Foreign Competition and Domestic Innovation: Evidence from U.S. Patents*

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Abstract

Manufacturing is the locus of U.S. innovation, accounting for more than three quarters of U.S. corporate patents. The rise of import competition from China has represented a major competitive shock to the sector. We study how U.S. manufacturing firms have responded to this shock. The impact of increasing product market competition on innovation is theoretically ambiguous. On the one hand, greater import penetration resulting, for example, from deepening supply chains in Asia, may reduce overall U.S. presence in industries where opportunities for innovation are most abundant. On the other hand, foreign competition may increase domestic innovation within industries by encouraging firms to concentrate on product segments that are more intensive in R&D or to engage in defensive innovation within existing segments. We confront two empirical challenges in assessing how rising import competition has affected U.S. innovation. We map all U.S. utility patents granted by March 2013 to firm-level data using a novel internet-based matching algorithm that corrects for a preponderance of false negatives when using firm names alone. And we contend with the fact that patenting is highly concentrated in certain product categories and that this concentration has been shifting over time. From 1991 to 2007, patenting increased strongly in computers and electronics, industries that also registered a large rise in import exposure. Patents decreased by equal measure in chemicals, a sector with little change in foreign competition from China. Superficially, this would suggest that rising competition has spurred innovative activity. Accounting for strong secular trends in innovative activities in these two broad sectors, however, we find that the impact of the change in import exposure on the change in patents produced is strongly negative. It remains so once we add an extensive set of further industry- and firm-level controls. Rising import exposure also reduces global employment, global sales, and global R&D expenditure at the firm level. It would appear that a simple mechanism in which greater foreign competition induces U.S. manufacturing firms to contract their operations along multiple margins of activity goes a long way toward explaining the response of U.S. innovation to the China trade shock.

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1 Introduction

China's spectacular economic growth has represented a major shock to U.S. manufacturing. As the country reduced barriers to foreign trade and investment in the 1990s and 2000s, its manufacturing exports surged, rising from 2.3% of the world total in 1991 to 18.8% of the world total in 2013 (Autor, Dorn, and Hanson, 2016). The presence of Chinese goods in U.S. markets expanded commensurately. The share of imports from China in U.S. industry absorption (shipments plus imports minus exports) grew by an annual average of 0.3 percentage points over the period 1991 to 1999 and by an annual average of 0.8 percentage points over the period 1999 to 2007.

A now substantial literature evaluates the impact of China's rise on the U.S. economy. Manufacturing industries more exposed to import competition from China have seen higher rates of plant exit (Bernard, Jensen, and Schott, 2006), larger contractions in employment (Pierce and Schott, 2015; Acemoglu, Autor, Dorn, Hanson and Price, 2016), and lower lifetime incomes for affected workers (Autor, Dorn, Hanson, and Song, 2014). Adjustment to the trade with China is also manifest in the local labor markets that are home to more-exposed industries, which have endured substantial employment reductions and persistent increases in rates of unemployment, non-participation in the labor force, and uptake of government transfers (Autor, Dorn, and Hanson, 2013).

However, these contractionary impacts of China trade on manufacturers and manufacturing workers may mask the longer term benefits for domestic manufacturing that increased competition spurs. Bloom, Draca and Van Reenen (2016) find that European firms, in response to greater import competition from China, create more patents, expand investment in information technology, and have higher TFP growth.[1] These outcomes hint at an intriguing possibility: could competition spur enhanced innovative activity that ultimately strengthens import-competing industries, generating benefits for manufacturing firms, workers, and consumers? An extensive literature argues that innovation is a fundamental driving force of economic growth (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). Though manufacturing now accounts for less than one-tenth of U.S. private non-farm employment, it still generates more than two-thirds of both U.S. R&D spending and U.S. corporate patents.[2] The impact of foreign competition on innovation is one of immense importance for the U.S. economy.

In theory, the impact of more intensive product-market competition on innovation is ambiguous.

[1]These impacts of course apply only to surviving firms. Consistent with results for the U.S., Bloom, Draca and Van Reenen (2016) find that more trade-exposed European industries are subject to higher rates of plant shutdown and lower overall employment growth.

[2]Helper, Krueger and Wial (2012) compute a manufacturing share in U.S. R&D spending of 68%, based on data from the National Science Foundation's Business R&D Survey. In our data analysis below, manufacturing accounts for more than 71% of all corporate patents with U.S.-based inventors and application year 2007.

In standard oligopoly models, a more competitive product market tends to generate lower investment in innovative activity (Dasgupta and Stiglitz, 1980). The underlying logic is straightforward: more competition means lower profits and reduced incentives to invest. The competition-innovation nexus becomes more complex once one allows for firm heterogeneity or incumbency, however. In Aghion, Bloom, Blundell, Griffith, and Howitt (2005), the relationship between competition and innovation follows an inverted U shape. Innovation is relatively low when firms are either too dissimilar—such that laggards are unable to overtake leaders—or at the opposite extreme, when competition is close to perfect, leading to almost no room for rent capture. At intermediate levels of competition, however, post-innovation rents may exceed rents pre-innovation, resulting in relatively high levels of investment in R&D in these market segments. An alternative mechanism is at work in Bloom, Romer, Terry, and Van Reenen (2014), who consider incumbent firms facing an exogenous increase in import penetration. If moving costs temporarily "trap" some productive factors inside firms (i.e., because the market for these factors is thin), an increase in product-market competition temporarily lowers the cost of redeploying these factors from production to innovation. Greater import competition may, consequently, lead to accelerated productivity growth.

Further ambiguity arises when one allows for global production networks. Lower costs to firms in high-wage countries of moving production offshore may result not just in greater offshoring but in higher productivity of factors in the home market (Grossman and Rossi-Hansberg, 2008), which conceivably could raise the incentive for investing in innovation. At the same time, if offshoring causes R&D and production to occur in locations that are distant from each other, innovation may suffer (Fuchs, 2014), especially when the firm's ability to create new production processes is enhanced by the proximity of designers to the factory floor (Pisano and Shih, 2012). How import competition and innovation are related thus is intrinsically an empirical question, and the relationship may differ across countries, episodes, and competitive structures.[3]

In this paper, we revisit how import competition affects innovation by estimating the impact of greater exposure to trade on patents by U.S. manufacturing firms. As in recent literature, we measure trade exposure using the change in industry import penetration resulting from increased U.S. trade with China. We isolate the component of U.S. import growth that is driven by export-supply growth in China, and not by U.S.-specific product-demand shocks, using the identification strategy in Autor, Dorn, Hanson, and Song (2014). This approach instruments for the change in U.S. industry trade exposure using growth in industry imports from China in high-income economies other

[3] Related work examines how reductions in trade barriers affect industry productivity. See, e.g., Pavcnik (2002), Trefler (2004), Dunne, Klimek and Schmitz (2011), Eslava, Haltiwanger, Kugler, and Kugler (2013), Steinwender (2015), and Halpern, Koren and Szeidl (2015).

than the U.S. To construct firm-level data on patents, we match the assignees of all U.S. patents granted between 1975 and March 2013 to publicly held firms listed in CompuStat.[4] Matching is complicated by inconsistencies in how firm names are listed in patent records due to spelling variations, typographical errors, and optical scanning issues. Patent filings on behalf of IBM, for instance, utilize more than 100 different spellings of the company's name. Existing methods use string match based on standardized firm names (Bessen, 2009; Belezon and Berkovitz 2010; Bloom, Draca, and Van Reenen 2016). Absent manual intervention, however, string match has limited ability to capture all of the possible name variations of firms, resulting in false negative matches. We improve upon these methods by combining string match with a novel algorithm that harnesses the machine learning capabilities of Internet search engines. Our method is fully automated and scalable, which significantly improves efficiency without sacrificing accuracy. We are able to assign 70% of all corporate patents with U.S.-based primary inventors to entities in CompuStat.[5]

To preview our findings, we estimate impacts of trade exposure on innovation for the U.S. that differ substantively from the results of Bloom, Draca, and Van Reenen (2016). U.S. industries or firms that are subject to larger increases in trade exposure show smaller, not larger, increases in patenting. This finding emerges once we control for the broad sector of production. The high concentration of patenting in two broad sectors—computers and electronics, and chemicals and pharmaceuticals—is a potential confounding factor in the estimation that tends to obscure these relationships. Whereas firms in computer and electronics industries registered large increases in trade exposure in the 1990s and 2000s, industries that create new chemical patents faced little competition from China. Given the these countervailing patterns in these two large, patent-intensive sectors, it is perhaps unsurprising that in raw correlations, industries with larger increases in trade exposure during the sample period of 1991 to 2007 have contemporaneous changes in patents that are small and statistically insignificant. Once we introduce main effects for just these two sectors, chemicals and computers/electronics, the impact of trade exposure on changes in patenting becomes strongly negative and precisely estimated. This negative impact remains when we add extensive additional controls to the regression analysis, employ alternative weighting schemes to account for the differential importance of patents across sectors, and expand the sample to include patenting either by foreign firms in the U.S. or by foreign-based inventors employed by U.S. firms. Further analysis reveals that greater import exposure also has negative impacts on firms' global sales, global employment, and global R&D spending. Together, our results suggest that the China trade shock

[4] We use the U.S. Patent and Inventor Database from Lai, D'Amour, Yu, Sun, Doolin, and Fleming (2013), which also contain detailed information on the inventors.

[5] In 1995, CompuStat firms accounted for 62% of R&D in the U.S. (Bloom, Schankerman, and Van Reenen, 2013).

reduces firm profitability in U.S. manufacturing, leading firms to contract operations along multiple margins of activity, including R&D and patenting.

Patents are, of course, an imperfect measure of innovative output. Firms could be innovating in other ways without patenting. Our analysis suggests that this is unlikely to be the case here since we find that trade competition reduces firms' global R&D expenditure. Our results might alternatively be explained by the fact that innovative firms have simply become less inclined to patent. Countering this line of reasoning, prior work shows that U.S. patent applications—including unsuccessful attempts—have increased substantially over the recent decades, while the approval rate has decreased drastically (Lerner and Seru, 2015; Carley, Hegde, and Marco 2015). The opposite possibility could be at play: firms facing greater import competition may be more likely to protect their existing knowledge by engaging in defensive and strategic patenting, in which case our analysis would provide conservative estimates of the impact of import competition on innovation.

Three distinctive features of our approach may account for why our results differ from Bloom, Draca and Van Reenen (2016). First, and most obviously, we study the U.S. and not Europe. Given the underlying theoretical ambiguity in the relationships examined, it is conceivable that the impacts of foreign competition on innovation in the two regions are of opposite sign. Viewed through the lens of Aghion, Bloom, Blundell, Griffith, and Howitt (2005), the difference between our results and those of Bloom, Draca and Van Reenen (2016) would require that Europe begins with its industries being much less competitive than those in the U.S. (such that greater import competition from China moves Europe up the left leg of the innovation-competition inverted U, whereas it moves the U.S. down the inverted U's right leg). We are however unaware of research that establishes such stark continental differences in industry competition. Second, we study all U.S. manufacturing sectors, whereas the Bloom, Draca, and Van Reenen (2016) identification strategy, which exploits the termination of the Multi-Fibre Arrangement in 2005, is best suited for apparel and textiles, two sectors that are important in terms of labor-intensive production but only account for a small fraction of overall patenting in the U.S. Third, the longer time frame for our analysis (1975 to 2007) relative to theirs (1995 to 2005) allows us to examine how pre-trends in patenting complicate the estimation. There is, for instance, a positive and significant correlation between the change in industry patenting in the pre-sample period of 1975 to 1991 and the change in industry trade exposure in the later sample period of 1991 to 2007. This correlation, which disappears once we add controls for chemicals and computers/electronics, indicates that sectors later exposed to import competition from China enjoyed earlier success in their R&D. Incomplete controls for these industry trends may make the impact of trade exposure on patenting appear more positive than it is.

Other work, contemporaneous to ours, documents a mixed and inconsistent relationship between trade exposure and innovative activity among U.S. publicly listed firms.[6] Two recent studies, Arora, Belenzon, and Patacconi (2015) and Gong and Xu (2015), show a negative impact of import competition on R&D spending. R&D spending is, however, a measure of inputs into innovation and does not directly capture realized innovations and knowledge creation. Moreover, it is observed only for a small subset of firms.[7] By focusing on patenting activity, we capture a larger set of firms and focus on innovation output rather than expenditures on innovative activities. As a side result of their analysis of changing time trends in innovation output by large corporations, Arora, Belenzon, and Patacconi (2015) also study the relationship between import exposure, patenting, and scientific publications. Distinct from our work, they find a positive correlation between import exposure and patenting—as well as a negative correlation with firms' scientific publications. As Arora, Belenzon, and Patacconi (2015) note, their evidence is purely correlational in that they do not attempt to isolate exogenous sources of import exposure. This leaves open the possibility that trends in import penetration and patenting are driven by demand shifts that simultaneously increase foreign purchases and spur efforts at rent capture through the patent system. Furthermore, their analysis does not include controls for sector time trends, which we find to be critical.[8] Current work is also hampered by the temporal coverage of the NBER Patent Data Project (NBER PDP) database, which at present links patents to their CompuStat firm owners only for patents granted by 2006.[9] Since China's rise as a world manufacturing leader accelerated dramatically after its WTO accession in 2001, the time window of NBER PDP arguably fails to capture the years of data that are most relevant to assessing China's impact on U.S. innovation. The current paper overcomes both limitations of existing literature (endogeneity, time horizon), first, by exploiting plausibly exogenous cross-industry, over-time variation in Chinese import competition arising from China's "reform and opening" (Naughton, 2007), and second, by extending the temporal coverage of the existing patent-CompuStat to the year 2013 by using a novel matching methodology outlined below.

In section 2, we discuss the measurement of trade exposure and our novel approach for matching patents to firm data, and we describe broad trends in industry innovation and trade exposure. In section 3, we present our baseline estimation results. In section 4, we describe additional estimation

[6]Scherer and Huh (1992) provide some of earliest evidence on how U.S. manufacturing firms respond to high-technology import competition. Using data on 308 manufacturing firms between 1971 and 1987, they find that import competition, on average, reduces R&D/sales ratios, but the response is highly heterogeneous across firms.

[7]We observe R&D spending for only 40% of the firm-year observations in CompuStat.

[8]Arora, Belenzon, and Patacconi (2015)'s data coverage is also much smaller than our sample of analysis. They have approximately one thousand firms in their sample. Our database contains four times that number.

[9]The data files are available at https://sites.google.com/site/patentdataproject/.

exercises. And in section 5 we conclude.

2 Data

In a first step of data construction, we match trade data to U.S. manufacturing industries in order to create measures of changing import penetration. In a second step, we match patent records to firm-level data that comprise firms' industry affiliation. In combination, the resulting data allow us to analyze the impact of industry-level trade shocks on firm-level patenting and other firm outcomes.

2.1 International Trade

Data on international trade for 1991 to 2007 are from the UN Comtrade Database, which gives bilateral imports for six-digit HS products.[10] To concord these data to four-digit SIC industries, we first apply the crosswalk in Pierce and Schott (2012), which assigns 10-digit HS products to four-digit SIC industries (at which level each HS product maps into a single SIC industry), and aggregate up to the level of six-digit HS products and four-digit SIC industries (at which level some HS products map into multiple SIC entries). To perform this aggregation, we use data on U.S. import values at the 10-digit HS level, averaged over 1995 to 2005. The crosswalk assigns HS codes to all but a small number of SIC industries. We therefore slightly aggregate the four-digit SIC industries so that each of the resulting 397 manufacturing industries matches to at least one trade code, and none is immune to trade competition by construction. All import amounts are inflated to 2007 U.S. dollars using the Personal Consumption Expenditure deflator.

Our baseline measure of trade exposure is the change in the import penetration ratio for a U.S. manufacturing industry over the period 1991 to 2007, defined as

$$\Delta IP_{j\tau} = \frac{\Delta M^{UC}_{j,\tau}}{Y_{j,91} + M_{j,91} - E_{j,91}}, \tag{1}$$

where for U.S. industry j, $\Delta M^{UC}_{j\tau}$ is the change in imports from China over the period 1991 to 2007 (which in most of our analysis we divide into two sub-periods, 1991 to 1999 and 1999 to 2007) and $Y_{j,91} + M_{j,91} - E_{j,91}$ is initial absorption (measured as industry shipments, $Y_{j,91}$, plus industry imports, $M_{j,91}$, minus industry exports, $E_{j,91}$) at the start of a period. We choose 1991 as the start year for the analysis as it is the earliest period for which we have the requisite disaggregated bilateral trade data for a large number of country pairs that we can match to U.S. manufacturing

[10]See http://comtrade.un.org/db/default.aspx.

industries.[11]

The year 1991 also coincides with the rapid acceleration of export growth in China. Between 1984 and 1990, China's share of world manufacturing exports had only ticked up modestly, rising from 1.2% to 1.9%. It began its rapid ascent in 1991, doubling to 4.0% by 1999, and subsequently more than quadrupling to 18.8% by 2013. The literature associates China's post-1990 export surge with the relaxation of barriers to foreign investment (Yu and Tian, 2012), the progressive dismantling of state-owned enterprises (Hsieh and Song, 2015), and the reduction of trade barriers associated with the country's accession to the World Trade Organization in 2001 (Bai, Krishna, and Ma, 2015; Pierce and Schott, 2015), all of which emanated from a broader process of "reform and opening" (Naughton, 2007) and contributed to rapid productivity growth in manufacturing (Brandt, Van Biesebroeck, and Zhang, 2012; Hsieh and Ossa, 2015). The quantity in (1) can be motivated by tracing through export supply shocks in China—due, e.g., to reform-induced productivity growth—to demand for U.S. output in the markets in which the United States and China compete. Supply-driven changes in China's exports will tend to reduce output demand for U.S. industries.

One concern about (1) as a measure of trade exposure is that observed changes in the import penetration ratio may in part reflect domestic shocks to U.S. industries that determine U.S. import demand. Even if the dominant factors driving China's export growth are internal supply shocks, U.S. industry import demand shocks may still contaminate bilateral trade flows. To capture this supply-driven component in U.S. imports from China, we follow Autor, Dorn, Hanson, and Song (2014) and instrument for trade exposure in (1) with the variable

$$\Delta IPO_{j\tau} = \frac{\Delta M^{OC}_{j,\tau}}{Y_{j,88} + M_{j,88} - X_{j,88}} \tag{2}$$

where $\Delta M^{OC}_{j,\tau}$ is the growth in imports from China in industry j during the period τ.[12] The denominator in (2) is initial absorption in the industry in 1988. The motivation for the instrument in (2) is that high-income economies are similarly exposed to growth in imports from China that is driven by supply shocks in the country. The identifying assumption is that industry import demand shocks are uncorrelated across high-income economies.[13] In the first-stage regression of the value in (1) on the value in (2) across four-digit U.S. manufacturing industries, the estimated coefficient is

[11] Our empirical approach requires data not just on U.S. trade with China but also on China's trade with other partners. Specifically, we require trade data reported under Harmonized System (HS) product codes in order to match with U.S. SIC industries. The year 1991 is the earliest in which many countries began using the HS classification.

[12] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, which represent all high-income countries for which we can obtain disaggregated bilateral trade data at the Harmonized System level back to 1991.

[13] See Autor, Dorn and Hanson (2013) and Autor, Dorn, Hanson and Song (2014) for further discussion (and many robustness tests) of possible threats to identification using this instrumentation approach.

0.98 and the t-statistic and R-squared are 7.0 and 0.62 respectively, indicating the strong predictive power of import growth in other high-income countries for U.S. import growth from China.[14]

A potential concern about our analysis is that we largely ignore U.S. exports to China, focusing primarily on trade flows in the opposite direction. This is for the simple reason that our instrument, by construction, has less predictive power for U.S. exports to China. Nevertheless, to the extent that our instrument is valid, our estimates will correctly identify the direct and indirect effects of increased import competition from China. We also note that imports from China are much larger—approximately five times as large—as manufacturing exports from the United States to China.[15] To a first approximation, China's economic growth during the 1990s and 2000s generated a substantial shock to the supply of U.S. imports but only a modest change in the demand for U.S. exports.

2.2 Patent and Firm-Level Data

Following the large literature on technological progress and innovative activity (Jaffe and Trajtenberg, 2002; Cohen 2010), we measure innovation using utility patent grants. One attractive feature of patent data relative to other measures of innovative activity is that the year in which a patent application is filed provides a reasonable proxy for the year in which an invention occurs.[16] A second attractive feature is that the patent record contains a wealth of information on the nature of the invention, including the technology class of the patent; the name and address of the original assignee (owner), which allows us to match corporate patents to firm data based on firm names; and the residential address of listed inventors, which we use to determine whether the invention occurred in the U.S. or abroad. A third attractive feature of patents is that patent citations provide an ex post indication of the quality and impact of the innovation (Trajtenberg, 1990). In extensions of our main empirical results, we also use citations to weight patents as a means of approximating their

[14]Modeling the China trade shock as in equation (1) does not exclude the role of global production chains. During the 1990s and 2000s, approximately half of China's manufacturing exports were produced by export processing plants, which import parts and components from abroad and assemble these inputs into final export goods (Feenstra and Hanson, 2005). Our instrumental variable strategy does not require China to be the sole producer of the goods it ships abroad; rather, we require that the growth of its gross manufacturing exports is driven largely by factors internal to China (as opposed to shocks originating in the United States), as would be the case if, plausibly, the recent expansion of global production chains involving China is primarily the result of its hugely expanded manufacturing capacity.

[15]A second rationale for our import focus is data constraints. Much of U.S. exports to China are in the form of indirect exports via third countries or embodied services of intellectual property, management expertise, or other activities involving skilled labor. These indirect and service exports are difficult to measure because the direct exporter may be a foreign affiliate of a U.S. multinational or because they occur via a chain of transactions involving third countries.

[16]The year in which a patent is *granted* is not, however, a good measure due to the long and variable time lag between patent applications and patent grants. In January 2014, the average processing time was 34 months, with considerable variation around that mean (Lerner and Seru, 2015).

innovative value.

We use the U.S. Patent and Inventor Database from Lai, D'Amour, Yu, Sun, Doolin, and Fleming (2013), which covers patents granted by the U.S. Patent and Trademark Office (USPTO) between 1975 and March 2013. We focus on utility patents applied for in the years 1975, 1983, 1991, 1999, and 2007. The 1991-1999 and 1999-2007 periods coincide with the intervals during which the Chinese export surge occurs. The 1975-1983 and 1983-1991 periods provide two earlier spans of the same length to the later periods, which we utilize to analyze industry pre-trends in patenting. Since we use patents applied for by 2007, and because most patent applications are processed in six years, right censoring is unlikely to pose a serious problem for our analysis.[17]

Despite providing a wealth of information, patent records notably lack both a unique firm identifier variable and an industry code. The lack of industry information in the patent records cannot be readily overcome by using a patent's technology class code. While technology class indicates the nature of the invention (e.g., software), it does not indicate the manner in which the invention is used. A firm in the apparel industry, for instance, may create a new platform for computer-automated design of clothing. The patent may be assigned to Class 703 (Data Processing: Structural Design, Modeling, Simulation, and Emulation), even though the invention will most directly affect production in the apparel sector. The patent class may thus be a poor signal of the industry where the invention originates. Our approach is to use the industry of the original assignee of the patent when it was first granted. To obtain the industry information of the assignees, we match patents to the CompuStat database, which records publicly listed firms' primary industry, as well as annual sales, employment, R&D expenditure and other outcomes of interest. This allows us to link a firm's patenting to its industry-level trade shock. We preserve information on the technology class of the patent to control for the possibility that trends in patenting vary not just by the industry of the assignee (e.g., apparel) but by the technology deployed (e.g., software).[18]

A key challenge in matching between patents and firm-level data is that inconsistencies in how firm names are recorded on patents will often generate false negative matches. Because patent applications leave it to the applicant to state the name of the assignee, there is little uniformity in how company names appear. This non-uniformity of assignee names, combined with the lack of a unique firm identifier variable in the patent data, makes it extremely challenging to correctly group patents belonging to the same firm. IBM, for instance, has over 100 different spellings on its patents

[17]In our data, the average difference between grant year and application year is around 2.5 years and the standard deviation is around 1.5 years.

[18]Following Hall, Jaffe, and Trajtenberg (2001), we categorize patents into six main technology fields based on their primary technology class: Chemical; Computers and Communications; Drugs and Medical; Electrical and Electronics; Mechanical; and Others.

and is listed as International Business Machines, IBM, IBM Corporation, IBM Corp, etc. The traditional methods employed by prior work, most notably the NBER Patent Data Project (NBER PDP), accommodate some of this name variation by standardizing commonly used words in firm names, e.g., changing “Corp” to “Corporation” and “Ltd” to “Limited” (Bessen 2009). This simple string standardization, however, does not account for customized abbreviations or misspellings of firm names. For instance, the data also contain dozens of entries for assignees such as International Business Machine, International Bussiness Machines, and Information Business Machines, all of which may be abuses of the IBM name. Here, standardization is intractable as none of these names is an officially recognized spelling of IBM. The researcher is then faced with the unpalatable choice of throwing observations away for unmatched patents or manually making subjective corrections to firm names (for hundreds of thousands of records). The NBER Patent Data Project employs extensive manual inspection in addition to string standardization to match between the patent data and CompuStat, but its coverage of patents ends in 2006.

We improve on existing methods and extend the match to 2013 by developing a novel, fully automated approach to correct for false negatives that would result from simple string matches. We exploit the fact that internet search algorithms function as repositories of information on common spelling variations of company names. If a patent applicant misspells the name of his or her employer on a patent application (e.g., International Business Machine), it is likely that others have made the same mistake when searching for the company online. If International Business Machine is a common abuse of IBM, an internet search will return ibm.com or IBM’s Wikipedia page as top search results. Thus, matching based on shared web addresses, as opposed to name strings, eliminates the need for the extensive manual efforts required to specify how different name spellings and typos may occur for different firms. This approach is readily scalable and generalizable to the matching between any two firm-level datasets.

We follow a four-step matching procedure. First, following NBER PDP, we clean the firm names (e.g., removing punctuations and accents) and standardize the commonly used words in firm names in both the patent and CompuStat data. This allows us to perform an initial matching based on names. Next, we search the name of each patent assignee (entered in quotation marks) using the search engine Bing.com. Our program retrieves the URLs of the top five search results, which serve as an input into the next step of the algorithm. Based on the URLs collected from Bing.com in August 2014, we consider an assignee and a CompuStat firm to be a match if the top search results contain the company website listed in CompuStat. Third, we apply transitivity: if two assignees share at least one URL in their top two search results and one is matched to CompuStat, we consider the other a match too. Finally, we append to our data the matching between assignees and CompuStat firms from NBER PDP that our method has failed to capture (a small number of cases). The Data Appendix discusses the details of this procedure and compares its coverage and accuracy to NBER PDP.

Our CompuStat data cover public firms that were listed between 1969 and 2015. To match a firm to its patents, we do not require it to be covered by CompuStat in the year of patent application. If a private company applies for patents before going public, we are nevertheless able to determine an industry affiliation for that firm. To this end, our baseline estimations will assign firms to industries based on the last available industry code that CompuStat recorded for a given firm. A challenge to this approach is that a firm's industry may change over time, or a firm may be active across multiple industries. However, for a subset of firms, CompuStat also provides historical industry codes and information on the distribution of sales across multiple industries. We use these historical data to alternately assign firms to their past industry, and to construct a firm-specific measure of trade exposure based on equation (1), using as weights the firm share of sales in each industry in which it operates.[19]

Table 1 describes the sample of patents we use in the analysis. Over the five sample years (1975, 1983, 1991, 1999, 2007), there are 586,200 applications for patents that are awarded by March 2013. Just over half (53%) of these patents list the first inventor as an individual based in the U.S.[20] Of these U.S.-based patents, 241,784 go to assignees who categorize themselves as corporations on the patents and whose names indicate that they are not universities, institutions, hospitals, or government agencies.[21] This group includes publicly held companies, which appear in CompuStat, and privately held companies, which do not. Of these corporate patents, we are able to match 70% to CompuStat firms, which provides industry codes for nearly all matched firms. The unmatched entities include non-publicly traded companies and public corporations that our matching procedure fails to capture.

[19]As it turns out, our results are robust to various schemes for assigning industry codes, including using historical industry affiliation, most recent industry affiliation, and weighted mixture of affiliations.

[20]The patents with a U.S. primary inventor make up for 98% of all patents with at least one U.S. inventor.

[21]The self-reported categorization variable comes from USPTO but is noisy. We identify universities, institutions, hospitals and government agencies using key words in assignee names following the NBER PDP.

Table 1: Construction of Main Patent Sample.

	No. Patents	% previous
All USPTO Patents (Application Years 75/83/91/99/07)	586,200	
w/ US-Based Inventor	312,991	53%
and Corporate Patent	250,256	80%
and Non-University/Government Assignee	241,784	97%
and Matched to Compustat Firm	168,551	70%
and with Valid Industry Code	168,512	100%
Main Patent Sample	168,512	

2.3 Trends in Industry Patenting and Trade Exposure

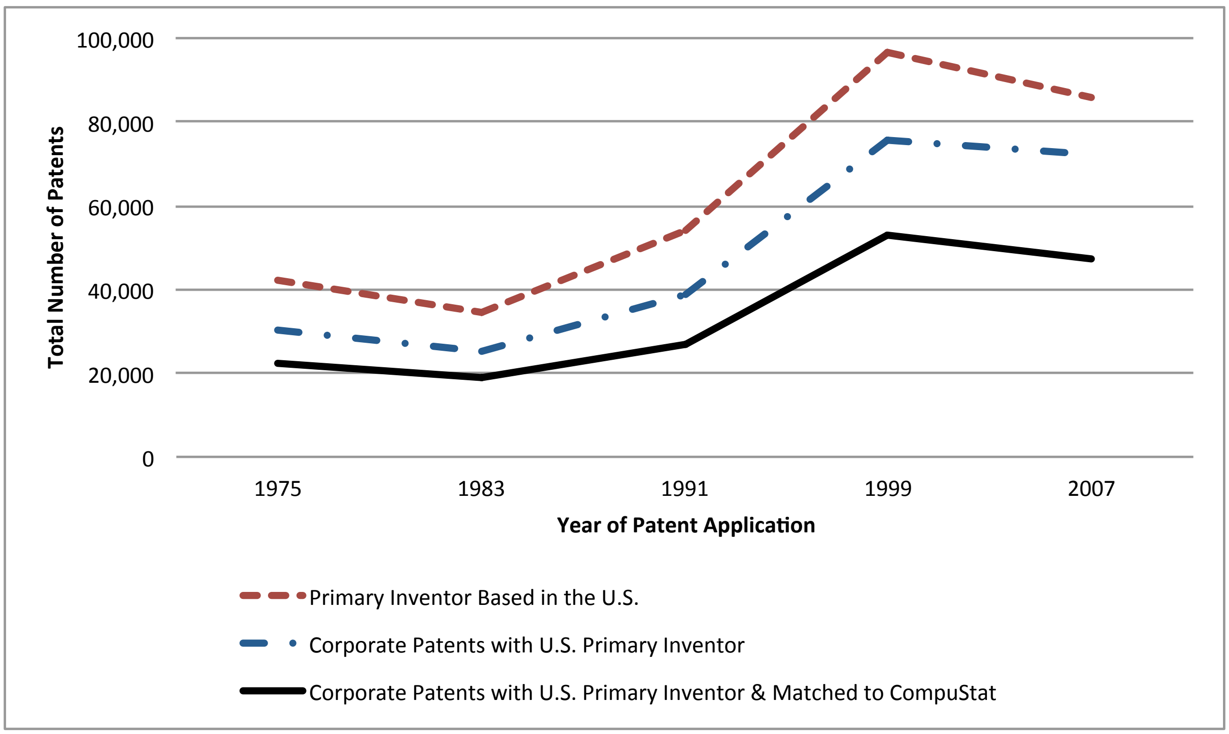
Figure 1 plots, by year of patent application, the total number of all patents by U.S.-based primary inventors, corporate patents by U.S.-based primary inventors, and our sample of patents, which includes corporate patents by U.S.-based primary inventors that are matched to CompuStat. All three series show the same trend: there is a sharp rise between 1983 and 1999 and a modest decline between 1999 and 2007. The match rate of the U.S.-based corporate patents to CompuStat firms is high at the start of our sample but declines modestly over time, from 75% in 1975 and 1983 to 70% in 1991 and 1999 and 65% in 2007, most likely because the share of privately-held firms among US corporations has risen over the past several decades.

There is wide variation in patenting activity across manufacturing industries. Table 2 shows the fraction of patents applied for in 1975, 1991, and 2007 and accounted for by 11 major manufacturing sectors, sorted by their share in overall manufacturing patents in 2007. In 1991, at the beginning of the sample period for our later analysis, just three sectors, computers and electronics, machinery and equipment, and chemicals and petroleum, comprised 78.8% of patents.[22] This sectoral concentration of innovation is both persistent and accelerating. In 1975, these three sectors already accounted for 72% of patents and by 2007, their collective share of patents had reached 83.5%. Furthermore, there

[22]Computers and electronics track NAICS three-digit industry 334, which comprises the following three and four-digit SIC industries: computer and office equipment (SIC 357, except 3579), calculating and accounting equipment (SIC 3578), household audio and video equipment (SIC 365), communication equipment (SIC 366), electronic components and accessories (SIC 367), magnetic and optical recording media (SIC 3695), search and navigation equipment (SIC 381), measuring and controlling devices (SIC 382, except 3821, 3827, 3829), x-ray apparatus and tubes and electromedical equipment (SIC 3844, 3845), and watches and parts (SIC 387). Machinery and equipment include two-digit SIC industries 35 and 36, except for those subindustries related to computers and electronics. Chemicals and petroleum include the two-digit SIC industries 28 and 29.

has been a reordering among these top industries in terms of which is the locus of innovation. In 1991, chemicals and petroleum accounted for 28.8% of manufacturing patents, a share that dropped to 13.4% by 2007. The declining share of chemicals in overall patenting may reflect in part a steady slowdown in the creation of blockbuster pharmaceutical products, which accounted for many of the inventions in the sector during the decades before 1990 (Munos, 2009). Computers and electronics, buoyed by the revolution in information technology, have displaced chemicals as the most prolific sector for the creation of new patents. In 2007, the sector accounted for the majority (53.1%) of all patents by manufacturing firms in CompuStat.

Figure 1: Number of Patents by Application Year



Other industries that figure prominently in overall manufacturing activity hardly register when it comes to patenting. Furniture and wood products (SIC 24, 25) and apparel, textiles, and leather (SIC 22, 23, 31) are large labor-intensive sectors that historically have been important sources of manufacturing jobs. However, these industries together accounted for only 1.2% of patent applications in 1991 and a paltry 0.9% in 2007. Two other major sectors, stone, clay, and glass (SIC 32) and paper products and printed matter (SIC 26, 27), account for only modestly higher shares.

Table 2: Patents by Technology Classes and Manufacturing Sectors, US-Based Inventors.

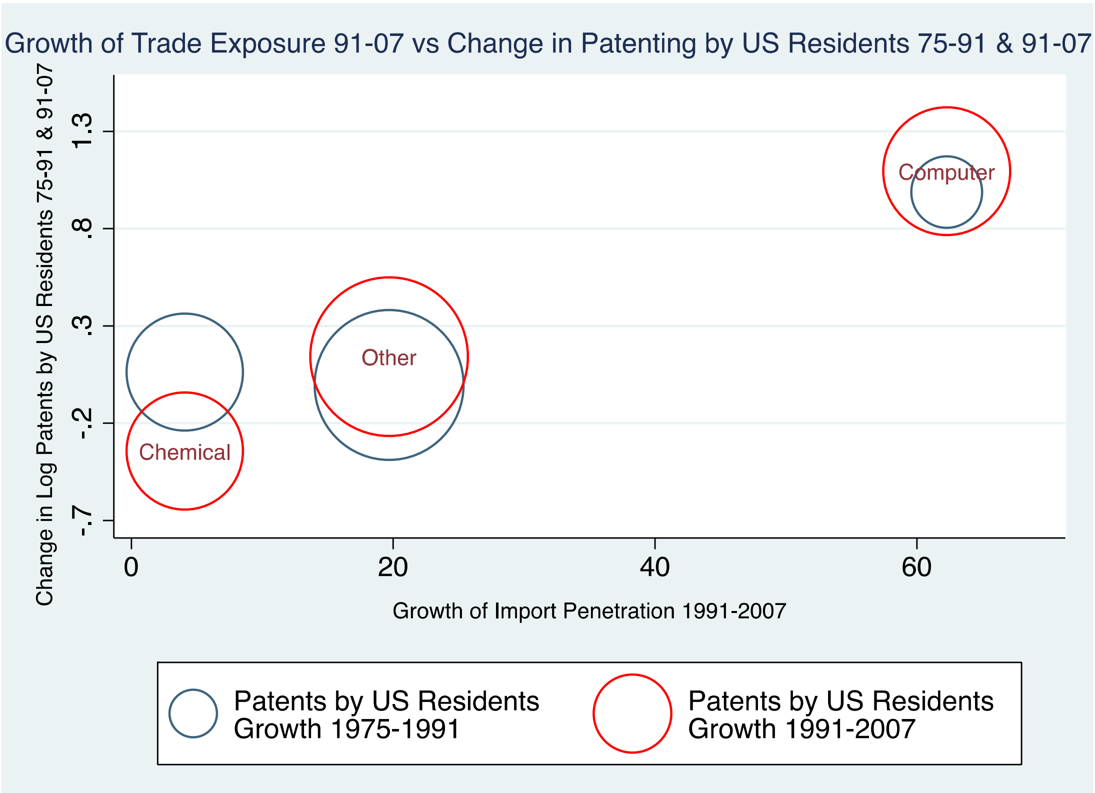
	1975	1991	2007
		A. Technology Classes	
Computers, Communic.	5.6%	13.6%	34.5%
Electrical, Electronic	16.7%	19.8%	23.8%
Mechanical	22.2%	17.7%	12.1%
Drugs, Medical	6.4%	10.4%	11.3%
Chemical	32.0%	24.5%	10.4%
Other	17.1%	13.9%	7.8%
		B. Sectors	
Computers, Electronics	12.4%	27.0%	53.1%
Machinery, Equipment	26.4%	23.0%	17.0%
Chem., Petrol., Rubber	33.2%	28.8%	13.4%
Transportation	11.0%	10.0%	8.8%
Paper, Print	3.4%	3.5%	2.0%
Metal, Metal Products	5.7%	2.7%	1.7%
Clay, Stone, Glass	4.4%	1.7%	1.5%
Other	0.8%	0.5%	1.2%
Wood, Furniture	0.6%	0.8%	0.6%
Food, Tobacco	1.7%	1.7%	0.5%
Textile, Apparel, Leather	0.5%	0.3%	0.2%

Notes: Computer and Electronics sector comprises the SIC industries that correspond to NAICS sector 334, while Machinery and Equipment sector is exclusive of NAICS sector 334. Statistics are based on patents by US-based inventors that are matched to Compustat manufacturing firms.

Persistent differences in patent intensity across sectors may reflect underlying industry variation in the technological potential for innovation. The malleable nature of cloth, for instance, has long impeded the automation of production in apparel (Abernathy, Dunlop, Hammond, and Weil, 1999). By contrast, the number of transistors that fit onto a microchip, a key determinant of the pace of technological change in computers and electronics, has displayed exponential growth for over four decades (Jorgenson, 2001; Byrne, Oliner, and Sichel, 2015).

These sectoral patterns of invention will matter for our analysis of how trade shocks affect innovation if an industry's pre-existing potential for creating new products and production processes is correlated with industry import exposure for any reason. Figure 2 plots the change in import penetration for 1991 to 2007 against the change in log patent applications over the same time frame for three sectoral aggregates: computers and electronics, chemicals and petroleum, and all other sectors. The raw correlation between patenting and trade exposure is positive at this broad sectoral level. Computers and electronics have seen both a sharp increase in import penetration from China and the already noted acceleration in patenting. Chemicals, on the other hand, have seen virtually no change in China's presence in the U.S. market and the noted deceleration in patenting. The bulk of other sectors lies somewhere in between.

Figure 2: Sectoral Patenting and Import Penetration from China, Pre-Sample and Sample Periods



As suggested by Table 2, the post-1990 sectoral patterns in patenting correspond to longstanding differences. To characterize secular trends in innovation, and their potential to be a confounding factor in our analysis, Figure 2 also plots the change in sectoral log patent applications for the pre-sample period of 1975 to 1991 against the sectoral change in import penetration from China for 1991 to 2007. Here again, the raw correlation is positive. The stagnation in chemical patenting and the acceleration in computer and electronic patenting that took place in the 1990s and 2000s was already well underway in the late 1970s and 1980s. We certainly would not want to attribute changes in innovation in the decades before 1990 to changes in import exposure that occurred in later decades.

Yet, because of the strong secular patterns in industry patenting, we would be in danger of making just such an attribution if we failed to adequately account for these sectoral trends.

3 Empirical Results

In the empirical analysis, we estimate the impact of changes in industry exposure to import competition from China on patenting at the firm level. The baseline regression specification is of the form,

$$\Delta P_{ij\tau} = \alpha_\tau + \beta_1 \Delta IP_{j\tau} + \gamma X_{ij0} + e_{ij\tau}, \tag{3}$$

where $\Delta P_{ij\tau}$ is the percentage change in patents for firm i in industry j over time period τ, defined as $100 \times (P_{ij,t1} - P_{ij,t0})/(0.5P_{ij,t1} + 0.5P_{ij,t0})$; $\Delta IP_{j\tau}$ is growth of import exposure (in percentage points) for industry j over period τ, as defined in equation (1); and X_{ij0} comprises controls for non-trade related factors that may affect the capacity of a firm to create patents, including sectoral time trends, industry factor and technology intensity, and firm scale and R&D spending, as measured at the start of each period.

The data consist of stacked first differences for two time periods, 1991 to 1999 and 1999 to 2007. A firm appears in the first time period if it had any patents in 1991 and (or) 1999; similarly, it appears in the second time period if it had any patents in 1999 and (or) 2007. Because some firms may have had patents in 1991, and not later, or in 2007, and not earlier, the panel is unbalanced. We thus allow for firm entry into and exit from patenting. Over the two sample periods, we have an average of 4,064 firms per period which in 1991, 1999, and 2007 collectively produced a total of 127,311 patents.[23] We assign a firm to an industry based on its main industry code in CompuStat, which is generally the most recent code. In later results, we experiment with using historical industry codes for firms whose main code changes over time (and we analyze whether trade shocks affect such industry switches). Following the discussion in section 2, we instrument for industry import penetration $\Delta IP_{j\tau}$ using $\Delta IPO_{j\tau}$, as defined in equation (2). Observations are weighted by the number of firm patents, averaged over the start and end period of τ; standard errors are clustered on four-digit SIC industries.

[23] Of the 168,512 patents awarded to firms in our data in 1975, 1983, 1991, 1999, and 2007, 127,311 were awarded in 1991 or later and 41,201 were award in 1975 or 1983.

3.1 Baseline Estimates

Table 3 gives estimation results for equation (3). Column 1 presents regressions for the first time period, 1991 to 1999; column 2 presents results for the second time period, 1999 to 2007; and column 3 contains results for the stacked first differences, 1991-1999 and 1999-2007. In panel A, we begin with a specification that includes no covariates beyond the change in import penetration and a time-period-specific constant term. The raw correlation between the change in firm patents and the change in industry import penetration is positive for 1991-1999, negative for both 1999-2007 and the stacked first difference model. The coefficient of interest is and not significantly different from zero in either OLS regressions (row a) or 2SLS regressions (row b).

Moving beyond the univariate regressions in panel A, panel B adds controls to address persistent differences across sectors in patent creation. Apparent in Table 2 and in Figure 2 is the dominance of a handful of technology-intensive industries in patenting within manufacturing. In rows (c) and (d) of Table 3, we add dummy variables for just two broad sectors, chemicals—in which patenting has been decelerating over time—and computers, in which patenting has been sharply accelerating. Once we add these sectoral controls to the stacked first-difference model, the impact of industry import penetration on firm patenting becomes negative and statistically significant, both in OLS (column 3, row c) and 2SLS (column 3, row d) specifications. The change in results from panel A to panel B illustrates the importance of controlling for industry trends in innovation, a finding that our subsequent analysis reinforces. While Figure 2 indicates a positive relationship between import growth and patenting across broad sectors, the relationship becomes negative once we assess the impact of import competition on patenting across industries within these broad sectors.

The remaining rows of Table 3 successively add further controls to account for other potentially confounding factors that may affect industry or firm incentives to innovate. Row (e) adds dummy variables for the 11 manufacturing sectors shown in Table 2; row (f) adds controls for industry factor and technology intensity at the start of period (share of production workers in industry employment, log capital over value added, log average industry wage, computer investment as a share of overall investment, and high-tech equipment as a share of total investment); row (g) adds firm characteristics at the start of period (a dummy variable for whether the firm is headquartered in the U.S., log firm sales in the U.S., and firm global R&D spending as a share of firm global sales); row (h) controls for the technology mix of firm patents (the fraction of a firm's patents that fall into each of the six major technology classes shown in Table 2, averaged over the start and end of period); and row (i) controls for lagged patenting (8-year and 16-year lags on the percentage change in firm patent applications). Stacked first difference estimates in column (3) find a negative and statistically significant impact of changes in industry import penetration on firm patenting across all of these additional specifications. Results estimated for the two sub-periods in columns (1) and (2) are consistently negative but less precisely estimated. Taking the 2SLS results with the full set of controls for the stacked first differences (column 3, row i), the parameter estimate of -1.31 indicates that a one standard deviation increase in import penetration (9.30) results in a 12.18 percentage-point decrease in patents.

Table 3: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007 and 1975-1991 (for Falsification Test). Dependent Variable: Change Number of Patents by US-Based Inventors in CompuStat Firms (in Percentage of Mid-Period Number of Patents).

	I. Exposure Period: 1991-2007			II. Pre-Period: 1975-1991			
	1991 - 1999	1999 - 2007	1991 - 2007	1975 - 1983	1983 - 1991	1975 - 1991	(3) vs (6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Models without Controls			
a. OLS, no controls	1.38	-0.37	-0.25	0.93 **	1.16 ~	1.07 *	-1.32 *
	(1.19)	(0.23)	(0.27)	(0.32)	(0.63)	(0.45)	(0.58)
b. 2SLS, no controls	0.48	-0.15	-0.12	1.09 **	1.76 *	1.49 **	-1.61 *
	(1.43)	(0.43)	(0.44)	(0.42)	(0.70)	(0.55)	(0.69)
				B. Models with Controls			
c. OLS, 2 mfg sector dummies (computers, chemicals)	-0.89	-0.63 **	-0.88 **	0.37	-0.32	-0.01	-0.88 *
	(1.02)	(0.15)	(0.15)	(0.24)	(0.64)	(0.38)	(0.37)
d. 2SLS, 2 mfg sector dummies (computers, chemicals)	-2.28 ~	-0.55	-1.18 *	0.38	0.11	0.25	-1.43 **
	(1.37)	(0.35)	(0.51)	(0.31)	(0.60)	(0.40)	(0.56)
e. 2SLS, 11 mfg sector dummies	-1.63	-0.45	-1.03 *	0.51	0.40	0.46	-1.49 *
	(1.11)	(0.37)	(0.49)	(0.37)	(0.67)	(0.48)	(0.62)
f. 2SLS, 11 mfg sector dummies + industry controls	-1.15	-0.46	-1.00 *	0.56	0.26	0.41	-1.41 **
	(1.16)	(0.37)	(0.44)	(0.39)	(0.54)	(0.42)	(0.52)
g. 2SLS, 11 mfg d. + industry/firm controls	-1.07	-0.43	-0.99 *	0.60	0.26	0.41	-1.40 **
	(1.01)	(0.36)	(0.44)	(0.38)	(0.57)	(0.42)	(0.52)
h. 2SLS, 11 mfg d. + industry/firm controls + technology mix	-1.16	-0.66 ~	-1.24 **	0.27	0.23	0.21	-1.45 **
	(1.27)	(0.37)	(0.47)	(0.31)	(0.62)	(0.39)	(0.52)
i. 2SLS, 11 mfg d. + industry/firm controls + technology mix + 2 lags	-1.34	-0.78 ~	-1.31 **	n/a	n/a	n/a	n/a
	(1.22)	(0.42)	(0.45)				
No. Observations	4086	4041	8127	2404	3003	5407	

Notes: Each coefficient is derived from a separate firm-level regression of the relative change in patents on the change of Chinese import penetration. The relative change in patents is defined as the first difference in patents over a period t,t+1, divided by the average number of patents across the two periods t and t+1. Columns 4-6 provide falsification test that regress the change in patents on the future increase in Chinese import penetration, averaged over the 91-99 and 99-07 periods. Columns 3 and 6 present stacked first differences models for the periods 75-83/83-91 and 91-99/99-07 and include a period dummy, while columns 7 indicates the difference between the import exposure coefficients of the column 3 and 6 models. Model (c) includes dummies for the computer/communication and chemical/petroleum industries. Model (d) includes a full set of dummies for 11 manufacturing sectors. Model (e) additional includes 5 industry-level controls for production characteristics (production workers as a share of total employment, log average wage, and the ratio of capital to value added, all measured at the start of each period; as well as computer investment and investment in high-tech equipment, both expressed as a share of total investment and measured in 1990 for the models of columns 1-3 and in 1972 for the models of columns 4-6) 5 additional industry-level controls (start of period share of production workers in an industry's employment, capital over value added, log average industry wage; computer investment as share of overall investment, high-tech equipment investment as share of overall investment, both measured in 1990 for models in columns 1-3 and in 1972 for models in columns 4-6). Model (f) additionally includes a dummy variable for US-based firms, and controls for the log US sales of a firm and for its global r&d expenditure expressed as a share of global sales. It also includes two dummy variables indicating firms for which the two latter controls are not available in the Compustat data. Model (g) additonally controls for the fraction of a firm's patents that fall into each of the six major patent technology categories defined by the US Patent Office, averaged over start-of-period and end-of-period patents. Model (h) additionally controls for two 8-year lags of the outcome variable. All models are weighted by number of patents in a firm, averaged over patents at the start and end of a period, and standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Figure 2 offers suggestive evidence as to why the impact of import penetration on patenting is sensitive to controls for chemicals and computers/electronics. Very simply, trade exposure appears to be positively correlated with industry pre-trends in patenting in these two major patent-producing sectors. Failure to control for pre-trends thus introduces a source of confounding variation that imparts upward bias to estimates of the impact of import competition on patenting. The correlation between import penetration and industry pre-trends in patenting is described in more detail in columns (4) to (6) of panel A in Table 3. We average the change in import penetration over the periods 1991-1999 and 1999-2007 and project this average onto the change in firm-level patenting in the preceding 16-year period of 1975 to 1991, which again is separated into two sub periods (1975 to 1983 in column 4, 1983 to 1991 in column 5, and both periods combined in column 6). In each of these periods, and for both the OLS (row a) and 2SLS (row b) specifications, there is a positive and statistically significant correlation between the later change in industry import exposure and the earlier change in firm-level patenting. This pattern demonstrates the presence of confounding pre-trends.

In panel B of Table 3 (rows c to i), we add to the estimation the progressively expanded set of controls discussed above. In rows (c) and (d), we see that doing no more than introducing dummy variables for the two broad sectors of chemicals and computers/electronics neutralizes the positive correlation between pre-sample changes in firm patenting and sample-period changes in industry trade exposure. The coefficient on import exposure is quantitatively small and imprecisely estimated in all of the panel B regressions for columns (4) to (6). The positive correlations in panel A thus seems to be a byproduct of the fact that the sector with the largest post-1975 increase in patenting—computers and electronics—is also one with a substantial post-1991 increase in exports by China, whereas the sector with the largest post-1975 slowdown in patenting, chemicals, is one with minimal change in trade exposure. Column (7) summarizes this information by reporting the contrast between the coefficient estimates in column (3) versus column (6), obtained from a stacked version of the column (3) and (6) models. All regression specifications in column (7) uniformly suggest that industries that faced greater import competition from China since the 1990s experienced a significant decline in patent growth in the 1991-2007 period relative to the pre-period of 1975-1991. For the 2SLS regressions, the point estimates range in value from -1.41 to -1.61. We interpret these coefficients as capturing the percentage-point change in patenting, relative to pre-trends, caused by a one-percentage-point increase in import penetration from China.

3.2 Alternative Industry Classification and Weighting Methods

In the sample used for the estimation results in Table 3, we classify firms according to their main industry code, as reported in CompuStat. This code generally corresponds to industry affiliation during the most recent period. It is possible that firms change their primary industries in response to trade shocks. Bernard, Jensen, and Schott (2006) find evidence of such movements at the level of U.S. manufacturing plants during the 1980s and early 1990s. Among plants that survive from one period to the next, those that are exposed to larger increases in import competition are more likely to change their initial industry of affiliation. Our sample is comprised of firms, not plants, where just one firm may own hundreds of manufacturing establishments. Inducing changes in primary industry affiliation at the firm level is thus likely to require a much stronger impetus than at the plant level. We proceed to examine whether our results are sensitive to changes in how we define a firm's primary industry.

Table 4: Effect of Chinese Import Competition on Firm-Level Patenting, and on Probability of Industry and Segment Change, 1991-2007. Dependent Variable: Relative Change of Number of Patents by US-Based Inventors, Probability of Industry or Segment Change (in Percentage Points).

	Relative Change of Patents					Pr(Ind Change)	Pr(Entered Segment)	Pr(Exited Segment)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Source of Industry Code	Main	Historical/ Main	Segment/ Historical/ Main	Exact Historical	Exact Segment	Exact Historical	Exact Segment	Exact Segment
Δ U.S. Industry Exposure to Chinese Imports	-1.31 **	-1.18 **	-1.17 *	-1.17 *	-1.51 *	0.15	-0.57	0.36
	(0.45)	(0.43)	(0.48)	(0.53)	(0.62)	(0.24)	(0.62)	(0.42)
No. Observations	8127	8127	8127	2711	2651	2711	2651	2651

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from model 3i in table 2. The relative change in patents is defined as the first difference in patents over a period t,t+1, divided by the average number of patents across the two periods t and t+1. The column 1 model assigns each firm to its main, time-invariant industry code as reported in Compustat, and corresponds to model 3i in table 2. The column 2 assigns each firm-period observation to the historical Compustat industry code at the start of the respective period if available, or else to the earliest available subsequent historical industry code, or else to the main industry code. The column 3 model uses the same industry codes as model 2, except for firms where historical information on the distribution of firm sales across different firm segments is available. For these firms, import exposure is defined as the average exposure across all industries in which the firm was active in a given year, weighted by each of these industry segments' share in the firm's total sales. Models 4 and 5 only retain firms for which a historical industry code or historical segment data is avialable both for the start-of-period and end-of-period year. Model 6 uses the same sample and industry definition as model 4, and estimates the probability that a firm will have a different industry code at the end of a period than at the start. Models 7 and 8 use the same sample and industry definition as model 5, and estimate the probability that a firm has positive sales in a some industry segment only at the end of a period (entry into new industry segment) or only at the start of the period (exit from industry segment). The mean of the outcome variable in models 6-8 is 16.8, 50.9, 56.9. All models are weighted by the sum of a firm's start-of-period and end-of-period patents. Standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In Table 4, we compare our baseline results in column (1), taken from column (3) and row (i) of Table 3, to those obtained from alternative definitions of a firm's industry affiliation. In column (2), we designate a firm's primary industry to be that at the start of the respective period, when available, or else from the earliest available period. For firms where CompuStat provides no historical industry information, we retain the main industry code that was used in the baseline estimation. Therefore, the sample size is unchanged. The coefficient estimate on trade exposure declines modestly from −1.31 in column (1) to −1.18 in column (2) and retains its statistical significance when using this modification. In column (3), we incorporate information on historical firm sales by industry, where available, and construct average import penetration across all industries in which the firm was active in a given year, weighted by firm sales. Again, a firm's main industry code is used when such segment sales data is unavailable. The resulting coefficient estimate on trade exposure is essentially identical to that in column (2). In column (4), we retain only firms for which a historical industry code is available both at the start and end of the respective period. We thus only retain firms that had full CompuStat coverage in the years for which we measure patent applications. The resulting estimate for the impact of trade exposure on patenting is again nearly identical to that in column (2). Finally, in column (5) we retain only firms that have historical sales data by industry segment at the start and end of a period. This regression model, which retains only firms for which we can define a firm-specific trade shock as opposed to an industry-level shock, produces a modestly larger impact coefficient for trade exposure. Overall, adjusting for changes in firm industry of affiliation or the industry composition of firm sales leaves our coefficient estimate on import penetration materially unchanged.

These estimation results suggest that changes in import competition may have little impact on firm industry representation. In columns (6) to (8) of Table 4, we test this proposition formally. The column (6) specification has as the dependent variable an indicator for whether a firm changes its primary industry of affiliation between the start of the period and the end of the period.[24] The impact of import penetration on industry switching is positive but small and quite imprecisely estimated (t-ratio of 0.62). A one-standard-deviation increase in import penetration produces only a 1.4 percentage-point increase in the likelihood of changing the primary industry, relative to a mean period likelihood of change of 16.8 percentage points. In columns (7) and (8), we examine the related possibility that changes in import competition affect firm entry into an industry segment, as indicated by zero segment sales at the start of period and positive segment sales at the end of period, or exit from an industry segment, as indicated by sales moving from positive to zero over the relevant time interval. There is a modest negative impact of import competition on a firm entering a new sales segment and a modest positive impact of import exposure on a firm exiting an existing segment, though neither result is close to statistical significance. At the level of corporate entities represented in CompuStat, greater import penetration suppresses patenting but appears to have little impact on a firm's major industry orientation.

[24]The firm sample for this analysis corresponds to the one used in column (4).

Table 5: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007: Robustness to Alternative Samples and Weights. Dependent Variable: Relative Change of Number of Patents by US-Based Inventors.

		I. Reduced Patent Samples			II. Alternative Firm Weights		
	Baseline Spec	Excluding Grant Lag >6 Years	Excluding Comp/Cmm Tech	Excluding Chem/Drug Tech	Patent Citations	Global R&D	Global Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ U.S. Industry Exposure to Chinese Imports	-1.31 **	-1.33 **	-1.72 **	-1.47 **	-1.53 **	-2.17 **	-2.01 **
	(0.45)	(0.45)	(0.54)	(0.49)	(0.54)	(0.50)	(0.69)
No. Observations	8127	8030	6710	6478	7044	3383	4308

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from model 3i in table 2. The relative change in patents is defined as the first difference in patents over a period t,t+1, divided by the average number of patents across the two periods t and t+1. Model 1 corresponds to model 3i in table 2. Model 2 omits patents that were granted more than six years after patent application. Model 3 excludes all patents in the computer and communications technology category, and model 4 excludes all patents in the chemical or drug technology category. Model 5 weights firms by the number of citations to their start-of-period and end-of-period patents. Models 6 and 7 weight firms by their start-of-period global r&d expenditures or global sales. Standard errors are clustered on 4-digit SIC industries. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

One potential concern about the sample of patents that we use in our analysis is that the implicit maximum permissible time to patent approval varies over the sample period. That is, we observe patents with application dates between 1991 and 2007 that were *granted* by 2013. Whereas for the first year in the sample we observe patents granted within 22 years of the application date, for the last year in the sample we see only patents granted within six years of the application date. In column (2) of Table 5, we examine the robustness of our results to imposing a uniform time to approval for all patents considered in the analysis. We restrict the sample to patents granted within six years of the time of application. Because the vast majority of patents are granted within a few years after an application is submitted, the impact of this restriction on the sample size is small. The number of firm-years included in the analysis falls from $8,127$ in our baseline specification in column (1) to $8,030$ in column (2). The coefficient estimate on import penetration with the six-year patent approval restriction (-1.33) is nearly identical to that in the baseline (-1.31), suggesting that right censoring in patent approval times is of little significance for the results.

Given the importance of innovations in computer applications and in chemical processes for patenting by manufacturing firms, it is natural to wonder whether our results our sensitive to including patents in these technology classes in the analysis. In Table 3, we have already explored such sensitivity by incorporating controls for the technology mix of patenting by the firm, as measured by the average shares of firm patents that fall into the six major patent classes shown in panel A of Table 2. The results in Table 3 reveal that after adding controls for the firm's broad sector of activity, controlling for the technology mix of the firm's patents has little extra effect. In columns (3) and (4) of Table 5, we take the further step of dropping all patents with the primary technology class in computers and communications or in chemicals and pharmaceuticals. Under either restriction, the change in firm patents is thus calculated over new innovations in the remaining five technology classes. These exclusions result in larger point estimates for the negative impact of greater trade exposure on the firm-level change in patenting, with coefficient values rising from -1.31 in the baseline specification to -1.72 when computer and communication patents are excluded and to -1.47 when chemical and pharmaceutical patents are excluded. The responsiveness of patenting to import competition thus appears to be slightly greater, rather than smaller, outside of the dominant technological areas for manufacturing innovation.

In the estimation results considered so far, we weight observations by firm patents averaged over the start and end of period. Our motivation for doing so is to capture the impact of trade exposure on the overall scale of innovative activity in manufacturing. However, economists have long recognized that patent counts may provide an imperfect indication of the magnitude of innovations by a firm (Trajtenberg, 1990). Only a small share of patents lead to major innovations, with the rest mattering relatively little for firm profitability. Citations of a patent in subsequent patent applicants is a commonly used metric of the importance of an innovation (Jaffe and Trajtenberg, 2002).

With this reasoning in mind, column (5) of Table 5 reports estimates where we weight observations by the total number of subsequent citations to each firm's start-of-period and end-of-period patents. Relative to the baseline results in column (1), citation weighting produces a modestly larger negative estimated impact of trade exposure on firm patenting (-1.53). This suggests that greater import competition is more consequential for patenting by firms that tend to create more influential innovations. An alternative measure of a firm's innovative heft is its total spending on R&D. R&D is an input to innovation rather than an output, as noted above, and thus may imperfectly reflect a firm's contribution to technological progress. Still, R&D offers an intuitive measure of a firm's attempts to advance the technology frontier. Weighting by firm global R&D spending, shown in column (6) of Table 5, yields even larger impacts of trade exposure on firm patenting (-2.17), when compared to patent-citation weighting in column (5) or patent-count weighting in column (1). Finally, in column (6) we employ perhaps the simplest metric of firm capability, which is its global sales. Coefficients based on sales-weighted observations (-2.01) are slightly smaller than those based on R&D weights but still much larger than those for our baseline patent-count weights. We conclude that our approach of weighting firm-years by patent counts produces a conservative estimate of the impact of greater import penetration on the change in firm patenting.

3.3 Additional Firm-Level Outcomes

The estimation results in Tables 3, 4 and 5 provide robust evidence that U.S. firms exposed to greater increases in import competition from China have experienced relatively large reductions in patenting. To conclude our analysis, we explore possible mechanisms behind the negative impact of trade exposure on U.S. innovation.

Table 6: Effect of Chinese Import Competition on Firm Sales, Employment and R&D Expenditures, 1991-2007 and 1975-1991 (for Falsification Test). Dependent Variable: Relative Change in Sales, Employment and R&D.

	US Sales		Global Sales		Global Employment		Global R&D Expenditure	
	(1)		(2)		(3)		(4)	
			I. Exposure Period 1991-2007					
Δ U.S. Industry Exposure to Chinese Imports	-1.15		-0.83	*	-0.75	**	-0.87	**
	(0.76)		(0.36)		(0.28)		(0.33)	
No. Observations	1717		2380		2176		1886	
			II. Pre Period 1975-1991					
Δ U.S. Industry Exposure to Chinese Imports	0.17		0.01		0.10		0.27	
	(0.30)		(0.26)		(0.21)		(0.34)	
No. Observations	1495		1649		1580		1183	

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from model 3i in table 2. The relative change of an outcome variable is defined as the first difference in the outcome over a period t,t+1, divided by the average of the outcome across the two periods t and t+1. Panel II provides falsification test that regress the change in outcomes on the future increase in Chinese import penetration, averaged over the 91-99 and 99-07 periods. All models are weighted by number of patents in a firm, averaged over patents at the start and end of a period, and standard errors are clustered on 4-digit SIC industries. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

Perhaps the most concise explanation for our results is that greater foreign competition reduces firm profitability and thereby spurs firms to contract their operations along multiple margins of activity, including innovation. This logic of a negative equilibrium relationship between innovation and product-market competition underlies the seminal analysis in Dasgupta and Stiglitz (1980). In Table 6, we examine the impact of trade exposure on four alternative measures of firm outcomes: total sales in the U.S. market (column 1), total sales in the global market (column 2), total employment in the firm's global operations (column 3), and total R&D spending in the firm's global operations (column 4).[25] In all four specifications, the estimated impact of a change in industry

[25] Firms' U.S. employment and R&D spending would also be of interest for this analysis, but are not observed in

import penetration on the change in firm activity is negative; the impact coefficient is statistically significant for three of the four outcomes, global sales, global employment, and global R&D expenditure. These results drive home the breadth of the competitive consequences that import growth from China has meant for U.S. manufacturing firms. It is not simply that U.S. production employment has contracted. Sales revenues worldwide and aggregate firm investments in new technology have diminished as competitive conditions have tightened.

Many of the companies listed in CompuStat are multinational enterprises with subsidiaries located around the world. Most are owned by parent companies headquartered in the U.S., though some are owned by parent companies headquartered abroad. Through offshoring, multinational companies have relocated a substantial share of their U.S. manufacturing employment to their subsidiaries or to arms-length contractors located in other countries (Harrison and McMillan, 2011). As a final set of exercises, shown in Table 7, we examine whether greater import competition may have had differential effects on innovation at home versus innovation abroad in a manner analogous to the impacts of trade on the global location of employment engaged in production.

The data allow us to track the location of innovation via the address of the lead inventor listed in the patent. In its worldwide operations, IBM, for instance, has 12 R&D labs located in 10 different countries.[26] Presumably, patents created in one of IBM's three U.S.-based labs would list the lead inventor as being located domestically, whereas patents created in one of IBM's labs in Australia, China, Israel, Japan, or Switzerland would list the lead inventor as being located abroad. To review the sample definitions discussed in section 2, our baseline specification includes in the analysis all CompuStat firms, whether or not the firm's parent company is U.S. owned. It also restricts patents to those whose lead inventor has a U.S. address. In what follows, we differentiate between firms that are owned by a U.S. parent company versus a foreign parent company and expand the sample to include patents created by inventors located abroad.

CompuStat except for a small number of firms over a short time period.

[26] See https://www.research.ibm.com/labs/.

Table 7: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007: Alternative Firm and Inventor Samples. Dependent Variable: Relative Change of Number of Patents.

	Relative Change of Patents								
	All Firms, Inventors	All Firms, US Inventor	All Firms, Foreign Inventor	US Firm	US Firm, US Inventor	US Firm, Foreign Inv.	Foreign Firm	Foreign Firm, US Inv.	Foreign Firm, For. Inv.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ U.S. Industry Exposure to Chinese Imports	-1.00 **	-1.31 **	-0.83 **	-1.12 *	-1.11 *	-1.40 *	-0.97 **	-1.87 **	-0.80 *
	(0.34)	(0.45)	(0.29)	(0.48)	(0.50)	(0.56)	(0.35)	(0.52)	(0.34)
No. Observations	9213	8127	3161	7906	7916	2049	1307	643	1112

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from model 3i in table 2. The relative change in patents is defined as the first difference in patents over a period t,t+1, divided by the average number of patents across the two periods t and t+1. Column 1 uses all patents of the U.S. patent office that could be matched to Compustat. The subsequent columns use subsamples of patents defined based on the location of a patent's main inventor (as observed on the patent), and based on the location of the firm's headquarters (as observed in the most recent Compustat data). All models are weighted by number of patents in a firm, averaged over patents at the start and end of a period, and standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In column (1) of Table 7, we expand the set of firm patents to include all inventors, whether based in the U.S. or abroad; in column (2), we repeat the baseline result for U.S.-based inventors; and in column (3), we limit patents to those created by foreign-based inventors. The impact of import competition on patenting by foreign inventors (-0.83, column 3) is negative and precisely estimated but substantially smaller than in the baseline specification for U.S. inventors (-1.31, column 2). Though the difference in magnitude between these two coefficient estimates is not statistically significant, the results offer suggestive evidence that greater U.S. import competition affects innovation in firms' U.S. facilities by more than in firms' foreign facilities.

If trade shocks hitting U.S. manufacturing affect patent creation in the U.S. more than patent creation in other countries, one may expect that we would see a comparable pattern of impact effects when separating firms according to the nationality of ownership. To explore this possibility, in columns (4) to (6) of Table 6, we restrict firms to those whose parent company is headquartered in the U.S., and in columns (7) to (9) we restrict the sample to firms whose parent company is headquartered abroad. For both samples, we examine impacts of trade exposure on all patents, patents with a U.S.-based lead inventor, and patents with a foreign-based lead inventor. Columns (1), (4), and (7) reveal similar impacts of trade exposure on global patenting by inventors regardless of location. The effect is modestly larger for U.S.-owned firms (-1.12, column 4) than for foreign-owned firms (-0.97, column 7), but the difference is slight. More substantive differences between U.S. and foreign-owned firms emerge when we examine impacts according to the location of invention. Whereas in U.S.-owned firms, greater trade exposure affects patenting by foreign-based inventors (column 6) more than patenting by U.S.-based inventors (column 5), we see the opposite pattern in foreign-owned firms, with trade exposure having larger impacts on U.S.-based inventors (column 8) than on foreign-based inventors (column 9). Though it is possible to interpret this pattern as reflecting home-bias in firm's innovation priorities (e.g., shielding domestic operations at the expense of foreign operations), the large standard errors in those sub-samples of the data caution against drawing strong inferences. What is clear is that we see substantial negative impacts of greater import competition on U.S. patenting, regardless of the nationality of firm ownership or the location of firm innovation teams.

4 Discussion

Does innovation offer U.S. manufacturing firms an avenue of escape from escalating import competition? Our analysis suggests that the answer is no. Firms in industries that have seen larger increases in import penetration from China have suffered larger reductions in patenting, both in their U.S. and foreign R&D facilities. This finding emerges once we control for persistent broad sectoral trends in innovation and remains after adding extensive controls for industry and firm-level characteristics associated with more rapid productivity growth.

A second avenue for firms to insulate themselves from greater trade exposure is to change their main line of business. Famously, IBM has largely given up producing computers to focus on software and business services. In 2004, IBM sold the intellectual property surrounding its ThinkPad laptop to Lenovo, a Chinese company, which now manufactures and markets the product. However, IBM's experience appears to be the exception and not the rule. There is little evidence that U.S. corporate entities change their primary industry of operation in response to greater foreign competition. Distinct from results for European firms identified by Bloom, Draca, and Van Reenen (2016), we find that greater import competition causes U.S. firms to contract along every margin of activity that we observe, including innovation. However U.S. manufacturing manages to survive the competitive threat from China, innovating their way out does not appear to be a prevalent strategy.

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