aggregated at the industry level, limiting its use cases. National surveys of firms will often distinguish product and process innovation, but these surveys generally focus on binary measures that capture whether the firm introduced any product innovation or any process innovation in the last year.[1] The lack of intensive margin measurement limits the use cases for these surveys in empirical work. Finally, modern classifications of the product/process distinction generally look for the presence of process innovation keywords in patent text to distinguish product and process innovations (Bena and Simintzi 2019; Banholzer et al. 2019). While this allows for measurement of the intensive margin, I will provide evidence that keyword searches tend to systematically over-classify patents as process innovations. This paper takes a step forward in measuring product and process innovation by removing some of the systematic misclassification present in keyword-based patent classifications. In addition, my classification retains the virtues of patent-based methods of classification and distinguishes product and process innovation for all publicly traded U.S. manufacturing firms over a long period of time.

Next, my paper contributes to the theoretical and empirical literature on competition and innovation. The theoretical predictions about how product and process innovation respond to increased competition are quite numerous and varied,[2] in large part due to the lack of a

[1] An example of this is the "National Survey on Innovation and Technological Behavior of Industrial Argentinian Firms" which is used in (Bustos 2011).

[2] Greenstein and Ramey 1998 find that competition increases the incentive for process innovation but

"common framework" (Boone 2000). I contribute to this literature by providing empirical evidence on the topic, and my results are most consistent with models, such as the one in Vives 2008, which predict a positive effect of competition on product innovation and a null or negative effect on process innovation.

This paper adds to the empirical literature about whether competition has a positive or negative effect on innovation. Using various empirical strategies such as import competition, compulsory licensing of patents, and the breakup of firms, a group of studies has found evidence of a positive relationship between competition and innovation (Bertschek 1995; Correa and Ornaghi 2014; Bloom et al. 2016; Watzinger et al. 2020; Poege 2021). On the other hand, there are several other studies who use a similar set of empirical strategies but in different contexts, and find negative effects of competition on innovation (Hashmi 2013; Autor et al. 2020; Kang 2021). Aghion et al. 2005 and Im et al. 2015 reconcile these results by finding evidence for an inverted-U shape relationship between competition and innovation where a moderate amount of competition fosters the most innovation. Taking the Aghion et al. 2005 model seriously, my results suggest that my observations were on the upward sloping leg of the Aghion et al. 2005 inverted-U relationship.

My results also contribute to a small set of empirical papers examining how other types of innovative activity respond to foreign import competition. Morandi Stagni et al. 2021 find that in response to import competition, firms lower their technological exploration and prefer to innovate in areas of knowledge they are familiar with. Liu and Rosell 2013 also uses import penetration to show that corporate innovation becomes less basic and more applied 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 innovation but not process innovation.

there is relatively less incentive to engage in product innovation because more market power increases the return to a given product innovation. Based on the efficiency of a firm relative to its competitors, Boone 2000 finds conditions that can accommodate all combinations of product innovation increasing or decreasing and process innovation increasing or decreasing in response to more competition. Vives 2008 finds that when competition goes up, the incentive to engage in product innovation increases while process innovation declines. The reason process innovation declines comes from the insight that process innovation scales with output, in the sense that there is little to no cost of applying a process innovation to 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 we get the result that there is less incentive for process innovation in a competitive market, what Vives 2008 calls the "size effect".

I proceed as follows. Section 2 describes how I create the data used in the analysis, including how I classify patent claims as product or process innovations. Section 3 examines the effect of large tariff cuts on import competition and product and process innovation. It also includes results on potential mechanisms that explain my findings. Section 4 concludes the paper by discussing the implications of the paper and possibilities for future work.

2 Product/Process Patent Data

2.1 Sample Selection

The starting point for my patent data is a match between USPTO patents and Compustat firms, described in Arora et al. 2021. This data provides the most comprehensive and accurate match of USPTO patents to publicly traded U.S. firms that is currently available. The match is completed by starting with the set of Compustat firms who are ever recorded as conducting R&D and matching to patents on the basis of assignee and firm name. This match updates the NBER patent database (Hall et al. 2001) by including all patents granted from 1980-2015. The data from Arora et al. 2021 also has the virtue of carefully tracking parent companies and subsidiaries in Compustat data as well as how name changes and mergers & acquisition activity may affect which subsidiaries belong to the parent company. I aggregate to their identification of parent companies when conducting firm level analysis. I webscrape Google Patents to obtain characteristics of the patents such as: the title, CPC code, and publication claim text. Since the distinction between product and process innovation is most salient for manufacturing firms, I limit my analysis to only include patents granted to manufacturing firms.[3]

In order to make the problem of classifying patents as product or process innovations tractable, I limit to firms whose primary 4-digit Standard Industrial Classification (SIC) code belongs in the top 100 patenting SIC codes. This restriction allows me to retain over 95% of the manufacturing patents in the original sample, but it reduces the number of industries from 272 to 100, making the classification problem significantly easier. In the end,

[3]See the detailed discussion on how I classify manufacturing firms in Appendix A.1.

I am left with a sample of 1,016,871 patents assigned to 3,092 manufacturing firms. While it may seem that limiting to patents granted to manufacturing firms would be restrictive, my sample of patents captures 75.4% of the total number of patents in the Arora et al. 2021 match. This fits with the findings of Autor et al. 2020 who report that more than three-quarters of corporate patents are granted to manufacturing firms in their sample.

2.2 Classifying Product and Process Innovation in Patent Data

With the data in hand, I now turn to the task of classifying patents as product or process innovations. There are two main obstacles to classifying patents as product or process innovations. The first issue is fundamental: I need to create definitions of product and process innovations that can be applied to patent data. Second, I have over one million patents to classify, so I need to use a method which can classify a large number of patents in a reasonable amount of time. My method handles these difficulties in turn.

2.2.1 Defining Product and Process Innovation

I define a product innovation as an innovation that describes a physical object that the firm sells in the output market with no discussion about how the object is created. All other innovations are defined to be process innovations. To more concretely see how this definition works in practice, I have taken three patents granted to Micron Technology, a firm operating in the semiconductor industry and specializing in the production of computer memory. The semiconductor industry is highly innovative, having the most patents of any industry in my data. As an example of a product patent, consider US patent number 6952359, which is titled: "Static content addressable memory cell" and pictured in Panel (a) of Figure 1.

[Figure 1 about here.]

This patent is for a content addressable memory cell, a product that Micron sells in the output market. The motivation for the patent is described in the text of the patent which says: "There is a...need for an alternative CAM cell design that is relatively small and yet has acceptably low soft-error rates." There is no discussion of how the product is created, making this patent a product innovation that is meant to address shortcomings in currently available product offerings.

Now consider Panel (b) of Figure 1 which shows a different patent assigned to Micron Technology that has the title: "Thermal conditioning apparatus." The description of the patent's CPC classification reads: "Apparatus specially adapted for handling semiconductor or electric solid state devices during manufacture or treatment thereof..." Further the patent goes on to state: "A problem that arises with the prior art...is that when the heating or cooling assemblies must be repaired or replaced, extensive and costly amounts of downtime occur." From the CPC description and the text of the patent, it is clear that this machine is used to more effectively produce semiconductors. According to my definition this invention is a process innovation since it describes a physical object that Micron does not sell but is used to produce physical objects that Micron will sell.

But not all inventions are strictly product or process innovations. Consider, US patent number 7271654, which has the title: "Low voltage CMOS differential amplifier" and is shown in Panel (c) of Figure 1. From the title, it would appear that the patent is for an object that Micron Technology will sell, yet the second sentence of the abstract states that: "there is provided a method of manufacturing a device..." This indicates that the patent contains information about how this object is constructed. In this sense, the patent has both a product component since it describes features of a physical object that Micron will sell, but it also has a process component since it describes how to manufacture the product. Fortunately, the publication claims of a patent enumerate all the individual innovations that make up the invention in the patent. Specifically, the publication claims of a patent legally define what is protected by the patent, with each independent publication claim standing on its own. Because dependent publication claims rely on independent publication claims, I restrict my attention to independent publication claims. The current patent of consideration, US patent number 7271654, has four independent publication claims, which will henceforth be referred to as claims for brevity:

1. A method of manufacturing a device comprising...

2. A device comprising...

3. A method of operating a set of differential pairs comprising...

4. An input buffer comprising...

The first claim refers to a process innovation since it discusses a process used to create an object that the firm will sell. The next three claims pertain to descriptions of the CMOS differential amplifier, along with descriptions about how to use it. To capture the fact that this patent contains both product and process innovations, I assign this patent a product share of 0.75 where the product share is the proportion of a patent's claims that are product innovations. In the previous two examples, all the claims were either product innovations, as in the case of the memory cell in US6952359, or process innovations as in the case of the thermal conditioning apparatus in US6051074. I apply this method of individually classifying patent claims as product or process innovations and then calculate a product share for each patent. This method ensures that I capture the fact that patents can contain both product and process innovations.

These patents also highlight how product and process innovations have different information properties. Process innovations such as Micron's thermal conditioning apparatus tend to be more internally focused, making it less likely that their knowledge leaks out to rivals. On the other hand, product innovations, such as Micron's memory cell, are more easily reverse engineered since the product is available for purchase. This fits with the finding in other literature that product innovations generate more knowledge spillovers than process innovations (Mansfield 1985; Ornaghi 2006; Davison 2022).

2.2.2 Classifying Patents

The final hurdle is determining a method of systematically, accurately, and efficiently classifying the 1,016,871 patents in my sample. There are two main approaches I could take. The first is specifying an algorithm for deciding whether a publication claim is a product or process innovation. In the current literature (Bena and Simintzi 2019; Banholzer et al. 2019), the algorithm is often an indicator function that classifies the claim as a process innovation when certain keywords are in the claim text. I could follow the spirit of this approach and create a more complex classification rule that takes into account other features of the patent such as the CPC code, firm, industry, and year. Alternatively, I could hand classify a sample of claims and then use predictive methods, such as machine learning, to predict the status of claims that I have not hand classified. This approach has been used recently in the economics literature to classify various types of patents but has not been used for the product/process distinction (Chen, Wu, and Yang 2019; Clemens and Rogers 2020; Lerner et al. 2021).

I chose the latter approach for several reasons. First, after reading several hundred patents, it was clear to me that the functional form which would best identify whether a claim is a product or process innovation is a very complicated function that would be extremely difficult for me to specify. For example, the phrase "a method" followed by words such as "of" or "comprising" and then followed by a verb can indicate that the claim should be classified as a process innovation. This is true in the case of US8185230, assigned to Advanced Micro Devices Inc where the first claim states: "a method comprising: ...performing a first fabrication process on the semiconductor device...". On the other hand, this is not always the case, even in the same industry. The last claim of US8185666, assigned to Texas Instruments, states: "A method of executing a single instruction, comprising...comparing the array index value to the array size value..." This is a claim related to executing instructions on a microprocessor and should be classified as a product innovation. Being able to create a pre-determined rule that could distinguish between these situations seemed an incredibly challenging task.

To classify claims as product or process innovations, I start by hand classifying the claims of 100 patents for each of the 100 4-digit SIC industries. I classify industries separately since there is significant heterogeneity in how vocabulary is linked with the product/process distinction. For industries where prediction was less accurate, I classified more claims in order to improve the accuracy and precision of the prediction. My hand classification process involved evaluating each claim in the sample, one industry at a time. For each new firm where I was unfamiliar with the products the firm sold, I would retrieve several of their 10-Ks and read their product description section in order to understand what their final products were and how they may have evolved over time. I would then read the text of each claim, examining whether it met the definition of a product or process innovation as outlined above and reviewing the 10-Ks if I needed more information to make a decision.

In the end, I hand classified 40,682 claims (over 14,000 patents). I then cleaned the claims text of all patents by removing stopwords, punctuation, whitespace, and numbers. Further, I lemmatize the text which involves reducing each word to its lemma in order to analyze it as a single concept. For example, "forming" would be transformed to its lemma, "form." For each industry, I then assess the performance of sixty different machine learning models.[4] Each model has three components to it: a machine learning classifier, a text feature set (the independent variables), and a dummy for whether to drop certain coefficients. I use three different machine learning classifiers: multinomial naive bayes, complement naive bayes, and a passive aggressive classifier developed by Crammer et al. 2006. I experiment with ten different text feature sets (i.e. the entire claims text and the 4-digit CPC code). I also experiment with either all features in a given feature set or dropping features that are below median "importance" in predicting the outcome, where importance is determined using a meta-transformer called "SelectFromModel" that is available in Python's scikit-learn package. In total this gives me $3 \times 10 \times 2 = 60$ models for each industry. In Appendix A.2, I include a comprehensive list of the elements that make up each model. I now turn to discussing how I choose a model for each industry and how I validate the quality of my classifications.

2.3 Model Validation

2.3.1 Quantitative Validation

For each of these 60 models, I assess its quality using repeated k-fold cross validation where I choose k = 5 (Raschka 2018). This process works by taking 20% of my hand classified claims data for the industry as the evaluation sample. I then fit the model to the other 80% of the data. I use this fitted model to make predictions about whether each claim in the 20% evaluation sample is a product or process innovation. I repeat this procedure 5 times so that each claim is in the evaluation sample exactly once. I then repeat this entire procedure k = 5 times, randomly shuffling the data each time. In the end, each claim will be classified

[4]For some industries, I pool together several similar industries in order to increase accuracy and precision. Whenever industries are pooled together, the diagnostic statistics only reflect how well the model is able to predict for the focal industry.

five times. After running this procedure for all 60 models, I choose the model that has the highest correlation coefficient between the vector of binary hand classifications and the vector of binary predictions. In a final step, I estimate seven more models where I add various features to the final selected model which again are described in detail in Appendix A.2. If any of these extra seven models obtain a higher correlation coefficient between the truth and the prediction then the new model is chosen; otherwise I retain the previously chosen model. I use the correlation coefficient to asses the model as it effectively trades off type-I and type-II error and it performs well in the case of imbalance, where one category far outnumbers the other (Chicco and Jurman 2020). This is relevant in my case since most industries are imbalanced, with fewer process innovations. In practice, the model with the highest correlation coefficient often achieves the highest balanced accuracy, which is another popular evaluation metric that also performs well in the presence of imbalance and is used in Clemens and Rogers 2020.

Table 1 displays the resulting diagnostic statistics from 5-fold repeated cross validation for each industry where the model used is the one with the highest correlation coefficient. Observations are at the industry level and all statistics are calculated with weights, where the weights correspond to the number of patents in the industry.

[Table 1 about here.]

I achieve a mean correlation coefficient of 74% with a standard deviation of 9% across industries and balanced accuracy of 85%. To put these results into context, I compare them to two patent categorization projects in the economics literature. Chen, Wu, and Yang 2019 assign financial patents to FinTech technologies and Clemens and Rogers 2020 categorize various features of prosthetic device patents. The diagnostic statistics in Table 1 exceed those of Chen, Wu, and Yang 2019 across all reported metrics, but Clemens and Rogers 2020 are able to achieve a balanced accuracy above 90%, exceeding my 85%. Therefore, the quality of my classification falls between these two modern and accepted patent classification projects. To further help with contextualizing the results, Table A2 displays the confusion matrix for the semiconductor industry which uses an example to show how each of the diagnostic statistics is calculated. One thing to notice from Table 1 is that process recall is lower than process precision, meaning that with respect to process innovations the models are making more type-II (false negative) errors than type-I (false positive).

For each industry, I use the model with the highest correlation coefficient and fit it using the entire set of hand classified claims. I then use the fitted model to predict the status of each unclassified claim in my data, allowing me to classify the claims of all 1,016,871 patents in my sample. In order to further asses the validity of the classification I pursue several strategies. In panel (a) of Figure 2, I plot the mean process share in the machine learning classified sample against the mean process share in the hand classified sample for each industry. The points cluster on the 45 degree line, indicating that the mean process share within industries aligns well across the hand classified and machine learning samples. The points are generally shifted below the 45 degree line, consistent with Table 1 which showed that the machine learning classifiers made more false negative predictions for process innovations. Next, I examine the robustness of my classification across time. Panel (b) of Figure 2 shows that the average correlation coefficient over time is stable, assuaging any concerns that analyses over time would be mechanically driven by misclassification bias. Panel (c) plots the process share over time for both the hand classified and machine learning samples. Over time, there is a clear downward trend that is highly correlated across the hand classified and machine learning classified sample. The preceding tables and figures provides evidence that the machine learning classifiers are able to accurately replicate my hand classification across the patents in my sample.

[Figure 2 about here.]

2.3.2 Qualitative Validation

To better understand the value of my classification and how it improves on prior work that has used keyword-based classification, I examined how my classification compares to the product/process classifications of Banholzer et al. 2019 and Bena and Simintzi 2019. I took a random set of patents where the Banholzer et al. 2019 process share disagreed with my classified process share by at least .5. Consider the first of these, US5086041 assigned to Monsato Co. and falling under the NBER drugs & medical category. It's first claim is:

A method for achieving prolonged release of a biologically active somatotropin into the circulatory system of an animal which comprises parenteral administration...

This claim is classified as a product claim by my machine learning classifier, while the presence of the word "method" causes it to be classified as a process innovation for Banholzer et al. 2019. The claim is clearly describing a drug which is something that Monsanto sells and the claim does not talk about a method of production for the drug. This makes the claim a product innovation according to my definition. This issue of misclassifying product innovations as process innovations is not isolated to drug & medical patents, it is also prevalent in the computer & communications category. Consider US6469707, assigned to NVIDIA Corp who operates in the semiconductor industry. The first claim of this patent is:

A method for efficiently rendering and displaying color intensity information of pixels in a computer system, the pixels including a plurality of fragments, the method comprising the steps of...

Describing a computational product using process language is very common for computer & communication patents. Given that NVIDIA Corp makes graphical processing units, this claim is clearly a product innovation according to my definition, but it is mistakenly identified as a process innovation using a simple keyword search. I inspected ten patents in total and found that the patterns outlined in these two randomly selected examples are common and that my machine learning method is more accurately able to distinguish product and process innovations even for claims where keywords used by Banholzer et al. 2019 would indicate that the claim is a process innovation. This suggests that my classification contains significantly fewer cases where product innovations are misclassified as process innovations.

How large is this systematic misclassification? In Figure 3, I plot the mean process share by year across broad six-digit NBER categories of patents using my classification and the classifications of Banholzer et al. 2019 and Bena and Simintzi 2019.

[Figure 3 about here.]

First, note the similarity between the keyword based classifications of Banholzer et al.

2019 and Bena and Simintzi 2019. The classifications are almost indistinguishable in every NBER category. While the two keyword based classifications are very similar, they both exhibit significant differences with my classification. The starkest differences are in the computer & communication and drugs & medical categories. The computer & communication category exhibits a large and steady increase in the keyword based process share of innovation that is not present in my classification. This finding is consistent with my qualitative examination of the NVIDIA patent data where I found that my classification was able to identify the innovation as a product innovation even in the presence of a process keyword. In the drugs & medical category, all three classifications exhibit flat trends, but there is a significant level difference in the share of process innovations between my measure and the keyword based measures. Again, the lower process share in my data is consistent with my qualitative findings. The other categories exhibit more similarity in levels, but in all cases my measure exhibits a steeper decline relative to the keyword based classifications. The large upward trend in the computers & communications process share, combined with the steeper downtrends in my data lead to very different aggregate conclusions about the process share of innovation. My classification has a clear secular downtrend in the process share, whereas the keyword classifications have positive trends.

In order to help provide some color to the data, Table 2 lists the industries with the highest and lowest process shares. The industry with the second highest process share is petroleum refining which is consistent with other product/process classifications. Using a set of hand classified patents in 1974, Cohen and Klepper 1996 comment that almost three-quarters of total R&D is spent on process innovations for petroleum refining firms, consistent with what I find. Other industries with high shares of process innovation include industries engaged in metal, food, and chemical manufacturing. On the other hand, industries with low levels of process share are generally those producing machinery, highly specialized equipment (3829, 3823), or computer and communication devices. Using the same data as Cohen and Klepper 1996, Scherer 1983 finds that process R&D was 24.6 percent of total 1974 company-financed R&D spending. Not only that, but the National Science Foundation estimated that in 1981 about 75% of industry R&D was directed to product innovations (Gilbert 2006). My estimates are remarkably similar, I find that the process share of innovations is 27.9%

in 1980.

[Table 2 about here.]

3 Import Competition and Product/Process Innovation

3.1 Data & Empirical Strategy

With this classification of product and process patents, I now turn to answering the question of how foreign import competition affected the creation of product and process innovation. I start with the set of patents that I classify as product or process innovations and match them back to the underlying Arora et al. 2021 data. 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 my tariff data, I use all firm-year observations in the data from the years 1980-2005. This leaves me with an unbalanced panel of 16,007 firm-year observations and 1,438 firms.

To generate plausibly exogenous variation in the amount of foreign import competition a firm faces, I utilize variation in the tariffs faced by an industry. Tariffs have been recognized as an important barrier to trade, protecting home country industries from foreign competition by raising the cost of foreign goods (Anderson and Van 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 foreign import competition, most changes in tariffs that a firm faces are small and insignificant. Figure 4 plots the cumulative distribution function for the annual change in tariff rates for all industries in my sample and clearly shows that the mass of tariff changes is concentrated around zero.

[Figure 4 about here.]

In my empirical strategy, I will 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. In this literature, the most common empirical specifications uses 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 (Frésard 2010; Flammer 2015; Frésard and Valta 2016; Boubaker et al. 2018; Chen and Wu 2019; Morandi Stagni et al. 2021). I start with granular product (HS-10) level import 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. The tariff rate for an industry $\times$ year observation is calculated as the duties collected by U.S. custom divided by the free-on-board value of imports. This gives me tariff rates for each 4-digit SIC industry from 1974-2005. 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. In my baseline specifications, I use four as my multiple.

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 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.[5] 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 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 industry

[5]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.

of the firm.

Panel (a) of Figure 5 displays 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.[6] 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) 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.[7] 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. Industries experiencing a large tariff cut are highly innovative and represent aggregate innovative activity well. Of the ten 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 5 about here.]

Table A3 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. 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. This 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.

[6] 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.

[7] 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 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

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).

3.1.1 Matching

I identify treated firms as firms in my product/process data who are operating in 4-digit SIC codes in the year of a 4x tariff cut.[8] Using a tariff cut which exceeds 4 times the mean annual change as my threshold of defining treatment, I identify 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 3 tests the equality of means across treated firm-year observations and all untreated firm-year observations and implicitly presents summary statistics on the data. The first row of Table 3 shows the average of the inverse hyperbolic sine (IHS) of firm-year product patents. The IHS transformation approximates a natural logarithm transformation, but allows me to retain zero values. This allows me to loosely interpret a .01 change in an IHS variable as a 1% change in the variable. On average, treated firms apply for approximately 52% (50%) more product (process) patents in a given year and have 35% higher sales than untreated firms. Scaling the R&D expenditures by the firm's assets or sales reveals that treated firms have higher R&D intensity. Finally, treated firms have similar levels of profitability as measured by their profit margin or the return on assets respectively. Given that treated firms make up a small proportion of the untreated sample and the results in Table 3 clearly show that treated and control firms have significant differences in the cross section, I follow Frésard and Valta 2016 and pursue a matched difference-in-difference strategy as my baseline empirical specification. A matched difference-in-difference strategy also allows me to explore the dynamic impact of any effect through event study analyses.

[Table 3 about here.]

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

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

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 net cash to asset ratio, and the return on assets. 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. 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. The matching algorithm is described in detail in Appendix A.3.

In addition to my baseline matching variables, I use several alternative measurements of the matching characteristics. My baseline matching procedure controls for research intensity by matching on the firm's product and process patenting. Other variables I use to measure a firm's research intensity include the R&D to asset ratio and the R&D to sales ratio. To measure a firm's cash position I use the cash to asset ratio and the net cash to asset ratio where net cash is defined as cash holdings less long term debt and debt in current liabilities. I measure profitability using return on assets, defined as the income before extraordinary items divided by assets and a firm's profit margin. Detailed definitions of all measures are described in Table A4.

To test the robustness of my results to the specific set of matching characteristics chosen, I replicate my results using 28 different combinations of these matching variables. 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 the other characteristics (research intensity, cash holdings, profitability) where at least two of the three characteristics are used. Also, in every combination where all five characteristics are used, I include a set of matching variables with and without a supplemental measurement of firm size (log of sales). In the end this gives me 28 unique sets of matching variables which are detailed in Appendix A.3. Table 4 tests the difference in means across the treatment and control firms using my baseline set of matching variables. The means across treatment and controls observations are similar, with only the difference in one characteristic being statistically distinguishable from zero.

[Table 4 about here.]

Using all firm-year observations in my matched sample of treatment and control firms, I present summary statistics in Table 5. The average firm-year observation faces 16% import penetration which is calculated at the industry-year level and is defined as the value of foreign imports divided by total US expenditure on goods.[9] The average firm-year observation applies for 31 (8) product (process) patents in a year, and has approximately 13,500 employees. Patenting activity and employment are highly skewed with some firms applying for no patents in a given year and others applying for very large numbers of patents.

[Table 5 about here.]

3.2 Tariff Cuts and Import Penetration

With the sample of matched treatment and control firms, I first test whether large tariff cuts increase foreign import competition. I use import penetration to measure the level of foreign import competition a firm faces. I explore the dynamic impact of tariff cuts on the import penetration faced by firm f, operating in 4-digit SIC industry z, belonging to treatment-control pair m, and operating in year t by estimating 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 include the 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.

[9]Total US expenditure is measured as US gross output plus US imports minus US exports

Panel (a) of Figure 6 shows the coefficients and 95% confidence intervals from estimating equation (1) via OLS. 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.

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 Panel (a) of Figure 6 shows no significant pre-trend in differences between treatment and control firms before the arrival of the tariff cut.[10] This suggests that the gap in import penetration between treatment and control firms would have evolved similarly in the absence of the tariff cut.

[Figure 6 about here.]

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 (Borusyak and Jaravel 2017; De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021; Callaway and Sant'Anna 2021). One of the issues with TWFE models is that they impose undesirable weights on groups that are treated at different times. Under treatment effect heterogeneity this can result in biased estimates as certain groups are given more weight relative to others. The weighting scheme of TWFE can also put weight on comparisons between treated units and already treated units, an unsavory comparison.

[10]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 3.39 and a p-value of 0.01, the coefficients are small in magnitude and display no clear trend before the arrival of the tariff cut.

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. Panel (b) of Figure 6 displays the coefficients along with 95% confidence intervals from this estimation procedure. There are no pre-trends going into the tariff cut, and after the tariff cut the gap in import penetration between treated and control firms widens. Comparing the results in Panels (a) and (b), both the magnitude and the dynamic profile of the post-tariff cut coefficients are similar. In the first three years after the arrival of the tariff cut, there is an increase in import penetration for firms experiencing a large tariff cut. Panels (a) and (b) both show a further increase in import penetration that happens in the fourth year after the tariff cut. Overall, these results indicate that the large tariff cuts that I identified are followed by robust and significant increases in import penetration that are not driven by confounding pre-trends.

3.3 Tariff Cuts and Innovation

3.3.1 Event Study

Now that I have documented that large tariff cuts have a meaningful impact on foreign import competition, I turn to examining how these tariff cuts, and the subsequent import penetration they create, affect a firm's product and process innovation. With this 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 innovation. As my baseline measures of innovation I use the IHS of the number of product or process patents the firm applies for in the year. Panel (a) of Figure 7 displays the coefficients and 95% confidence 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.[11] After the large tariff cut, treated firms display persistent increases in their product patenting relative to control firms. The dynamic profile of the effect matches nicely with the effect on import penetration exposure shown in Figure 6. In Figure 6, import penetration increased immediately after the tariff cut and maintained at that level for three years, followed by another significant increase that persists 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 27% more product patents than control firms.

Panel (b) of Figure 7 displays the results when the IHS of process patents is the dependent variable. There are no confounding pre-trends before the arrival of the tariff cut, with the coefficients being close to zero and not statistically significant.[12] 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 innovation of treated firms after the tariff cut.

[Figure 7 about here.]

As before, my TWFE models are subject to concerns about biased estimates since I have staggered treatment timing. To address this, 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 8 presents coefficients and 95% confidence intervals from event studies that implement the Callaway and Sant'Anna 2021 estimator. In Panel (a) 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 import penetration over time. On the other hand, when

[11] 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 0.20 and a p-value of 0.96

[12] 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 0.66 and a p-value of 0.65

the IHS of process innovation is the dependent variable in Panel (b), 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 a contemporaneous increase in import penetration.

[Figure 8 about here.]

3.3.2 Difference-in-Differences

Now that we have found evidence that large tariff cuts increase import penetration and product innovation and that the results are not driven by pre-trends, I turn estimating average effects using the difference-in-differences specification outlined in equation (2). This specification is similar to the event study specification in equation (1) but does not allow the treatment effect to vary by year. Instead β captures the average effect, as $\mathbb{1}\{\text{Cut}_{zt}\}$ 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 6 shows the substantial effect that these large tariff cuts have on the amount of import penetration a firm faces. After the arrival of a large tariff cut, import penetration increases by 2.1 percentage points which equates to around 13% off the mean level. In addition, the F-statistic is large, at around 19. In column (2), when the IHS of product patenting is the dependent variable, there is approximately a 20% increase in product patenting following the large tariff cuts. This stands in contrast to the small effect estimated in column (3) when the IHS of process patenting is the dependent variable. Although the point estimate in column (3) is positive, the size of the effect is small and not statistically distinguishable from zero. Further, the two coefficients in columns (2) and (3) are statistically distinguishable from one another (p-value=0.01), indicating that product innovation responds more to foreign import competition than process innovation. Columns (4) and (5) incorporate patent value into the analysis by using market value weighted patenting in the construction of the dependent variable instead of weighting all patents equally. Estimates of patent market value are provided by Kogan et al. 2017 and rely on using abnormal stock returns around the issuance of a patent. In columns (4) and (5) the results are remarkably similar, there is a strong positive effect of tariff cuts on product innovation but not process innovation. Again, I reject the null hypothesis that the two coefficients are equal to one another (p-value = 0.00). Taken together, the results suggest that the arrival of a large tariff cut is followed by substantial increases in innovation that is entirely driven by a rise in product innovation.

[Table 6 about here.]

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 7. Although the strategy involves no matching and uses a different estimation technique relative to my OLS estimation, the results are remarkably similar. Column (1) of Table 7 indicates that firms experience a 2.5 percentage point increase in import penetration after large tariff cuts, an 11% increase off the mean level. Columns (2) and (4) indicate that product innovation increases by around 20% while columns (3) and (5) show that the effect of tariff cuts on process innovation is a precisely estimated null effect. Overall, the results from the Callaway and Sant'Anna 2021 estimation are similar to what I find using my matched OLS estimation in Table 6. Overall, the results provide evidence that increased foreign import competition increases product innovation but not process innovation.

[Table 7 about here.]

The prior literature on import competition and innovation is mixed, with some studies finding positive effects of foreign import competition on innovation while others find negative effects. Two prominent studies in this area are those of Bloom et al. 2016 and Autor et al. 2020 who both examine the effect of Chinese import competition on innovation but in Europe and the United States respectively. Bloom et al. 2016 finds a positive effect of Chinese import competition on European innovation while Autor et al. 2020 finds a negative effect of Chinese import competition on American innovation.

Taking the Aghion et al. 2005 model seriously suggests an explanation for why Bloom et al. 2016 and I find positive effects of import competition on innovation while Autor et al. 2020 find negative effects. In Autor et al. 2020, the rise of China causes the average firm to face an increase in import penetration of 8.5 percentage points, while the average firm in my sample only experiences an increase of 2.1 percentage points. Consistent with this, Bloom et al. 2016 points out that the US faced a much more dramatic increase in Chinese import competition, relative to Europe. It is plausible that the size of the competitive shock from China in the US was sufficiently large to push firms into the downward-sloping leg of the Aghion et al. 2005 inverted-U relationship, while the increase in competition that Bloom et al. 2016 and I observe is small enough to keep firms on the upward-sloping leg of the inverted-U relationship. In addition, Bena and Simintzi 2019 document that reductions in the cost of offshoring cause firms to lower their process innovation. Since the rise of China led to significant offshoring opportunities which were correlated with competitive import exposure (Pierce and Schott 2016), the negative estimates in Autor et al. 2020 likely pick up some of this negative offshoring effect on process innovation. Indeed, in unreported regressions that follow the empirical strategy of Autor et al. 2020 and are available upon request, Chinese import competition lowers the product and process innovation of U.S. manufacturing firms at equal rates. The finding in this paper, that process innovation is not responsive to import competition, suggests that a large part of the decline in process innovation resulting from the China shock is related to increased offshoring opportunities.

3.3.3 Robustness

Before exploring potential mechanisms that explain my findings, I turn to a discussion of the robustness of the results. I include a brief discussion here and provide a full discussion with tables and figures in Appendix A.4. First, I ensure that my results are not sensitive to choosing a particular set of matching variables. To do this, 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. On average, the results from the 27 other matches are similar to those found in the baseline specification, indicating that the results I found are not specific to a particular set of matching variables.

One concern with using tariff cuts as a plausibly exogenous change in foreign import competition is that trade policy can be influenced through lobbying and may be the result of strategic decision making on the part of policymakers. To address this concern, I create a sample that only utilizes tariff cuts that come from multilateral agreements where endogenous selection of treatment is significantly less likely because it is much harder for one country or industry to effectively lobby the negotiations. I find that the effect of a multilateral tariff cut on product innovation is significantly more than its effect on process innovation. One difference between my baseline specification and only using multilateral tariff cuts is that I observe a significantly smaller effect on import penetration.

My results are similar using a zero-inflated negative binomial regression with the count of product or process patents being the dependent variable, addressing concerns that the IHS transformation may be driving my results. I also examine the robustness of the effect to different definitions of treatment. First, I change my definition of a large tariff cut to be 3x the mean absolute value annual change in tariff rates. Using this definition, I find that the effect of a tariff cut on import penetration is a little more than half of what it was using the baseline definition of a tariff cut. In line with this, the positive effect on product innovation is weakened by a similar proportion. 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 where an annual decline in the tariff rate of 1.5 percentage points or greater is considered a large tariff cut. Using my matching strategy along with this new definition of tariff cuts, I get similar results as what I find in my baseline specification.

3.4 Mechanisms

What are the reasons that in response to foreign import competition firms increase their product innovation but not their process innovation? While there are many possible reasons why this might be the case, I propose a simple framework for thinking about the firm's choice between product and process innovation. In response to foreign import competition, firms can compete directly with foreign competitors on costs by lowering their cost of production through process innovation. Another strategy that firms could take is "escaping the competition" though product innovation. Product innovation allows firms to differentiate themselves from their competition, escaping some of the harmful demand destruction that could come from foreign import competition (Yang et al. 2021).

Given these two strategies, when would it be useful for a firm to compete directly on cost of production by engaging in process innovation? I start with the well established fact that the value of a process innovation is increasing in the firm's size (Cohen and Klepper 1996). This occurs because once a process innovation is discovered it can be applied to all of a firm's output. For example, using an identical process technology, a firm in the automobile industry that makes two million automobiles a year would get roughly twice as much cost savings from a process technology relative to if the firm only made one million automobiles a year. These observations suggest that process innovation would be more useful in combating foreign competition for larger firms, simply because process innovations are relatively more valuable for large firms.

The alternative strategic choice would be to focus on product innovation as a way for the firm to differentiate itself from the increased foreign competition. Using product innovation as 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, is likely to have little scope for product differentiation relative to 4-digit SIC industry 3571 that makes electronic computers. The homogeneous nature of the bolt industry's products makes it difficult to escape the competition through product innovation. On the other hand, an industry like the electronic computer industry should find product innovation a more profitable strategy to use when coping with foreign import competition since there are many ways to differentiate one's product and increase demand in that industry.

To test whether these theories are supported in the data, I need measurements of firm size and a firm's scope for product differentiation. I use two measures of firm size: the log of firm employment and the log of firm sales. I quantify scope for production differentiation at the industry level using the quality ladder measure of Khandelwal 2010 and the share of differentiated products from Rauch 1999. I measure each of these variables in the year before the tariff cut occurs[13] 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 example, France has high quality in the category of leather shoes because conditional on the price of its leather shoes it has a high market share. For each HS-10 product p, the quality ladder 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[14] 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, indicating that there is a wide range of quality across countries. 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 (long) quality ladders will have little (much) scope for product differentiation due to the nature of the products in their industry. Of the industries experiencing a large tariff cut, the bolt (electronic computer) industry had the shortest (longest) quality ladder.

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 product to one of three groups: homogeneous, reference-priced, and differentiated. Homogeneous products are traded in organized exchanges, reference-

[13]For control firms that are matched to treated firms, I measure the variables at the control firm in the year before the treated firm matched to the control firm experiences the tariff cut.

[14]For most products, this is 1989.

priced products have a quoted reference price, and differentiated products have no reference price. 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.

I first test the hypothesis that firms operating in industries with higher scope for product differentiation are more likely to use product innovation to escape the competition. To implement this test, I use my baseline specification outlined in equation (2), but I add an interaction term between a measure of product differentiation and the tariff cut. Table 8 displays the resulting point estimates and 95% confidence intervals from the analysis. In column (1) of Table 8, I use the quality ladder metric of Khandelwal 2010 as my measure of an industry's scope for product differentiation. The main effect on the tariff cut is similar to what was estimated in my baseline specification. Firms at the mean level of the quality ladder metric have a 20% increase in product patenting after the tariff cut. The interaction term is positive and marginally significant. For every standard deviation increase in a firm's scope for product differentiation, the effect of a large tariff cut on product innovation increases by approximately 12 percentage points. When the IHS of process innovation is the dependent variable in column (2) the interaction term is small and statistically insignificant. Using the Rauch 1999 share of differentiated goods measure, I obtain similar results. Firms operating in industries with a higher share of differentiated goods respond to tariff cuts with more product innovation. This suggests that the desire to differentiate their products is a driving force behind why firms innovate in response to increased import competition. By differentiating their products firms no longer have to compete directly with foreign competitors.

[Table 8 about here.]

Next, I test the hypothesis that large firms will use more process innovation as a way to cope with import competition. I use the same strategy as before, but I substitute my measures of scope for product differentiation with measures of firm size. In column (1) of Table 9, I use log employment as my measure of firm size, and I find that being a large firm has no effect on the amount of product innovation a firm engages in when they experience a large tariff shock. On the other hand, when the IHS of process innovation is the dependent variable in column (2) the coefficient is positive and marginally significant. For every standard deviation increase in log employment, firms increase their process innovation by an extra 10 percentage points in response to a tariff cut. In columns (3) and (4) when the log of sales is used to measure firm size, I find positive interaction terms both when the IHS of product and the IHS of process innovation are used as dependent variables. While the evidence is mixed, the results suggest that larger firms may find it advantageous to engage in process innovation in response to import competition. The results are consistent with firms playing to their strengths. Firms operating in industries with higher scope for product differentiation capitalize on the potential to differentiate their products and engage in product innovation. There is suggestive evidence that large firms who stand to gain more from process innovation, use process innovation as part of their strategy for competing with foreign rivals.

[Table 9 about here.]

4 Conclusion

This paper addresses the question of how import competition affects a firm's decision to engage in product and process innovation. I address the lack of large-scale, high quality data on product and process innovation by using the text of patents and machine learning techniques to classify corporate patents as product or process innovations. With this data, I find that in response to large tariff cuts, firms face more import competition, and increase their innovation. This is entirely driven by an increase in product innovation, process innovation does not respond. I find evidence that the effect is stronger in industries with a higher scope for product differentiation, suggesting that firms seek to differentiate their products from foreign competitors in order to mitigate the demand destruction that comes from increased competition.

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. The results in this paper suggest that import competition has the potential to create more socially beneficial knowledge spillovers through two channels. First, is the direct effect from import competition creating more knowledge. 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.

This work opens up several interesting areas of future research. Developing a more detailed understanding of the welfare implications from this paper's findings would be useful in applying these findings to innovation and trade policy. While this paper offers the first empirical evidence on how product and process innovation respond to import competition, further evidence on how these two types of innovation respond to other changes in incentives would be valuable in developing our understanding of these types of innovation. Moving beyond the product/process distinction, the methodology for classifying patents that is outlined in this paper could be applied to other distinctions in patent data. I hope that by providing my data and code for public use, researchers will be able to make further progress on these topics.

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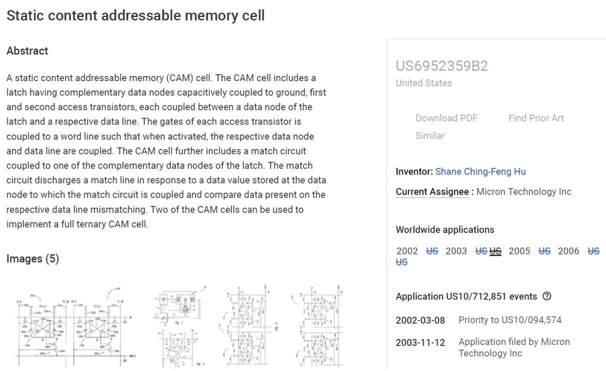
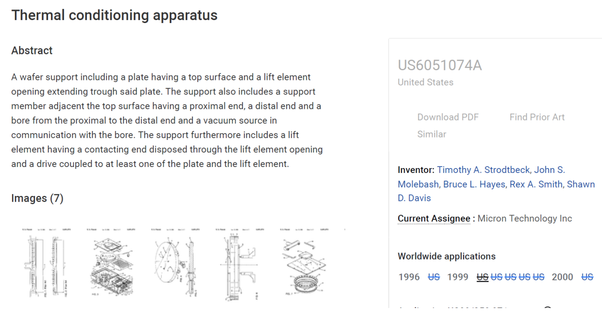
Figure 1: Three “Micron Technology” Patents

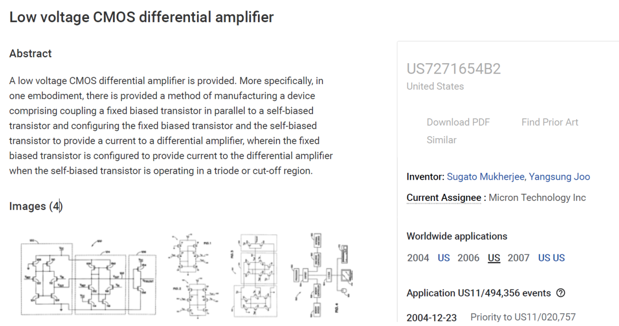
(a) Product



(b) Process



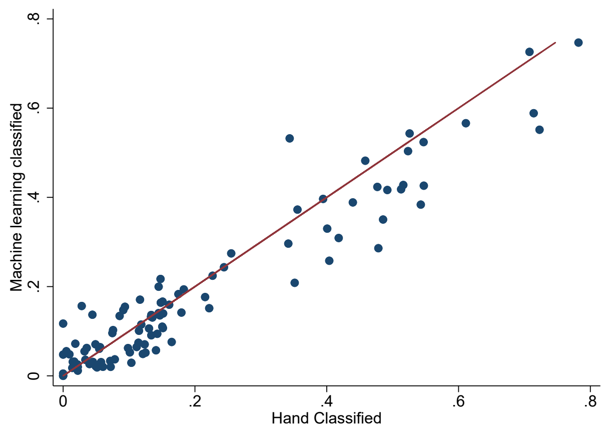
(c) Product & Process



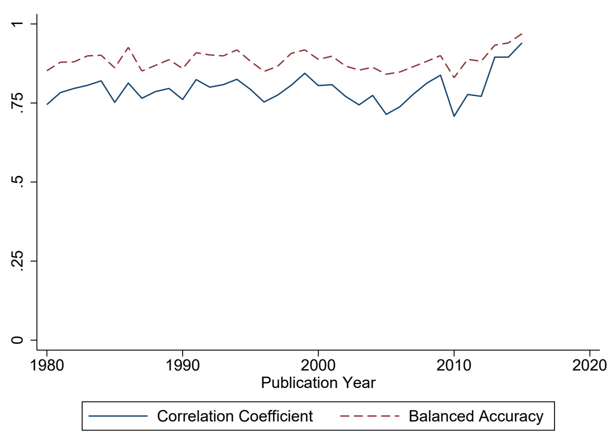
Notes: This figure depicts the Google Patents webpages for three Micron Technology patents. Panel (a) depicts a product patent, US6952359. Panel (b) depicts a process patent, US6051074. Panel (c) depicts a patent that contains both product and process innovations, US7271654.

Figure 2: Classification Robustness

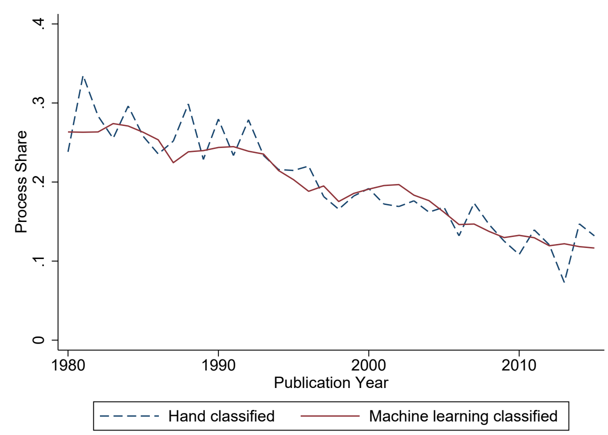
(a) Process Share by Industry



(b) Diagnostic Metrics Over Time



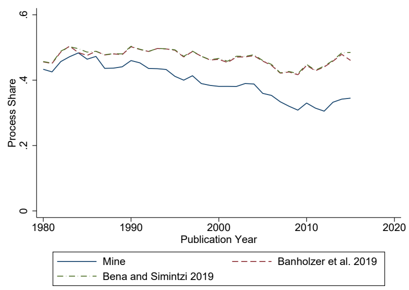
(c) Process Share Over Time



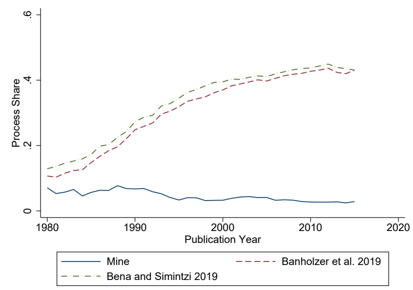
Notes: The process share is defined as the average proportion of claims that are process innovations for each patent. Panel (a) displays the mean process share across industries with the 45 degree line corresponding to the same process share in the hand classified and machine learning classified data. Panel (b) displays the mean correlation coefficient and balanced accuracy over time. Panel (c) displays the mean process share over time for both the machine learning and hand classified samples.

Figure 3: Comparison with Banholzer et al. 2019 and Bena and Simintzi 2019

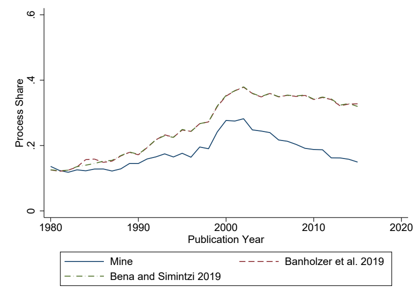
(a) Chemical



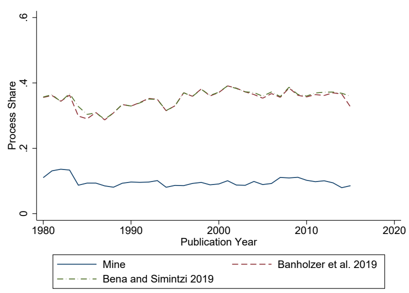
(b) Computers & Comm



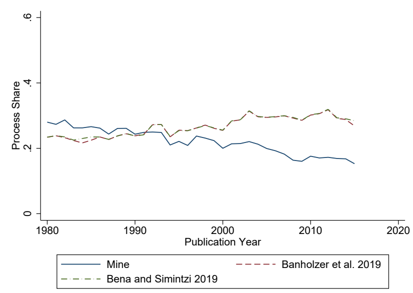
(c) Electrical & Electronics



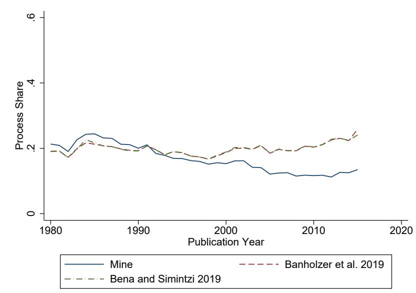
(d) Drugs & Medical



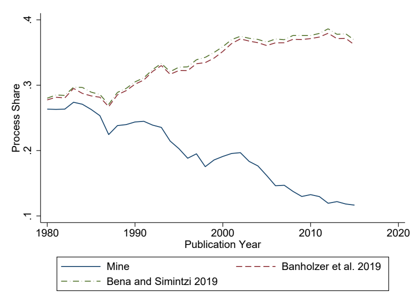
(e) Mechanical



(f) Other

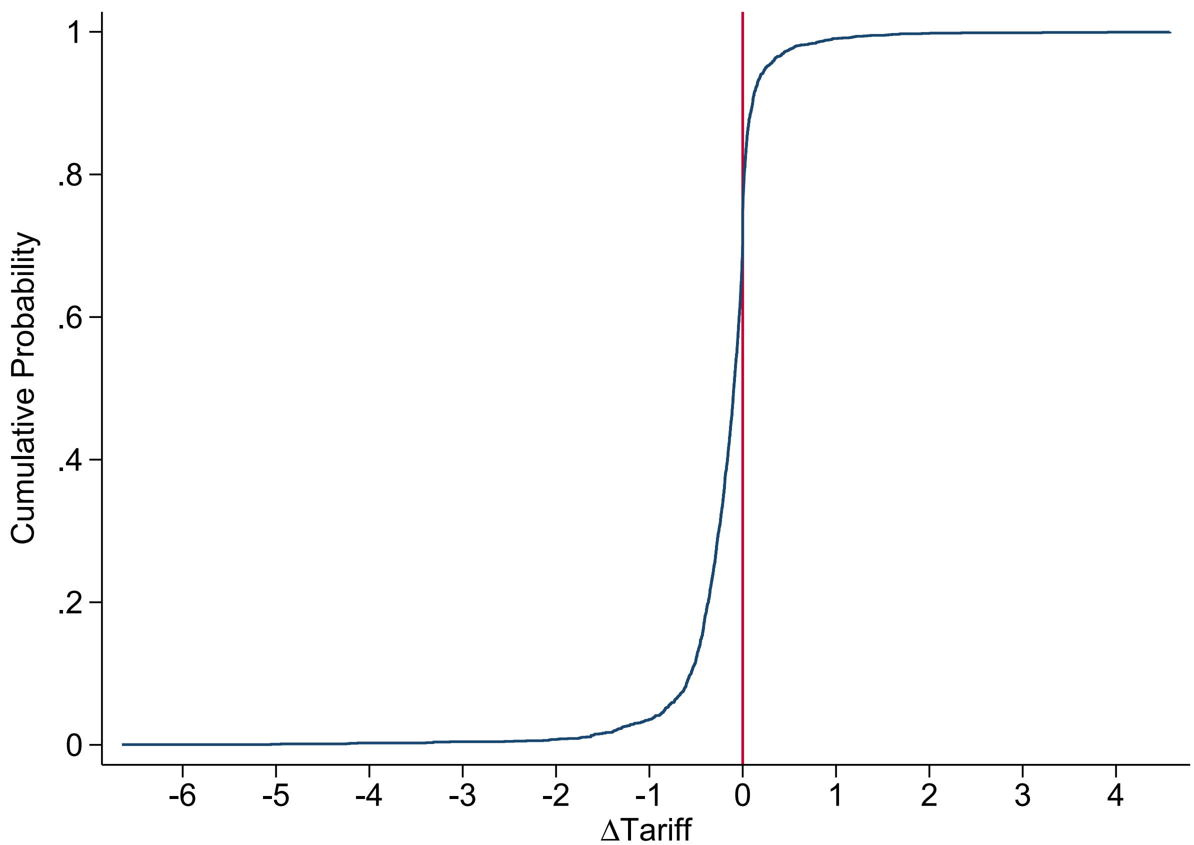


(g) Aggregate



Notes: Panels (a)-(f) of this figure plot the process share over time from my classification (solid navy line), the Banholzer et al. 2019 classification (dashed maroon line), and the Bena and Simintzi 2019 classification (dashed/dotted green line) by NBER six-digit category. Panel (g) plots the aggregate process share.

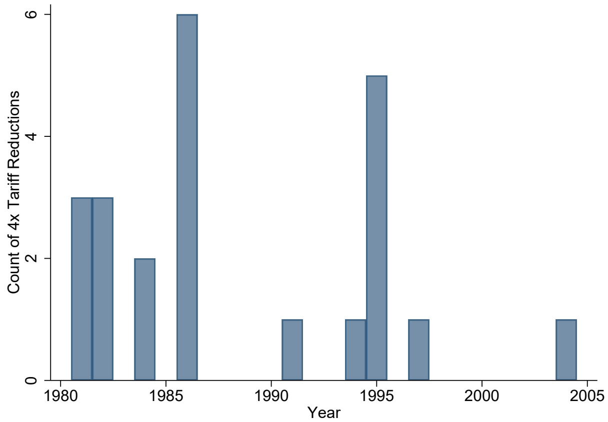
Figure 4: Cumulative Distribution Function of Tariff Cuts



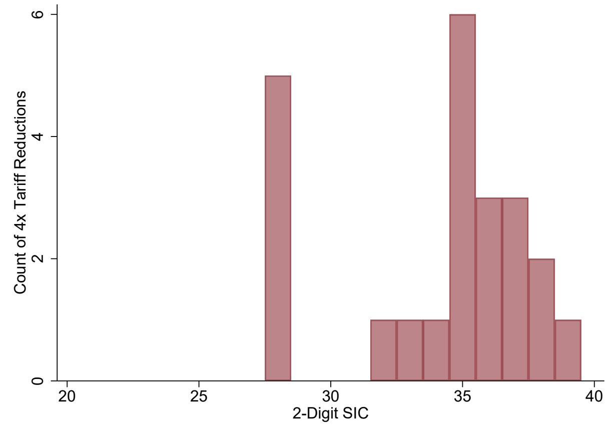
Notes: This figure presents the cumulative distribution function over the size of all annual tariff cuts. I use industry level data from 1980-2005 for all industries associated with firms in my unrestricted sample of firms.

Figure 5: Large Tariff Cuts

(a) Annual Counts



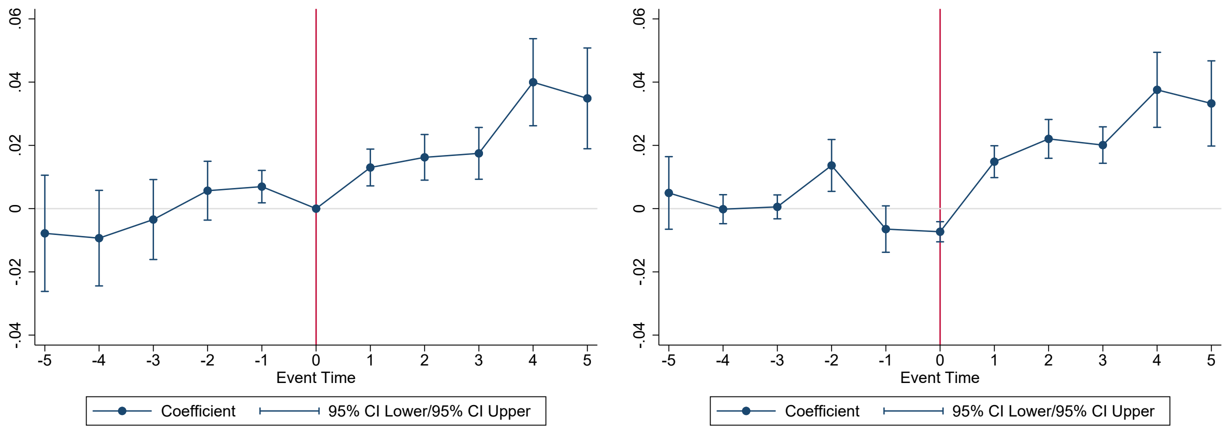
(b) Manufacturing Sector Counts



Notes: This figure presents histograms of the number of industry $\times$ 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.

Figure 6: Import Penetration Event Studies

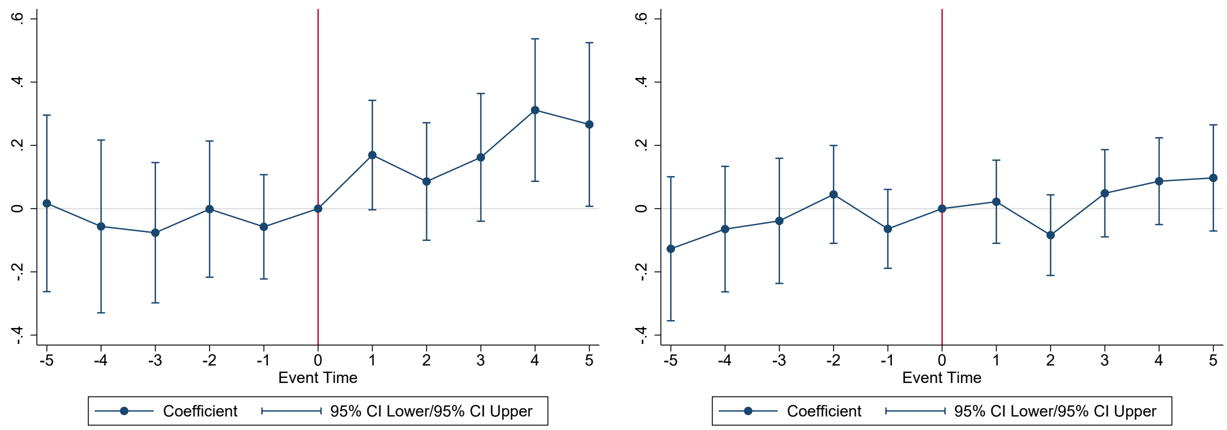
(a) OLS (b) (Callaway and Sant'Anna 2021)



Notes: In Panels (a) and (b) the dependent variable is import penetration. Panels (a) 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 3.1 and Appendix A.3. Panel (b) implements the estimation procedure outlined in Callaway and Sant'Anna 2021. Standard errors are clustered at the treatment-control pair level.

Figure 7: Tariff Cut: Event Studies

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

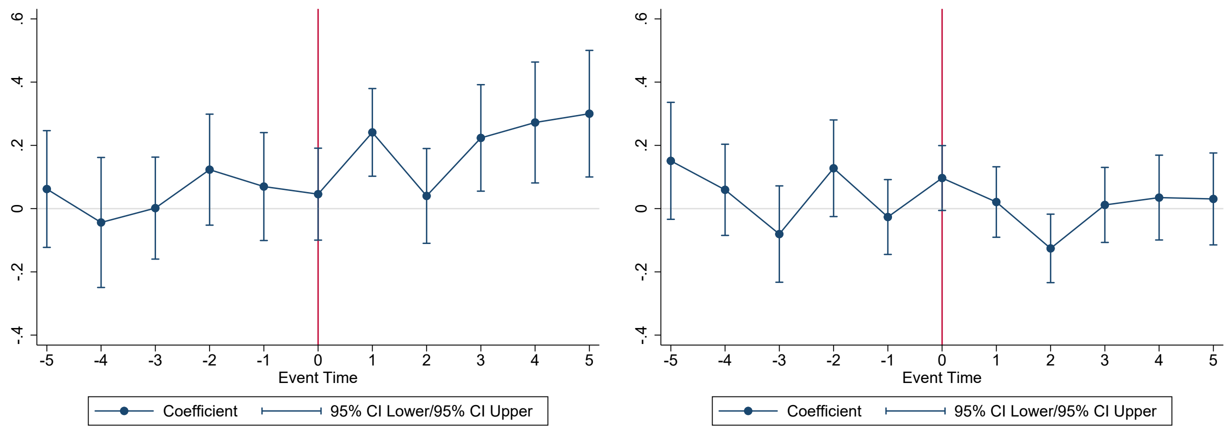


Notes: Panels (a) and (b) of this figure display the point estimates and 95% confidence intervals from estimating equation (1) via OLS using the baseline matched sample. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. In Panel(a) the dependent variable is the IHS of product patents. In Panel(b) the dependent variable is the IHS of process patents. Standard errors are clustered at the treatment-control pair level.

Figure 8: Event Studies with Callaway and Sant'Anna 2021 Estimator

(a) ihs(Product Patents)

(b) ihs(Process Patents)



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.

Table 1: Prediction Diagnostics

	Mean	St. Dev.	25%	50%	75%
Correlation Coefficient	0.74	0.09	0.65	0.77	0.80
Balanced Accuracy	0.85	0.06	0.81	0.86	0.89
Process Recall	0.73	0.13	0.65	0.77	0.81
Product Recall	0.97	0.03	0.96	0.98	0.99
Process Precision	0.84	0.11	0.81	0.85	0.91
Product Precision	0.95	0.05	0.94	0.95	0.97
Observations	100				

Notes: This table presents summary statistics across the 100 4-digit SIC industries weighted by the number of patents in the industry. The correlation coefficient is the correlation between the vector of publication claims predictions and true classifications. Process (product) recall refers to the fraction of true process (product) claims that were correctly classified as process (product). Process (product) precision refers the fraction of publication claims that were predicted as process (product) that are truly process. Balanced accuracy is defined as the unweighted mean of product and process recall.

Table 2: Industries with Highest and Lowest Process Shares

SIC	SIC Desc	Process Share	Patents
Panel A: Top 15 Process Share			
1311	Crude Petroleum and Natural Gs	0.747	7,541
2911	Petroleum Refining	0.726	25,777
3720	Aircraft and Parts	0.594	2,060
3312	Steel Works and Blast Furnaces	0.568	1,038
2052	Cookies and Crackers	0.555	2,235
2000	Food and Kindred Products	0.543	874
3350	Rolling and Draw Nonfer Metal	0.530	839
3221	Glass Containers	0.525	1,256
3290	Abrasive, Asbestos, Misc Minrl	0.504	2,274
2040	Grain Mill Products	0.481	1,162
2810	Indl Inorganic Chemicals	0.429	13,718
2821	Plastics,Resins,Elastomers	0.428	5,452
2860	Industrial Organic Chemicals	0.424	23,102
2631	Paperboard Mills	0.421	2,653
3411	Metal Cans	0.419	889
Panel B: Bottom 15 Process Share			
3559	Special Industry Machy, Nec	0.000	15,335
3578	Calculate, Acct Mach, Ex Comp	0.005	1,560
3579	Office Machines, Nec	0.012	3,504
3533	Oil and Gas Field Machy, Equip	0.020	1,891
3990	Misc Manufacturng Industries	0.020	3,258
3576	Computer Communications Equip	0.020	18,853
3540	Metalworking Machinery and Eq	0.021	5,193
3829	Meas and Controlling Dev, Nec	0.022	2,201
3523	Farm Machinery and Equipment	0.022	5,845
3669	Communications Equip, Nec	0.026	1,035
3651	Household Audio and Video Eq	0.027	2,413
3826	Lab Analytical Instruments	0.030	15,688
3571	Electronic Computers	0.031	13,983
3661	Tele and Telegraph Apparatus	0.031	5,256
3823	Industrial Measurement Instr	0.031	8,050

Notes: This table presents statistics on the 15 industries with the highest process shares and the lowest process shares. Industries with less than 500 total patents from 1980-2015 are excluded from the analysis.

Table 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 4: Treatment and Matched Control Balance Test

	Diff.	Treat	Control	p-value	Treat N	Control N
ihs(Product Patents)	0.02	1.97	1.95	0.91	172	172
ihs(Process Patents)	0.00	0.99	0.99	1.00	172	172
ln(Sales)	-0.29	4.30	4.59	0.36	172	172
$\frac{\text{R\&D}}{\text{Assets}}$	0.03	0.17	0.13	0.13	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	0.23	172	172
$\frac{\text{Net Cash}}{\text{Assets}}$	0.01	-0.06	-0.08	0.70	172	172
$1-\frac{\text{COGS}}{\text{Sales}}$	-0.00	0.19	0.19	0.94	172	172
$\frac{\text{Income}}{\text{Assets}}$	-0.01	-0.10	-0.09	0.65	172	172

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

Table 5: Summary Statistics

	Mean	St. Dev.	Min	Max	Obs
Import Penetration	0.16	0.15	0.00	0.69	2,895
Product Patents	30.84	102.30	0.00	1,258.14	2,895
Process Patents	7.81	25.90	0.00	323.30	2,895
$\frac{\text{R\&D}}{\text{Sales}}$	0.23	0.34	0.00	1.00	2,895
Employees (1,000)	13.49	47.02	0.00	876.80	2,895

Notes: This table presents summary statistics for the sample used in the baseline specifications.

Table 6: Innovation and Tariff Cuts

	Im Pen	ihs(Patents)		ihs(MVW Patents)	
	(1)	(2)	(3)	(4)	(5)
		Product	Process	Product	Process
Cut_{zt}	0.021***	0.205***	0.041	0.217***	0.035
	(0.005)	(0.074)	(0.051)	(0.075)	(0.050)
F-stat	19.36				
$\overline{\text{Y}}$	0.16				
$\text{H}_0 : \beta_{\text{pdt}} = \beta_{\text{prs}}$ (p-value)		.01**		.00***	
Observations	2,895	2,895	2,895	2,895	2,895

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. 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 3.1). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics: IHS of product patenting, the IHS of process patenting, the net cash to asset ratio, and return on assets. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

Table 7: Callaway and Sant'Anna 2021 Estimator

	Im Pen	ihs(Patents)		ihs(MVW Patents)	
	(1)	(2)	(3)	(4)	(5)
		Product	Process	Product	Process
Cut_{zt}	0.025***	0.212***	-0.008	0.209***	-0.017
	(0.004)	(0.067)	(0.049)	(0.066)	(0.049)
$\overline{\text{Y}}$	.22				
Observations	14,129	14,129	14,129	14,129	14,129

Notes: This table presents results from estimating equation (2) via the Callaway Sant'Anna (CS) DiD estimator 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) 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 Data & Empirical Strategy). Standard errors are clustered at the firm level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table 8: Product Differentiation

	ihs(Patents)			
	(1) Product	(2) Process	(3) Product	(4) Process
Cut_{zt}	0.200***	0.038	0.233***	0.049
	(0.075)	(0.052)	(0.077)	(0.050)
$\text{Cut}_{zt} \times$ Quality Ladder	0.116*	0.011		
	(0.069)	(0.043)		
$\text{Cut}_{zt} \times$ Share Diff			0.147**	0.043
			(0.064)	(0.039)
Observations	2,853	2,853	2,853	2,853

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 3.1). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics: IHS of product patenting, the IHS of process patenting, the net cash to asset ratio, and return on assets. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

Table 9: Firm Size

	ihs(Patents)			
	(1) Product	(2) Process	(3) Product	(4) Process
Cut_{zt}	0.193**	0.051	0.198***	0.048
	(0.076)	(0.054)	(0.076)	(0.054)
$\text{Cut}_{zt} \times \ln(\text{Emp})$	0.004	0.099*		
	(0.059)	(0.053)		
$\text{Cut}_{zt} \times \ln(\text{Sales})$			0.042	0.078
			(0.060)	(0.049)
Observations	2,853	2,853	2,853	2,853

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) [(3) and (4)], log employment [log sales] is used to measure firm size. 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 3.1). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics: IHS of product patenting, the IHS of process patenting, the net cash to asset ratio, and return on assets. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

A Appendix

A.1 Identifying Manufacturing Firms

Most studies identify manufacturing firms in Compustat as firms with two-digit SIC codes that fall within 20-39. I depart from this convention primarily because Compustat industry codes are based on the most current financial statements of the firm. For firms who exist for long periods of time and change their products, the current Compustat industry classification may not accurately reflect whether the firm primarily operated in manufacturing over its life. Instead, I use Compustat business segment data to classify a firm as primarily engaged in manufacturing if over 50% of its deflated sales from 1980-2015 are in manufacturing industries. I also remove 38 firms who fit my initial definition of a manufacturing firm, but whose patents don't consistently correspond with their manufacturing activity.[15] Table A1 shows that my definition of a manufacturing firm closely aligns with the standard SIC classification. Some examples of firms who I classify as manufacturing, but would not be classified as manufacturing under the standard SIC definition are: General Electric, Honeywell, and Monsanto.

[Table A1 about here.]

A.2 Classifying Patents

The below list itemizes the elements that make up each of the 60 machine learning models used to predict the product/process status of patent claims.

- Machine Learning Models
  1. Multinomial Naive Bayes
  2. Complement Naive Bayes
  3. Passive Aggressive Classifier
- Text Features

[15] One firm that I designate as not a manufacturing firm is IBM, due to their shift from IT manufacturing toward software services

1. First two words and 4-digit CPC code
2. First two words, first two words interacted with firm identifier, and 4-digit CPC code
3. First two words, first two words interacted with 4-digit CPC code, and 4-digit CPC code
4. First two words, first three words, ..., first ten words, and the 4-digit CPC code
5. First two words, first three words, ..., first ten words, first two words interacted with firm identifier, first three words interacted with firm identifier, ..., first ten words interacted with firm identifier, and the 4-digit CPC code
6. First two words, first three words, ..., first ten words, first two words interacted with the 4-digit CPC code, first three words interacted with the 4-digit CPC code, ..., first ten words interacted with the 4-digit CPC code, and the 4-digit CPC code
7. Entire claims text and 4-digit CPC code
8. The abbreviated claims text (everything that comes before the first colon) and the 4-digit CPC code
9. The abbreviated claims text (everything that comes before the first colon), the abbreviated claims text interacted with a firm identifier, and the 4-digit CPC code
10. The abbreviated claims text (everything that comes before the first colon), the abbreviated claims text interacted with the 4-digit CPC code, and the 4-digit CPC code

- Trimming

   1. Keep all features in a feature set
   2. Drop features that are below median "importance" in predicting the outcome variable

- Extended Text Features

1. Number of words
2. Fraction of words that are stopwords
3. Average word length
4. Fraction of words that are nouns, verbs, and adjectives
5. Number of words, fraction of words that are stopwords, average word length, fraction of words that are nouns, verbs, and adjectives
6. Number of words, fraction of words that are stopwords, average word length, fraction of words that are nouns, verbs, and adjectives, number of words interacted with the 4-digit CPC code, fraction of words that are stopwords interacted with the 4-digit CPC code, average word length interacted with the 4-digit CPC code, fraction of words that are nouns, verbs, and adjectives interacted with the 4-digit CPC code
7. Number of words, fraction of words that are stopwords, average word length, fraction of words that are nouns, verbs, and adjectives, number of words interacted with a firm identifier, fraction of words that are stopwords interacted with a firm identifier, average word length interacted with a firm identifier, fraction of words that are nouns, verbs, and adjectives interacted with a firm identifier

[Table A2 about here.]

A.3 Tariff Data & Matching Algorithm

[Table A3 about here.]

In order to uniquely match each treated firm to a control firm, I first eliminate any treated firms who do not have observations for at least one year before and after the tariff cut. 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 $\times$ control observation and discard the rest. 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. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
2. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA
3. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
4. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA
5. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
6. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA
7. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$
8. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA
9. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)
10. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA, ln(Sales)

11. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)

12. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA, ln(Sales)

13. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)

14. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Net Cash}}{\text{Assets}}$, ROA, ln(Sales)

15. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$, ln(Sales)

16. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Assets}}$, $\frac{\text{Cash}}{\text{Assets}}$, ROA, ln(Sales)

17. asinh(Product Patents), asinh(Process Patents), $\frac{\text{Net Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$

18. asinh(Product Patents), asinh(Process Patents), $\frac{\text{Net Cash}}{\text{Assets}}$, ROA

19. asinh(Product Patents), asinh(Process Patents), $\frac{\text{Cash}}{\text{Assets}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$

20. asinh(Product Patents), asinh(Process Patents), $\frac{\text{Cash}}{\text{Assets}}$, ROA

21. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$

22. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, ROA

23. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, $1 - \frac{\text{COGS}}{\text{Sales}}$

24. asinh(Product Patents), asinh(Process Patents), $\frac{\text{R\&D}}{\text{Sales}}$, ROA

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

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

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

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

[Table A4 about here.]

[Table A5 about here.]

A.4 Robustness

A.4.1 Other Matching Strategies

To ensure that my results are not sensitive to choosing a particular set of matching variables, I repeat my analysis 27 times in addition to my one baseline specification, each time using a different set of matching variables. The list of variables used to match on for each of the 28 matches can be found in Appendix A.3. While each of these 28 matches preserves the intent of matching on firm size, research intensity, cash holdings, profitability, and product/process composition, I achieve the goal using a unique set of matching variables. 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 A6 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, 46% 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.

[Table A6 about here.]

In Figure A1, I display the results of repeating the analysis across these 28 matches. I plot the event study coefficients from the baseline specification, the 27 additional specifications, and the mean coefficient across all 28 specifications.

[Figure A1 about here.]

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 generally follow the mean outcome assuring us that the baseline results are not an artifact of a particularly chosen control group. Figure A2 plots the density of the difference-in-differences coefficients from the 28 specifications. The mean coefficient when the IHS of product (process) patenting is used falls around 0.2 (0.0), right in line with my baseline specification. In addition, the density of the estimates is fairly tight, suggesting that the results obtained are robust to using various matching specifications.

[Figure A2 about here.]

A.4.2 Political Economy

One concern with using tariff cuts as a plausibly exogenous change in foreign import competition is that trade policy can be influenced through lobbying and may be the result of strategic decision making on the part of policymakers. This would be a particularly problematic for my empirical strategy if tariffs were reduced in industries which were subsequently changing their innovation strategy for reasons unrelated to the tariff reduction. For example, industries that are in decline may be able to successfully lobby for keeping tariff rates high as they argue that without trade protection their industry may suffer and possibly leave the United States entirely. Under this scenario, industries that saw large tariff cuts would be on a positive growth trajectory. On the other hand, the government may "give up" on failing industries and subject these industries to more foreign competition through the reduction in tariffs.

My matching strategy ensures that in the year before the tariff reduction treated and control firms are statistically indistinguishable based on observable characteristics. Despite this cross-sectional similarity, treated and control firms may be on different trends. If the government lowered tariffs in growing (declining) industries, we would expect that innovative activity should grow faster (slower) in treated industries relative to control industries before the arrival of the tariff cuts. In addition, my argument is that foreign competition alters the composition of innovative activity between product and process innovation. It is not clear how we would expect growing or declining industries to alter the composition of their innovative activity between product and process innovation. The event studies in Figure 7 and Figure 8 show that the level and composition of innovative activity was on a similar trend before the arrival of the tariff cuts. This suggests that it is not the case that treatment and control firms were on different innovation paths before the arrival of tariff cuts.

Despite all these considerations, lobbying and political economy considerations could still be biasing my results. One scenario is where declining industries were able to successfully lobby against tariff decreases and firms in treated industries were poised to increase their product innovation at the exact time the tariff cuts occurred. This scenario is consistent with the observed evidence: no pre-trends in innovative activity and an increase in product innovation following the tariff cuts. To provide evidence that my results are not being driven by this kind of endogenous lobbying and thus selection into treatment, I identify tariff reductions that were significantly harder for U.S. industries to influence. Specifically, I identify tariff reductions which were part of multilateral agreements established by GATT, WTO, or NAFTA. Tariff reductions resulting from these agreements are much harder for any one particular industry to influence since there are many countries present in the negotiations and there are rules and obligations that reduce the ability of special interest groups to influence the outcome. To identify these tariff reductions, I use data collected by Flammer 2015 and present each tariff cut along with indication if the tariff cut was a result of a multilateral agreement in Table A5. I was able to identify 5 of 24 tariff cuts as being the result of a multilateral agreement. Table A7 displays the results of repeating my baseline specification but only using the five multilateral tariff cuts. In columns (1) we see that the effect on import penetration is weaker than in the baseline specification. Consistent with this, we see a smaller and less precisely estimated positive effect of multilateral tariff cuts on product innovation. In columns (3) and (4) we continue to see no effect on process innovation. While none of the point estimates are statistically significant, the difference between the product and process coefficients is statistically significant at conventional levels, indicating that the effect of multilateral tariff cuts on product innovation is significantly larger than the effect on process innovation. Figure A3 shows the dynamic impact of multilateral tariff cuts on product and process patenting. The results here suggest that endogenous selection into treatment through lobbying and political pressure is not driving my results.

[Table A7 about here.]

[Figure A3 about here.]

A.4.3 Zero-Inflated Negative Binomial Specification

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 issues such as the fact that results can depend on the scale of the transformed variable (Aihounton and Henningsen 2021) and concerns with interpretation when there are "too many" zeros in the data (Bellemare and Wichman 2020). To address these concerns, I estimate a zero-inflated negative binomial specification where the dependent variable is now the count of either product or process patents the firm applies for in year t. Zero-inflated negative binomial models are useful for modeling count data when 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 logit with log employment as the predictor. Negative binomial estimation uses a tariff cut indicator and firm and year fixed effects as the independent variables. Column (1) yields a very similar effect as the baseline specification, in the five years after a large tariff cut, firms experiencing the cut see their product patenting go up by approximately 25%. On the other hand, when the count of process patents is the dependent variable the coefficient is much smaller and not statistically significant. The results indicate that my findings are not being driven by the IHS transformation.

[Table A8 about here.]

A.4.4 Definition of a Tariff Cut

In order to better understand how my results vary with the size of tariff cut, I create an alternate definition of a large tariff cut where large tariff cuts are those that are declines greater than 3x the mean absolute value change in an industry. I then repeat my prior analysis using this alternative definition of treatment and present the results in Table A9. In Panels A and B of column (1), the effect of 3x tariff cut on import penetration is approximately two-thirds of the effect from a 4x cut. Similarly, the F-stat falls from around 19 to 12. These results indicate that 3x tariff cuts do have an effect on import penetration, but the effect is weaker. Similarly, the positive effect of tariff cuts on product innovation is much smaller and no longer statistically significant when the 3x cut definition is used. Overall, the results indicate that smaller tariff cuts generate less import competition and subsequently have less of an impact on product innovation.

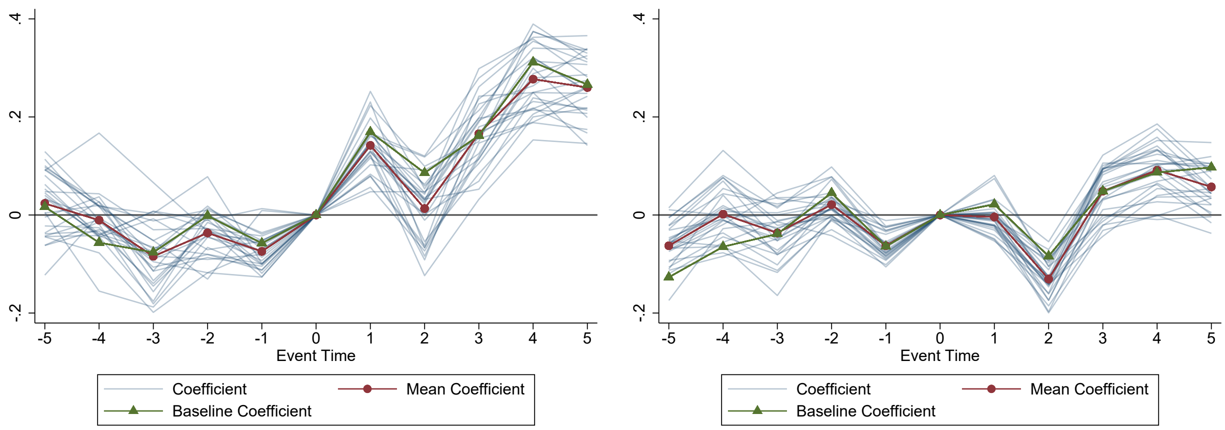
[Table A9 about here.]

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 where an annual decline in the tariff rate of 1.5 percentage points or greater constitutes a large tariff cut. I use my baseline matching strategy along with this new definition of tariff cuts and display the results in Table A10. Using this invariant definition of treatment, a tariff cut generates similar effects on import penetration, product innovation, and process innovation as in my baseline specification.

[Table A10 about here.]

Figure A1: 28 Matches Event Studies

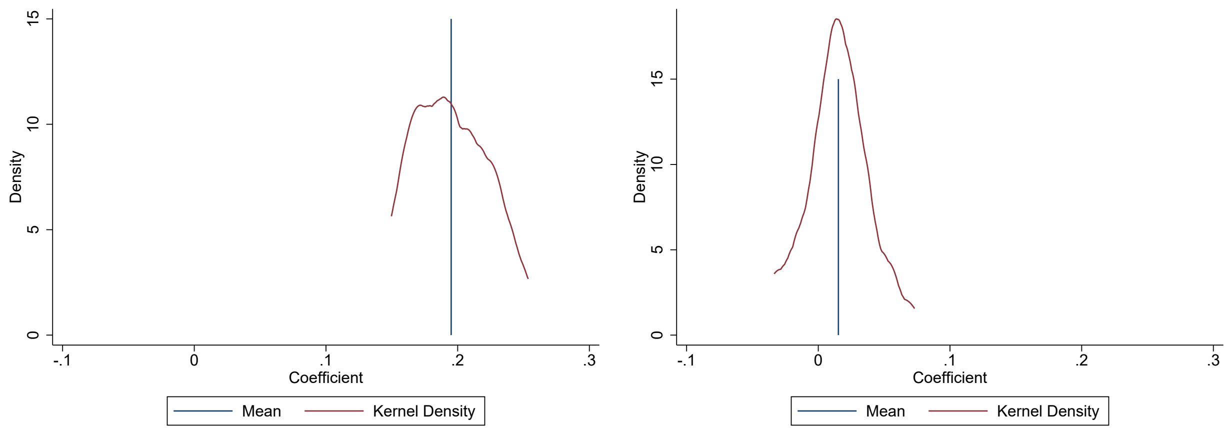
(a) ihs(Product Patents) (b) ihs(Process Patents)



Notes: Panels (a) and (b) 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.3. In Panel(a) the dependent variable is the IHS of product patents. In Panel(b) the dependent variable is the IHS of process patents.

Figure A2: Distribution of Difference-in-Differences Coefficients

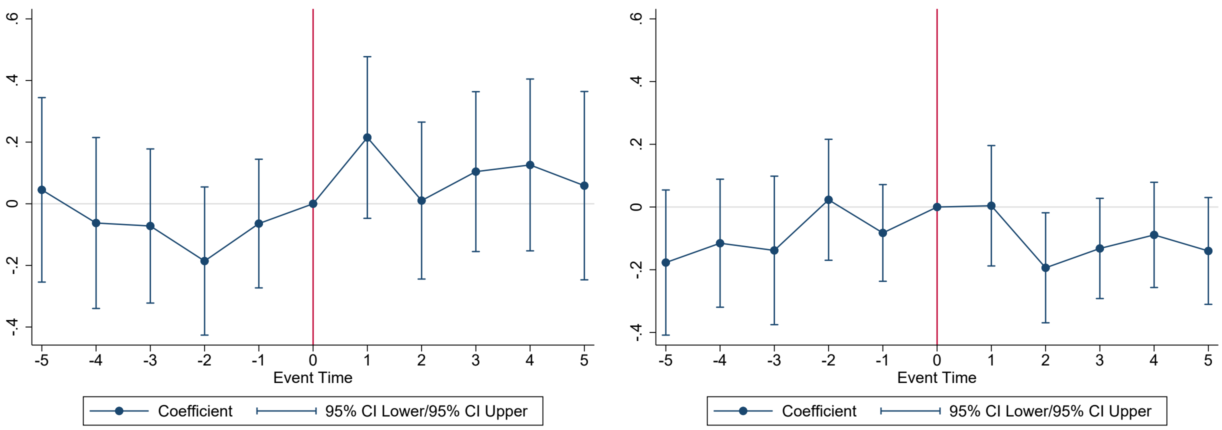
(a) ihs(Product Patents) (b) ihs(Process Patents)



Notes: Panels (a) and (b) 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. Details on the exact variables which are matched on are available in Appendix A.3. In Panel(a) the dependent variable is the IHS of product patents. In Panel(b) the dependent variable is the IHS of process patents.

Figure A3: Multilateral Tariff Cuts

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



Notes: Panels (a) and (b) of this figure display the point estimates and 95% confidence intervals from estimating equation (1) via OLS using the four multilateral tariff cuts and using the baseline matching characteristics. Details on the matching procedure can be found in Data & Empirical Strategy and A.3. In Panel(a) the dependent variable is the IHS of product patents. In Panel(b) the dependent variable is the IHS of process patents. Standard errors are clustered at the industry level.

Table A1: Defining Manufacturing Firms

		SIC Definition	
		Not Mfn	Mfn
Business Segment	Not Mfn	1,087	127
Sales Definition	Mfn	215	3,583

Notes: This table presents a cross-tabulation on the number of firms defined as manufacturing firms according to a SIC definition which defines all firms with primary SIC industry 2000-3999 as manufacturing firms and using a business segment sales definition that is outlined in Appendix A.1.

Table A2: Semiconductor Confustion Matrix (SIC 3674)

		Prediction		
		Product	Process	Total
Truth	Product	9,018	107	9,125
	Process	766	1,769	2,535
	Total	9,784	1,876	11,660

Notes: This table presents a confusion matrix for the semiconductor (SIC 3674) industry. Rows correspond to counts of publication claims that were hand classified as product or process publication claims. Columns correspond to counts of publication claims that were classified as product or process innovations by the machine learning classifier. I hand classified the claims of 2,332 semiconductor patents, leading to 2,332*5 = 11,660 predictions since I am using 5-fold repeated cross validation. Process recall is defined as the fraction of claims which are truly process that are predicted to be process. This is calculated as $\frac{1{,}769}{2{,}535} = 69.8\%$. Product recall is defined in an analogous way and receives a score of $\frac{9{,}018}{9{,}125} = 98.8\%$. Process precision is defined as the fraction of claims that are predicted to be process which are truly process. This is calculated as $\frac{1{,}769}{1{,}876} = 94.3\%$. Product precision is defined in an analogous way and receives a score of $\frac{9{,}018}{9{,}784} = 92.2\%$. Balanced accuracy is the unweighted average of product and process recall and is $\frac{69.8+98.8}{2} = 84.3\%$

Table A3: Tariff Cuts Summary Statistics

	Mean	St. Dev.	25%	50%	75%	Obs
Δ Tariff Rate ($\mathbb{1}\{\text{4x Cut}\} = 1$)	-3.30	1.73	-5.05	-3.22	-1.62	172
Δ Tariff Rate ($\mathbb{1}\{\text{4x Cut}\} = 0$)	-0.15	0.35	-0.27	-0.04	0.00	13,042

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

Table A4: 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

Notes: This table presents definitions for the variables used in the matching analysis conducted in Section 3.1.

Table A5: List of Tariff Cuts

SIC	SIC Description	Year	Multilateral
3221	Glass Containers	1981	
3743	Railroad Equipment	1981	
3827	Optical Instruments and Lenses	1981	
3452	Bolt, Nut, Screw, Rivets, Washrs	1982	
3674	Semiconductor,Related Device	1982	
3711	Motor Vehicles and Car Bodies	1982	
3842	Ortho,Prosth,Surg Appl,Suply	1984	
3949	Sporting and Athletic Gds, Nec	1984	
3570	Computer and Office Equipment	1986	
3571	Electronic Computers	1986	
3572	Computer Storage Devices	1986	
3670	Electronic Comp, Accessories	1986	
3674	Semiconductor,Related Device	1986	
3711	Motor Vehicles and Car Bodies	1986	
2835	In Vitro,In Vivo Diagnostics	1991	
3577	Computer Peripheral Eq, Nec	1994	GATT, NAFTA
2800	Chemicals and Allied Products	1995	
2834	Pharmaceutical Preparations	1995	WTO
2835	In Vitro,In Vivo Diagnostics	1995	WTO
2860	Industrial Organic Chemicals	1995	
3559	Special Industry Machy, Nec	1995	WTO, NAFTA
3578	Calculate, Acct Mach, Ex Comp	1997	WTO, NAFTA
3578	Calculate, Acct Mach, Ex Comp	1998	
3312	Steel Works and Blast Furnaces	2004	

Notes: This table presents the 24 industry tariff cuts that meet my 4x tariff cut criteria. I have identified the four tariff cuts that were the result of multilateral agreements and the entities associated with the cuts in the multilateral column (Flammer 2015).

Table A6: Relative to Baseline: Share of Control Firms Repeated

	Mean	St. Dev.	Min	25%	50%	75%	Max
Share Repeat	0.46	0.07	0.37	0.41	0.45	0.51	0.63
Observations	27						

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

Table A7: Multilateral Tariff Cuts

	Im Pen	ihs(Patents)		ihs(MVW Patents)	
	(1)	(2)	(3)	(4)	(5)
		Product	Process	Product	Process
Cut_{zt}	0.008	0.166	-0.029	0.145	-0.053
	(0.006)	(0.104)	(0.059)	(0.106)	(0.058)
F-stat	1.56				
$\overline{\text{Y}}$	0.16				
$\text{H}_0 : \beta_{\text{pdt}} = \beta_{\text{prs}}$ (p-value)		.02**		.01**	
Observations	1,601	1,601	1,601	1,601	1,601

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. 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 3.1). Only firms experiencing cuts induced by multilateral trade agreements are considered treated. Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics: IHS of product patenting, the IHS of process patenting, the net cash to asset ratio, and return on assets. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

Table A8: Zero-Inflated Negative Binomial Estimation

	Product Patents	Process Patents
	(1)	(2)
	ZINB	ZINB
Cut_{zt}	0.248^{***}	0.071
	(0.081)	(0.095)
Observations	2,896	2,896

Notes: Columns (1) and (2) use the baseline sample which includes data in the five years before and after the year before treatment where the dependent variables are the count of product and process patents applied for by the firm in a given year. Estimation is done using zero-inflated negative binomial estimation where excess zeros are modeled using a logit estimation with log employment as the independent variable. 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 3.1). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics: IHS of product patenting, the IHS of process patenting, the R&D expenditure to asset ratio, the net cash to asset ratio, the income to asset ratio, and the natural log of revenue. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * ($p<0.1$), ** ($p<0.05$), *** ($p<0.01$).

Table A9: Size of the Tariff Cut

	Im Pen	ihs(Patents)		ihs(MVW Patents)	
	(1)	(2) Product	(3) Process	(4) Product	(5) Process
Panel A					
4x Cut_{zt}	0.021***	0.205***	0.041	0.217***	0.035
	(0.005)	(0.074)	(0.051)	(0.075)	(0.050)
Panel B					
3x Cut_{zt}	0.013***	0.071	0.012	0.076	0.007
	(0.004)	(0.054)	(0.035)	(0.058)	(0.035)
Observations					
Panel A	2,895	2,895	2,895	2,895	2,895
Panel B	4,961	4,961	4,961	4,961	4,961
$\text{H}_0 : \beta_{\text{pdt}} = \beta_{\text{prs}}$ (p-value)					
Panel A		.01**		.00***	
Panel B		.19		.14	
F-statistic					
Panel A	19.36				
Panel B	11.89				

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. Treated firms are those with a primary industry that experiences a tariff cut of 4/3 times the mean annual absolute value change in the tariff rate (further details can be found in Section 3.1). Firms experiencing tariff cuts are matched to control firms on the basis of the following characteristics: IHS of product patenting, the IHS of process patenting, the R&D expenditure to asset ratio, the net cash to asset ratio, the income to asset ratio, and the natural log of revenue. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).

Table A10: 1.5 Percentage Point Tariff Cuts

	Im Pen	ihs(Patents)		ihs(MVW Patents)	
	(1)	(2) Product	(3) Process	(4) Product	(5) Process
Cut_{zt}	0.024^{***}	0.170^{**}	0.065	0.160^{**}	0.056
	(0.005)	(0.072)	(0.051)	(0.073)	(0.050)
F-stat	21.27				
$\overline{\text{Y}}$	0.15				
$\text{H}_0 : \beta_{\text{pdt}} = \beta_{\text{prs}}$ (p-value)		$.08^{*}$		$.09^{*}$	
Observations	3,061	3,061	3,061	3,061	3,061

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. 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: IHS of product patenting, the IHS of process patenting, the net cash to asset ratio, and return on assets. Details on the matching procedure can be found in Section 3.1 and Appendix A.3. Standard errors are clustered at the treatment-control pair level and shown in parentheses. * (p<0.1), ** (p<0.05), *** (p<0.01).