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, which in theory could benefit or stifle innovation. In this paper we empirically examine how rising import competition from China has affected U.S. innovation. We confront two empirical challenges in assessing the impact. 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. Accounting for secular trends in innovative activities, 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

What impact does foreign competition have on domestic firms' capacity to innovate? This issue has grown in importance over the past two decades with the rise of China and other developing economies as major players in the global economy. As China 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). Although a now substantial literature evaluates the impact of China's rise on such outcomes as plant closures (Bernard, Jensen, and Schott, 2006), industry employment (Pierce and Schott, 2015; Acemoglu, Autor, Dorn, Hanson and Price, 2016), worker incomes (Autor, Dorn, Hanson, and Song, 2014), and local labor market conditions (Autor, Dorn, and Hanson, 2013), far less is known about the impact of trade on innovative activities at the firm or industry level. Manufacturing still generates more than two-thirds of U.S. R&D spending and U.S. corporate patents despite accounting for less than one-tenth of U.S. private non-farm employment.[1] The relationship between competition in the global marketplace and the creation of new products and production processes is thus one of immense importance for the U.S. economy.

In theory, the effect of more intensive product-market competition on innovation is ambiguous.[2] 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, 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

[1]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, manufacturing accounts for 71% of all corporate patents with U.S.-based inventors and an application year of 2007.

[2]For reviews of the literature on competition and innovation, see Gilbert (2006) and Cohen (2010).

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 could raise the incentive for investing in innovation and the acquisition of knowledge. At the same time, if offshoring causes R&D and production to occur in locations that are distant from each other, innovation may be compromised (Fuchs, 2014; Arkolakis, Ramondo, Rodriguez-Clare, and Yeaple, 2016), 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 remains intrinsically an empirical question, and the relationship may differ across countries, episodes, and competitive structures. In the European context, Bloom, Draca and Van Reenen (2016) find that in response to greater import competition from China, firms create more patents, expand investment in information technology, and have higher TFP growth.[3]

In this paper, we study how import competition affects U.S. 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 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. We address the common problem of inconsistent or misspelled names of firms on patent records by developing a fully automated and scalable algorithm that harnesses the machine-learning capabilities of Internet search engines.[4] Compared to the traditional matching methods that rely on string matching and manual inspections (e.g., the NBER Patent Data Project), our method significantly improves efficiency without sacrificing accuracy. Our approach allows us to assign 72% of all corporate patents by U.S. inventors to a known entity in Compustat.[5]

[3]These impacts of course apply only to surviving firms. Consistent with empirical literature on 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.

[4]Patent filings on behalf of IBM, for instance, utilize more than 140 different spellings of the company's name. Existing methods use strings matched on standardized firm names (Bessen, 2009; Belezon and Berkovitz 2010; Bloom, Draca, and Van Reenen 2016). Absent manual intervention, however, string matching has limited ability to capture all possible name variations of firms, resulting in many false negative matches.

[5]Relative to string matching on firm names alone, our automated algorithm that leverages web engine technology increases the number of patents that are matched to Compustat records by 29% over all years in our sample, and

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) for Europe. 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. We analyze patenting over the long time window of 1975 to 2007, which commences well before China's rise as an exporter of manufactured goods. This long-term perspective reveals a secular growth in patenting in the computer and electronics industries and a secular stagnation of patenting in chemicals and pharmaceuticals, which are two of the most important sectors for innovation. Both of these trends predate the Chinese import competition of the 1990s and 2000s, which was much stronger in the computer and electronics industries than in industries that create new chemical patents. Given 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 by non-publicly listed corporations, foreign firms in the U.S., or foreign-based inventors employed by U.S. firms.

Further analysis reveals that greater import exposure also has negative impacts on a range of firm outcomes, including global sales, profit growth, global employment, and global R&D spending.[6] Our findings of negative impacts of trade exposure on firm R&D outlays helps allay concerns that our results on patents could reflect not a trade-induced decrease in innovation, but rather import competition causing firms to withhold their innovations from patenting in order to avoid releasing their intellectual property into the public domain. Such strategic non-disclosure of innovation would imply that trade impacts on patenting and R&D spending work in opposite directions, which they do not. We also provide evidence that firms with weaker initial performance tend to experience larger reductions in patenting in response to adverse trade shocks. Together, our results suggest that the China trade shock reduces firm profitability in U.S. manufacturing, leading firms to contract

by 44% in the final application year 2007. Our final sample of patents additionally incorporates a modest fraction of manually matched patents. For comparison, Compustat firms accounted for 62% of R&D in the U.S. in 1995 (Bloom, Schankerman, and Van Reenen, 2013). Unmatched corporate patents include those that belong to non-publicly traded firms, or to publicly traded firms whose names on patents and in Compustat records could not be linked in any step of our matching procedure.

[6] For similar findings on the connection between import exposure and firm sales and employment, see Hombert and Matray (2016). They find additionally that trade impacts are weaker in firms that are more intensive in R&D.

operations along multiple margins of activity, including innovation.

To our knowledge, we are the first study to provide a comprehensive analysis on how the recent import competition from China affects various measures of innovative activities of U.S. firms. Scherer and Huh (1992) provide early 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 penetration reduces R&D-sales ratios. Other current work also documents a negative impact of import competition on R&D spending among Compustat firms (Arora, Belenzon, and Patacconi, 2015; Gong and Xu, 2015).[7] By focusing on patenting activity and improving the matching of patents to companies, we capture a much larger set of firms[8] and study both innovation inputs and outputs.[9] Much recent literature is hampered by the temporal coverage of the NBER Patent Data Project, which at present links patents to their Compustat firm owners only for patents granted by 2006, many applications for which would have been submitted up to six years earlier, before China's accession to the World Trade Organization in 2001 and subsequent export surge. Our patent-firm matching algorithm allows us to extend the data forward in time to 2013 and therefore cover a substantial period after China's WTO entry and prior to the Great Recession. Our paper is also related to prior empirical work on the relationship between innovation and globalization in the 1990s (Gorodnichenko, Svejnar, and Terrell, 2010; Coelli, Moxnes, and Ulltveit-Moe, 2016) and on trade liberalization and industry productivity (Pavcnik, 2002; Trefler, 2004; Teshima 2010; Dunne, Klimek and Schmitz 2011; Eslava, Haltiwanger, Kugler, and Kugler, 2013; Halpern, Koren and Szeidl, 2015; Chen and Steinwender, 2016).

In section 2, we discuss our data and methods, along with descriptive analyses of trends in industry innovation and trade exposure. In section 3, we present our baseline estimation results. In section 4, we describe additional estimation exercises. We conclude in Section 5 with an interpretation of our results and a discussion of potential reasons why our results for the U.S. differ from those of Bloom, Draca, and Van Reenen (2016) for Europe.

[7] In correlational analysis, Arora, Belenzon, and Patacconi (2015) study the relationship between import exposure, patenting, and scientific publications. Distinct from our work, they find a positive correlation between import competition and patenting. The absence of exogenous sources of import exposure and controls for sectoral time trends in their analysis may account for differences with our results.

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

[9] For discussions on patents as a measure of innovation, see Jaffe and Trajtenberg (2002) and Moser (2016). For empirical work on the private economic values of patents, see Hall, Jaffe, and Trajtenberg (2005) and Kogan, Papanikolaou, Seru, and Stoffman (2016).

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 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 that we can match to U.S. manufacturing industries.[11]

The year 1991 also coincides with the rapid acceleration of export growth in China. Between 1984

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

[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.

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, 2016), 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 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] As documented by Autor, Dorn and Hanson (2016), all eight comparison countries

[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.

[14]Modeling the China trade shock as in (1) does not exclude a role for global production chains. During the

used for the instrumental variables analysis witnessed import growth from China in at least 343 of the 397 total set of manufacturing industries. Moreover, cross-country, cross-industry patterns of imports are strongly correlated with the U.S., with correlation coefficients ranging from 0.55 (Switzerland) to 0.96 (Australia). That China made comparable gains in penetration by detailed sector across numerous countries in the same time interval suggests that China's expanding product variety, falling prices, rising quality, and diminishing trade and tariff costs in these surging sectors are a root cause of its manufacturing export growth.

A potential concern about our analysis is that we 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 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 U.S. 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 (Cohen, 2010), we measure innovation using utility patents. 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 detailed 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; and the residential address of listed inventors, which we

1990s and 2000s, approximately half of China's manufacturing exports were produced by export processing plants, which import inputs from abroad and assemble them 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 U.S.), as would be the case if, plausibly, the recent expansion of global production chains involving China is primarily the result of its dramatically expanded manufacturing capacity. For work on the impact of globalization on innovation within U.S. firms that utilize offshore production facilities in China, see Bena and Simintzi (2016).

[15] A further rationale for focus on imports 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 exports are difficult to measure because the direct exporter may be a foreign affiliate of a U.S. multinational, they occur via a chain of transactions involving third countries, or they take the form of difficult-to-detect trade in services.

[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 for a patent application was 34 months, with considerable variation around that mean (Lerner and Seru, 2015).

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; Jaffe and Rassenfosse, 2016). In extensions of our main results, we use citations to weight patents as a means of approximating their innovative value.

We use the U.S. Patent and Inventor Database, which covers patents granted by the U.S. Patent and Trademark Office (USPTO) between 1975 and March 2013.[17] 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 within six years, right censoring (i.e., patents applied for but not yet granted) is unlikely to pose a serious problem for our analysis.[18]

Despite providing a wealth of information, patent records notably lack either a unique firm identifier variable or an industry code. The lack of industry information in the patent records cannot be readily overcome by using a patent's technology class. While the 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 provide an unreliable guide to 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 Compustat North America, which covers US, Canadian, and foreign companies with at least one regularly, actively, and publicly-traded issue listed on a US or Canadian exchange with a minimum price of at least $0.01 and which regularly file financial reports.[19] In addition to industry, Compustat also contains information on firms' 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 and to observe other firm-level characteristics and outcomes. 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). Following Hall, Jaffe, and

[17] The data files are available at https://github.com/funginstitute/downloads. See Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014) for a description of the data.

[18] In our data, the mean difference between the patent grant year and patent application year is 2.5 years (standard deviation 1.5 years).

[19] These include foreign companies that use American Depository Receipts (ADRs).

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.

A key challenge in matching patents and firm-level data is that inconsistencies in how firm names are recorded on patents generate many 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 in the patent data, makes it challenging to correctly group patents belonging to the same firm. IBM, for instance, has over 140 different spellings on its patents and is variably listed as International Business Machines, IBM, IBM Corporation, IBM Corp, etc. (see Appendix Table A1). 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, such as linking IBM to International Business Machines. Moreover, the data contains dozens of entries for assignees such as International Business Machine, International Bussiness Machines, and Information Business Machines, which are likely misspellings 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 either 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 with those granted by 2006.

We improve on existing methods and extend the match to 2013 by developing a 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 abbreviates or misspells the name of his or her employer on a patent application (e.g., International Bussiness Machines), it is likely that others have made the same mistake when searching for the company online. If International Bussiness Machines 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. Our approach is readily scalable and generalizable to the matching between any two firm-level datasets (and many other applications).

We utilize a four-step matching procedure. First, following NBER PDP, we clean the firm names (e.g., removing punctuation 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.[20] Columns (4a-b) of Table 1 show that name matching alone allows us to assign 50% of all corporate patents by U.S.-based inventors to firms in Compustat over our sample period.[21] However, the performance of name matching deteriorates notably over time, with a match rate that falls from 59% of corporate patents in 1975 to just 44% of patents in 2007, likely due to the increasing variety of inconsistent and misspelled firm names over time. Next, we search the name of each patent assignee and each Compustat firm (entered in quotation marks and clean of punctuation and accents) 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 a patent assignee and a Compustat firm to be a match if the top search results for the patent assignee contain the company website listed in Compustat. We also consider them a match if the top five search results for the patent assignee and the Compustat firm share at least two URLs in common. Columns (5a-b) in Table 1 show that web-based matching alone allows us to match 64% of corporate patents to Compustat firms. The internet-based matching yields a roughly constant match rate of 62 to 66% in each year of the sample. Pooled over all years, web matching links 26% more patents to Compustat than name matching (152,445 vs. 120,583). The relative gain is even larger in terms of assignee-years (distinct firm name strings that appear on the patents of a given year), where the match rate of the internet-based algorithm is 57% higher (14,278 vs. 9,085), as it is able to detect multiple variations of a firm's name in the patent records. In the final two steps of our matching procedure, we maximize sample size by appending to our data the manual matching between assignees and Compustat firms from NBER-PDP that our method has failed to capture, and then ourselves manually match a few large assignees that remained unmatched after the previous procedures.[22] Our final sample links 72% of all corporate patents to Compustat (column 2b of Table 1), compared to a match rate of 65% in the NBER-PDP up to the application

[20] In rare cases, the same patent assignee can be matched to multiple Compustat firm records, which are usually due to the same firm having multiple listings in Compustat. We apply tiebreakers based on the availability of segment sales data, historical industry affiliation, and R&D spending data.

[21] Table 1 describes the matching for patents that were applied for in the five years on which we will base most of our empirical analysis. Because our matching algorithm is easily scalable, we have also executed the matching of patents to Compustat records for all other patent application years from 1975 to 2007.

[22] Appendix Table A3 shows the share of the final sample of patents (and of assignee years) accounted for by each matching method. Across all years, name matching identifies 120,583 patents (70% of the sample), while web-based matching adds another 34,495 patents that would have been missed by name matching (20% of the sample). The fully automated matching algorithm thus links 90% of the patents in our sample, and we further improve the match rate by adding a modest number of patents that were manually matched in the NBER-PDP project (7% of the sample), or by ourselves (3% of the sample).

year 1999 (column 3b).

Appendix Table A1 provides a more detailed illustration of the success of our patent matching for the case study of IBM. Name matching alone successfully links the two most frequent name variations of IBM, but misses the dozens of alternative spellings. Web matching greatly improves the success of the automated matching by identifying 67 of the 70 most frequent name variations. The number of patents that are matched to IBM by our methodology corresponds extremely closely to the patent total that IBM states in its annual company reports. When sorting patents by the year in which they are granted (rather than the application year which is used in the empirical analysis below), we find that for each year between 1994 and 2012, our sample comprises between 99.5% and 100% of IBM's self-reported patent output. At least in case of IBM, our strategy of matching assignee names to firm records produces very few false negatives or false positives.

Table 1: Alternative Matches between Patent Data and Compustat Data

	All US Inventor Corporate Patents	A. ADHPS vs NBER-PDP Match				B. Name Matching vs. Web Matching			
		ADHPS	% Matched	NBER-PDP	% Matched	Name Matching only	% Matched	Web Matching only	% Matched
	(1)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
				I. Number of Patents					
1975 Patents	29,930	22,531	75%	20,785	69%	17,630	59%	19,619	66%
1983 Patents	24,918	18,696	75%	17,459	70%	14,704	59%	16,306	65%
1991 Patents	38,091	27,094	71%	24,851	65%	20,324	53%	23,714	62%
1999 Patents	74,496	53,617	72%	45,784	61%	36,671	49%	48,033	64%
2007 Patents	71,675	49,900	70%	0	0%	31,254	44%	44,773	62%
All Years	239,110	171,838	72%	108,879	46%	120,583	50%	152,445	64%
				II. Number of Assignee-Years					
1975 Patents	6,314	1,942	31%	1,614	26%	1,131	18%	1,392	22%
1983 Patents	6,207	2,010	32%	1,662	27%	1,149	19%	1,440	23%
1991 Patents	10,113	2,904	29%	2,239	22%	1,592	16%	2,184	22%
1999 Patents	19,525	6,493	33%	4,668	24%	3,190	16%	5,372	28%
2007 Patents	16,140	4,275	26%	0	0%	2,023	13%	3,890	24%
All Years	58,299	17,624	30%	10,183	17%	9,085	16%	14,278	24%
				III. Avg. Number of Patents per Assignee-Year (All Years)					
Matched Assignees		9.8		10.7		13.3		10.7	
Unmatched Assignees		1.7		2.7		2.4		2.0	

Notes: The NBER-PDP project matched patents granted up to the year 2006 to Compustat firms, and therefore does not cover any patents with application year 2007. Of the 71,675 corporate patents with U.S. inventors in 2007, 36,966 had an assignee that had been matched to a Compustat firm by NBER-PDP in a previous year, which implies that 47% of the 2007 patents could be matched to the firm data using information from NBER-PDP. For the applications years up to 1999, we match 73% of all patents and 32% of all assignee-years to Compustat while NBER-PDP matches 65% of patents and 24% of assignee-years.

Our Compustat data cover public firms that were listed on the North American stock markets 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 a patent before going public, we are able to determine an industry affiliation for the firm using the industry assignation in Compustat after its listing. To this end, our baseline estimations will assign firms to industries using 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 assign firms to their past industry, and to construct a firm-specific measure of trade exposure based on equation (1), using as weights the share of the firm's sales in each industry in which it operates. Or results are robust to these various schemes for assigning industry codes to firms.

Table A2 summarizes the final 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.[23] Of these U.S.-based patents, 239,110 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.[24] 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 72% to Compustat firms, which provide industry codes for nearly all matched firms. The 171,838 patents in the matched sample correspond to 17,624 assignee years, implying that we observe 9.8 patents per year on average for patent assignees that have been matched to Compustat. For assignee names that we failed to match, there are only 1.7 patents on average per assignee-year, which is consistent with the interpretation that unmatched patents either belong to small firms that never went public and are thus missing from Compustat, or to very unusual spellings of a public firm's name that our procedure failed to link to the corresponding Compustat record.

2.3 Trends in Industry Patenting and Trade Exposure

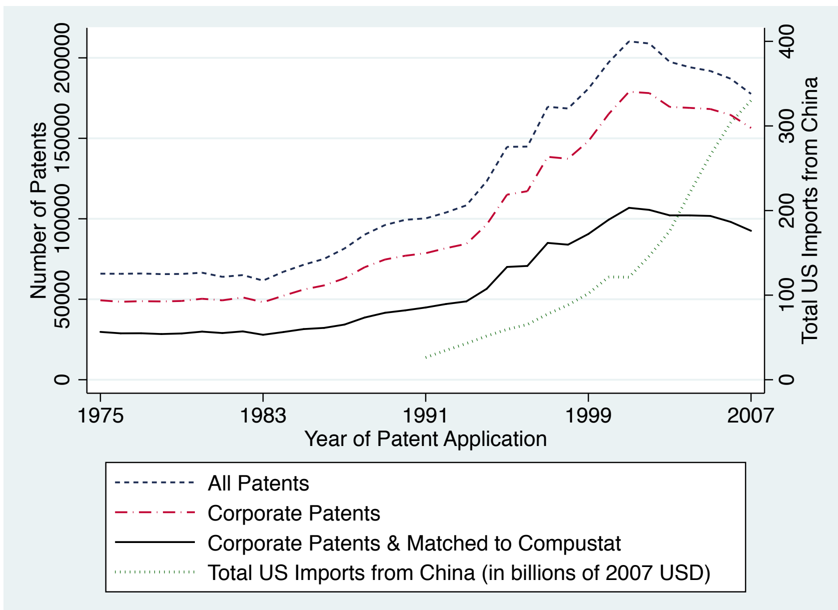
Panel A of Figure 1 plots by year of patent application, the total number of U.S. patents, corporate patents, and our sample of corporate patents matched to Compustat firms; panel B of Figure 1 repeats these plots limiting patents to those by primary inventors who are based in the U.S. All six series show the same trend: there is a sharp rise between 1983 and 1999 and a modest decline

[23] Patents with a U.S. primary inventor make up 98% of all patents with at least one U.S. inventor.

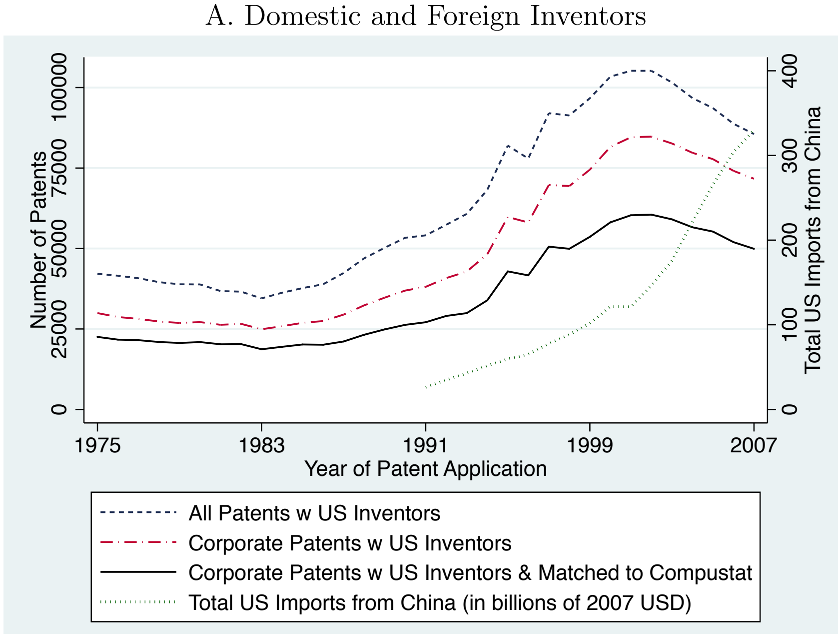
[24] The self-reported categorization variable comes from USPTO but is noisy. We identify universities, institutions, hospitals and government agencies using key words in assignee names following the NBER-PDP.

between 1999 and 2007. The timeline of U.S. imports from China follows a different pattern, with a rapid increase between 1991 and 1999, and even faster growth after 1999. The match rate of U.S.-inventor corporate patents to Compustat firms (lower panel of Figure 1) declines modestly over time, from 75.3% in 1975 to 71.1% in 1991 and 69.6% in 2007, most likely because the share of privately held firms among U.S. corporations has risen over the past several decades (Doidge, Karolyi, Stulz, 2015).

Figure 1: Number of Patents by Application Year



A. Domestic and Foreign Inventors



B. Domestic Inventors

The literature provides various explanations for the slowdown in patenting in the early 2000s.[25] These include the exhaustion of technological opportunities (Gordon, 2012), the lasting effects of the post-2001 dot-com bust (Jorgenson, Mun, and Stiroh, 2008), strategic non-disclosure of patents by firms so as not to reveal their intellectual property (Boldrin and Levine, 2013), and the increasing stringency of patent examiners (Carley, Hegde, and Marco 2015). These developments represent potentially confounding factors for which we must control in the empirical analysis. We address the first and second factors by including an extensive set of controls at the industry and firm level and by utilizing alternative weighting schemes that distinguish patents by their citations and firms by their size or R&D spending. We deal with the third and fourth factors by verifying that the impact of import competition on innovation is qualitatively the same for innovation inputs (R&D spending) and observed innovation outputs (patenting).

The similarity of the time series for overall U.S. patents, corporate patents, Compustat-matched patents, and patents by U.S. inventors in Figure 1 masks important heterogeneity in patenting across sectors. Appendix Table A4 shows the fraction of successful patent applications in 1975, 1983, 1991, 1999, and 2007 accounted for by 11 major manufacturing sectors, sorted by their share in overall manufacturing patents in 1991. In 1991, which is the beginning of the sample period for our analysis, just two sectors, chemicals and petroleum and computers and electronics, comprised 45.4% of all patents and 55.2% of patents by manufacturing companies.[26] This sectoral concentration of innovation is both persistent and accelerating. In 1975, the two sectors already accounted for 45.8% of manufacturing patents and by 2007, their collective share of patents had reached 63.2%. However, there has been a dramatic reordering among these top two sectors in terms of which is the locus of innovation. The share of the chemicals and petroleum sector in total manufacturing patents declined from 33.4% in 1975 to 29.1% in 1991 and then fell to 13.4% in 2007. The disaggregation of patents by technology class in panel II of Appendix Table A4 suggests that the declining share of chemicals in overall patenting is not primarily the result of a slowdown in breakthroughs in drugs or medical devices, but rather follows from a reduction in patenting in other parts of the chemical sector. Whereas the share of drug and medical patents in total patents is largely unchanged between 1991 and 2007 (declining from 9.0% to 8.8%), other chemical patents see their share fall precipitously

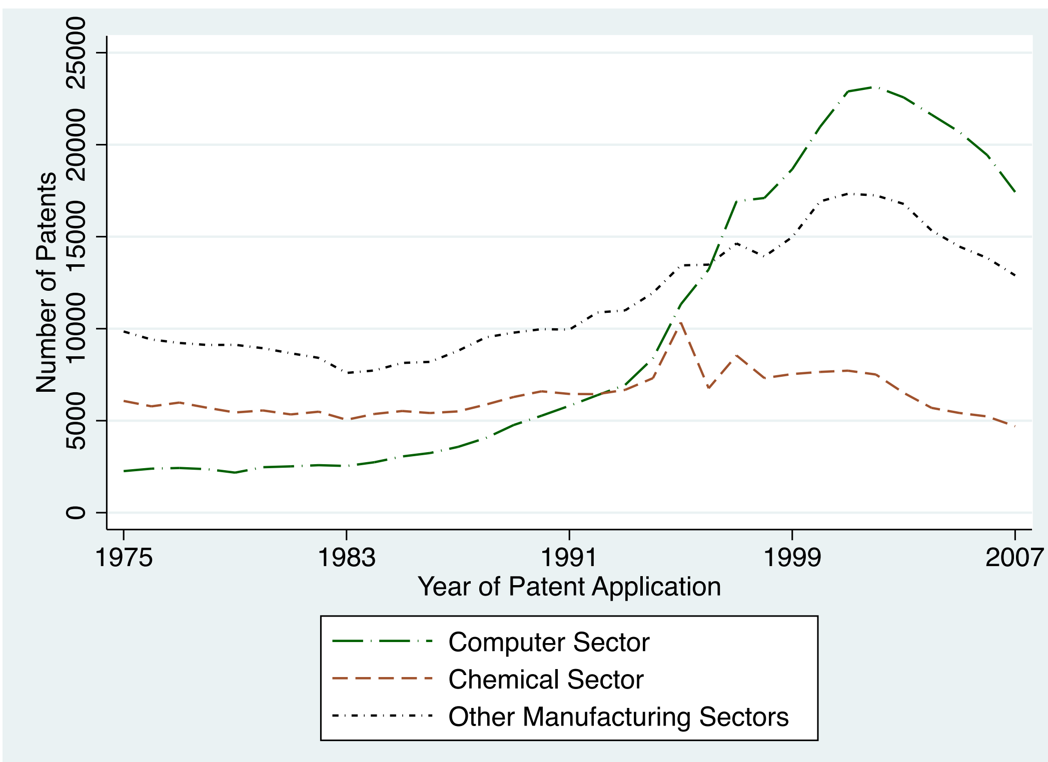
[25] Over the time period we examine, there is a jump in patenting by China both domestically and in the U.S., though the quality of these inventions appears to be low (Hu and Jefferson, 2009; Boeing and Mueller, 2016).

[26] Chemicals and petroleum include the two-digit SIC industries 28 and 29. 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).

from 23.7% of patents in 1991 to 8.4% in 2007. Computers and electronics, buoyed by the revolution in information technology, have displaced chemicals as the most prolific sector for the creation of new patents. The sector's share in manufacturing patents expanded from 12.4% in 1975 to 26.1% in 1991, and reached fully half (49.8%) of all patents by manufacturing firms in Compustat in 2007. By technology class, patents in computers, and communications rose from 8.0% of all patents in 1975 to 44.0% in 2007, while the patent share of electric and electronic technologies also expanded.

Figure 2 plots the time series of eventually successful patent applications by U.S. based inventors for the whole period of our data, while distinguishing patents from the chemical, computer, and all other manufacturing sectors. The stark difference in the sectoral trends for chemicals and petroleum, and for computers and communication patents is readily apparent. Chemical patents declined not only in their share of total patents, as discussed above, but also in absolute numbers. Successful patent applications from the computer sector in contrast expanded rapidly between the early 1980s and the early 2000s.

Figure 2: Number of Patents by Application Year and Broad Sector



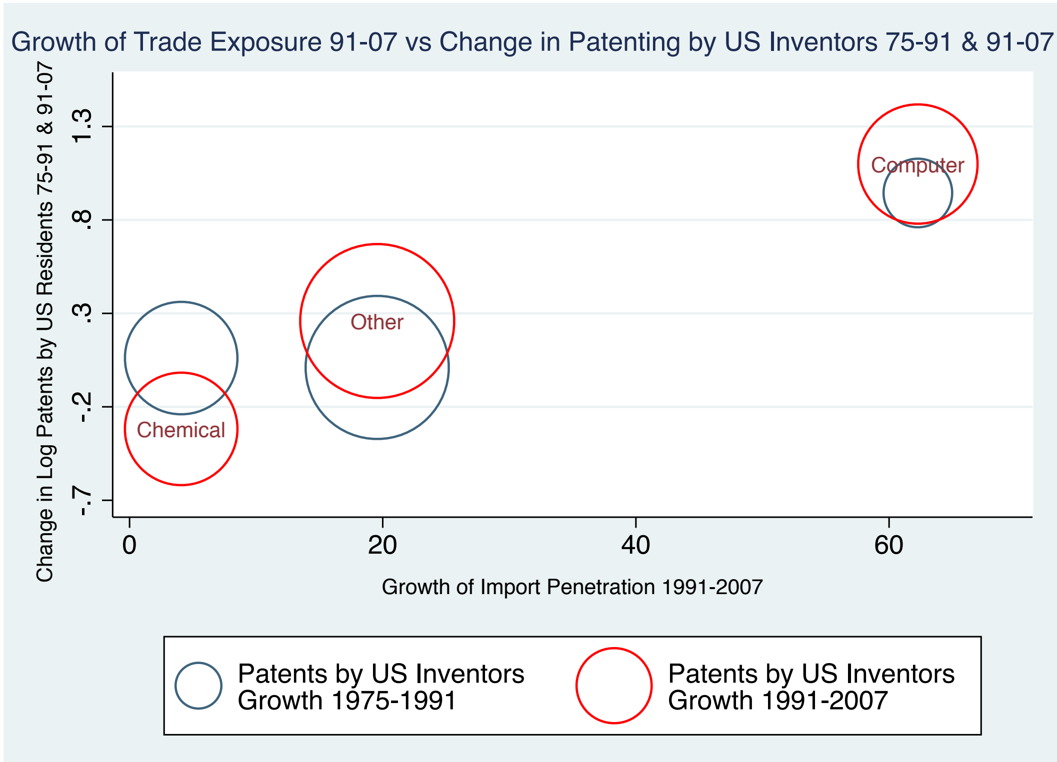
The number of patents in other manufacturing sectors, and their contribution to total patents, changed more modestly over time. Appendix Table A4 indicates that the third and fourth largest sectors in terms of patenting during the sample period, machinery and equipment and transportation, saw their combined share in manufacturing patents decline modestly over time, from 37.2% in 1975 to 33.2% in 1991 and 29.6% in 2007.[27] 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 1.3% of patent applications by manufacturing firms 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 of successful patent applications.

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). In parallel to the opposite sectoral trends in patenting, there is evidence that returns to R&D expenditure have increased in the computer sector and declined in pharmaceuticals (Hult 2014). Moreover, the broadening and strengthening of intellectual property protection for computer software patents has played an important role in the rise of computer patents, but there is limited evidence that strategic patenting has lowered the quality of computer patents or harmed firm performances (Graham and Mowery 2004; Bessen and Hunt 2007; Lerner and Zhu 2007).

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 for any reason correlated with industry import exposure. Figure 3 plots the change in log patent applications for 1991 to 2007 against the contemporaneous change in import penetration for three sectoral aggregates: computers and electronics, chemicals and petroleum, and all other manufacturing industries. 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 lie somewhere in between.

[27] Machinery and equipment comprises the two-digit SIC industries 35, 36 and 38, except for computers and electronics, while transportation corresponds to SIC industry 37.

Figure 3: Sectoral Patenting and Import Penetration from China, Pre-Sample and Sample Periods



As suggested by Figure 2, the post-1990 patterns in changes in patenting by sector correspond to longstanding differences in sectoral trends that commenced well before 1990. To characterize these innovation patterns, and their potential role as a confounding factor in our analysis, Figure 3 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.[28]

[28]The same sectoral patterns are also observed when we examine patenting by domestic and foreign inventors, rather than just the U.S.-based inventors who are shown in Figure 3.

3 Main Results

In the empirical analysis, we estimate the impact of changes in industry exposure to import competition from China on patenting, as measured by applications for ultimately successful patents, at the firm level.[29] 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 time 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 4,136 firms per period which in 1991, 1999, and 2007 collectively produced a total of 129,585 patents. Appendix Table A5 provides additional information on the firms in our sample which are observed in the base year 1991. In that year, we match patents to 31% of all the firms that are covered by Compustat, and to 57% of all Compustat manufacturing firms. Firms with patents are larger on average than those without. The average global sales, global employment and global capital of manufacturing firms with patents are four to six times larger than the corresponding variables for Compustat firms without patenting activity in 1991. The 57% of firms with patents thus account for 86% to 90% of all Compustat-recorded manufacturing sales, employment and capital. Most strikingly but plausibly, R&D expenditure is heavily concentrated in patenting firms. The firms with matched 1991 patents account for 97% of all R&D expenditure that Compustat records for that year, and more than 98% of R&D expenditure by manufacturing firms. We assign a firm to an industry based on its main industry code in Compustat, which is generally the most recent code. In

[29] To more closely reflect the date when an innovation occurs, our analysis uses the application date for ultimately successful patents rather than their award dates.

later results, we experiment with using historical industry codes for firms whose main code changes over time, and we analyze whether trade shocks affect the industry switches themselves. 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.

3.1 Baseline Estimates

Table 2 gives estimation results for (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 and negative for both 1999-2007 and the stacked first difference model. For stacked first differences (column 3), the coefficient of interest is not significantly different from zero in either the OLS (row a) or 2SLS regressions (row b).[30]

Moving beyond the univariate regressions in panel A, panel B adds controls to address persistent differences across sectors in patent creation. Apparent in Figure 2 are the divergent long-term trends of patenting in the most technology-intensive industries, computers and chemicals. In rows (c) and (d) of Table 2, we add dummy variables for just these 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 negative impact of industry import penetration on firm patenting increases in absolute value and becomes 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 3 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

[30]In analyzing the effect of competitive conditions on innovative activity, instrumenting for the trade shock from China is arguably less critical than in previous work studying the employment effects of the China trade shock (Autor, Dorn and Hanson, 2013). In that prior work, a key threat to validity is the possibility of unmeasured domestic demand shocks that cause Chinese imports and U.S. production to rise or fall in parallel, generating simultaneity bias between imports and domestic employment (confirmed by the pattern of results in Autor, Dorn, and Hanson, 2013). By contrast, the direction of OLS bias in the present analysis is unclear: if, for example, domestic firms' profits rise with greater U.S. demand, they may direct more resources towards innovative activity; alternatively, a rise in profits may reflect diminished competition, possibly lessening the incentive to innovate. While we do not have a strong prior on the direction of bias in OLS estimates, we rely on the IV models because the source of variation is well understood. Differences between OLS and IV estimates in this setting are, however, modest.

within these sectors.

Table 2: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007 and 1975-1991 (for Falsification Test). Dependent Variable: Change in Patents by US-Based Inventors (% pts), Relative to Mid-Period Number of Patents.

	I. Exposure Period: 1991-2007			II. Pre-Period: 1975-1991			III. Δ
	1991 - 1999	1999 - 2007	1991 - 2007	1975 - 1983	1983 - 1991	1975 - 1991	1991-07 - 1975-91
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				A. Models without Controls			
a. OLS, no controls	1.37	-0.45 *	-0.32	0.91 **	1.09 ~	1.02 *	-1.34 *
	(1.14)	(0.22)	(0.26)	(0.33)	(0.61)	(0.45)	(0.57)
b. 2SLS, no controls	0.40	-0.29	-0.26	1.06 *	1.70 *	1.44 **	-1.70 *
	(1.39)	(0.40)	(0.40)	(0.43)	(0.68)	(0.54)	(0.67)
				B. Models with Controls			
c. OLS, 2 mfg sector dummies	-0.87	-0.63 **	-0.91 **	0.36	-0.30	0.00	-0.92 *
(computers, chemicals)	(1.02)	(0.12)	(0.15)	(0.25)	(0.64)	(0.38)	(0.38)
d. 2SLS, 2 mfg sector dummies	-2.36 ~	-0.57 ~	-1.25 *	0.36	0.17	0.27	-1.53 **
(computers, chemicals)	(1.40)	(0.31)	(0.53)	(0.33)	(0.61)	(0.40)	(0.56)
e. 2SLS, 11 mfg sector dummies	-1.77	-0.46	-1.10 *	0.54	0.47	0.52	-1.62 **
	(1.16)	(0.34)	(0.51)	(0.41)	(0.68)	(0.49)	(0.62)
f. 2SLS, 11 mfg sector dummies +	-1.10	-0.50	-1.11 *	0.60	0.38	0.50	-1.61 **
industry controls	(1.26)	(0.34)	(0.48)	(0.44)	(0.55)	(0.43)	(0.55)
g. 2SLS, 11 mfg d. + industry/firm	-1.16	-0.52	-1.17 *	0.62	0.33	0.48	-1.65 **
controls	(1.06)	(0.34)	(0.48)	(0.42)	(0.58)	(0.43)	(0.54)
h. 2SLS, 11 mfg d. + industry/firm	-1.13	-0.72 *	-1.35 **	0.31	0.27	0.27	-1.63 **
controls + technology mix	(1.31)	(0.35)	(0.50)	(0.34)	(0.62)	(0.39)	(0.55)
i. 2SLS, 11 mfg d. + industry/firm	-1.29	-0.80 *	-1.39 **	n/a	n/a	n/a	n/a
controls + technology mix + 2 lags	(1.27)	(0.39)	(0.47)				
Mean Outcome Variable	65.37	-7.61	24.42	-18.65	36.46	10.33	19.88
No. Observations	4157	4114	8271	2437	3035	5472	13743

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 tests 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 column 7 indicates the difference between the import exposure coefficients of the column 3 and 6 models. Models (c) and (d) includes dummies for the computer/communication and chemical/petroleum industries. Model (e) includes a full set of dummies for 11 manufacturing sectors. Model (f) additionally includes 5 industry-level controls for production characteristics (production workers as a share of total employment, log of 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). Model (g) 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 (h) additionally controls for the fraction of a firm's patents that fall into each of the six major patent technology categories defined by Hall Jaffe Trajtenberg (2011), averaged over start-of-period and end-of-period patents. Model (i) 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. Standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The remaining rows of Table 2 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 Appendix Table A4; 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 Appendix Table A4, averaged over the start and end of period); and row (i) controls for lagged patenting (8-year and 16-year lags of the outcome variable).[31] Stacked-first-difference estimates in column 3 demonstrate 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 for the stacked first difference model without lagged outcomes (column 3, row h; our baseline specification henceforth), the parameter estimate of -1.35 indicates that a one standard deviation increase in import penetration from China (11.34) results in a 15.3 percentage-point decrease in patents.

Figure 3 offers suggestive evidence as to why the impact of import penetration on patenting is sensitive to controls for chemicals, computers, and 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 2. We project the change in firm-level patenting in the preceding 16-year period of 1975 to 1991 on the average change in import penetration over the periods 1991-1999 and 1999-2007. Paralleling the analysis for 1991 to 2007, we separate the analysis into two sub periods (1975 to 1983 in column 4, 1983 to 1991 in column 5) and estimate a stacked first difference model 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 illustrates the confounding pre-trends.

[31] To maintain a constant sample size over all specifications, missing values for the firm or industry controls in the row (f) and (g) models are replaced with a value of zero, and an indicator variable for each missing control is added to the regression models.

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 statistically insignificant 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 broad 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. The 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 -1.53 to -1.65. 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 2, 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, however, is comprised of firms, not plants, where any one firm may own hundreds of manufacturing establishments. Inducing changes in primary industry affiliation at the firm level is 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 3: Effect of Chinese Import Competition on Firm-Level Patenting, and on Probability of Industry and Segment Change, 1991-2007. Dependent Variable: Change in Patents by US-Based Inventors (% pts), Probability of Industry or Segment Change (% pts).

	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	-1.35	**	-1.33	**	-1.46	**	-1.34	**	-1.57 **	0.17	-0.58	0.37
	(0.50)		(0.49)		(0.54)		(0.50)		(0.58)	(0.24)	(0.63)	(0.42)
Mean Outcome Variable	24.42		24.42		24.42		27.86		27.05	16.24	51.16	56.90
No. Observations	8271		8271		8271		3160		2704	3160	2704	2704
No. Patents Used	129,585		129,585		129,585		102,431		94,910	n/a	n/a	n/a

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from column 3 model (h) 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 column 3 model (h) in table 2. The column 2 model 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 defines firm-level trade exposure by weighting industry-level import shocks with a firm's start-of-period distribution of sales across industries. If sales by industry segment are unavailable, then trade exposure is defined as in the column 2 model. Columns 4 and 5 only retain firms for which a historical industry code or historical segment data is available both for the start-of-period and end-of-period year. The column 6 model uses the same sample and industry definition as column 4, and estimates the probability that a firm will have a different industry code at the end of a period than at the start. Columns 7 and 8 use the same sample and industry definition as column 5, and estimate the probability that a firm has positive sales in an industry segment only at the end of a period (entry into new industry segment, column 7) or only at the start of the period (exit from industry segment, column 8). All models are weighted by number of patents in a firm, averaged over patents at the start and end of a period. Standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In Table 3, we compare our baseline results in column 1, taken from column 3 and row (h) of Table 2, 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. Historical industry codes are available for a subset of the firms in our sample as of the late 1980s. 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 minimally from -1.35 in column 1 to -1.33 in column 2 and retains its statistical significance when using this modification. In column 3, we incorporate information on historical firm sales by industry, again available for a subset of firms since the late 1980s. Where such data is available, we construct a firm-level measure of trade exposure, defined as the average import penetration across all industries in which the firm was active in a given year, weighted by firm sales across these industries. Again, a firm's main historical or its most recent industry code is used when such segment sales data are unavailable. The resulting coefficient estimate on trade exposure rises modestly in absolute value when compared to column 2. In column 4, we retain just those firms for which a historical industry code is available both at the start and end of the respective period, meaning we retain only 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 nearly identical to that in column 2, although it is computed based on a substantially smaller set of firms. 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 just includes 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 3, 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.[32] The impact of import penetration on industry switching is positive but small and quite imprecisely estimated (t-ratio of 0.71). A one-standard-deviation increase in import penetration produces only a 1.6 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.

In Table 4 we provide additional robustness tests on our main results. First, we address the concern that the implicit maximum permissible time to patent approval varies over the sample period, since 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 4, 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

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

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 8,271 in our baseline specification in column 1 to 8,167 in column 2, and the number of patents used for the analysis declines from 129,585 to 127,654. The coefficient estimate on import penetration with the six-year patent approval restriction (-1.37) is nearly identical to that in the baseline (-1.35), suggesting that right censoring in patent approval times is of little consequence for the results.

Table 4: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007: Robustness to Alternative Samples and Weights. Dependent Variable: Change in Patents by US-Based Inventors (% pts).

		I. Reduced Patent Samples					II. Alternative Firm Weights		
	Baseline Spec (1)	No Grant Lag >6 Years (2)	No Comp/ Cmm Tech (3)	No Chem/ Drug Tech (4)	No Manual Matches (5)	No Manual or NBER Matches (6)	Patent Citations (7)	Global R&D (8)	Global Sales (9)
Δ U.S. Industry Exposure to Chinese Imports	-1.35 **	-1.37 **	-1.83 **	-1.52 **	-1.32 **	-1.09 *	-1.47 *	-2.22 **	-2.40 **
	(0.50)	(0.50)	(0.54)	(0.54)	(0.44)	(0.45)	(0.58)	(0.48)	(0.59)
No. Observations	8271	8167	6837	6566	8257	7795	7150	3413	4392
No. Patents Used	129,585	127,654	83,690	99,440	125,533	117,847	126,855	109,071	113,656

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from column 3 model (h) 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 corresponds to column 3 model (h) in table 2. Column 2 omits patents that were granted more than six years after patent application. Column 3 excludes all patents in the computer and communications technology category, and column 4 excludes all patents in the chemical or drug technology category. Column 5 excludes patents from firms that we manually matched to Compustat, while column 6 additionally excludes patents matched via NBER-PDP, thus retaining only the result of fully automated matching based on firm names and web search. Column 7 weights firms by the number of citations to their start-of-period and end-of-period patents. Columns 8 and 9 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.

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 2, 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 II of Appendix Table A4. The results in Table 2 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 4, 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 -1.35 in the baseline specification to -1.83 when computer and communication patents are excluded and to -1.52 when chemical and pharmaceutical patents are excluded, with little effect on precision. 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.

Our sample of patents matched to Compustat firms includes patents matched on standardized firm names, using our web-based search procedure, or matched manually by NBER-PDP or by ourselves. These two latter sets of manual matches may arguably introduce researcher subjectivity into the construction of the data. We investigate whether our results are affected by dropping patents that are subject to manual matches. In column 5 of Table 4 we drop patents we matched manually (which excludes 14 firm-years from the sample) and in column 6 we drop patents matched manually in the construction of the NBER data (which excludes 276 firm years from the sample). In the first case, the resulting coefficient estimate is close to identical to our baseline estimate; in the second case which retains only patents that were matched using our automated algorithm, the coefficient is somewhat smaller in magnitude but still negative and precisely estimated. We take these results to mean that including manually matched patents in our data has little impact on our results.

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 7 of Table 4 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 (-1.47). This suggests that greater import competition is modestly 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. Because R&D is an input to innovation rather than an output, it may imperfectly reflect a firm's contribution to technological progress. Still, it offers an intuitive measure of a firm's attempts to advance technology frontier. Weighting by firm global R&D spending in the initial period, shown in column 8 of Table 4, yields even larger impacts of trade exposure on firm patenting (-2.22), when compared to patent-citation weighting in column 7 or patent-count weighting in column 1.

Finally, in column 9 we employ perhaps the simplest metric of firm capability, which is its global sales. Coefficients based on sales-weighted observations (-2.40) are larger still than those based on R&D weights.[33] 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.

4 Additional Analysis

The estimation results in Section 3 provide robust evidence that U.S. firms exposed to greater increases in import competition from China have experienced relatively large reductions in patenting. In this section we present three extensions to our main analysis. First, we explore possible mechanisms behind the negative impact of trade exposure on innovation by public companies in the U.S. by looking at additional outcome variables including sales, employment, R&D spending, and profit growth. We also explore the heterogeneity of the impact of trade shocks by firms' initial conditions. Second, we estimate the impact of import competition on patenting at the technology class level, which allows us to study the effects for corporate patents that are not matched to Compustat and for non-corporate patents. Third, we examine whether greater import competition may have had differential effects by geography.

4.1 Additional Firm-Level Outcomes and Heterogeneity by Initial Conditions

[33] Weighting firms by R&D spending or sales leads to a notable decline in sample size because some of the firms our sample do not have a Compustat record at the start of a given period, while others have an Compustat record with missing values.

Table 5: Effect of Chinese Import Competition on Firm Sales, Employment and R&D Expenditures, 1991-2007 and 1975-1991 (for Falsification Test). Dependent Variable: Change in Sales, Employment, Capital, Equity, and R&D (in % pts); 100 x Indicator for Profit Growth.

	A. Sales and Expenditure				B. Production Factors		C. Profit, Value and Debt			
	US Sales	Global Sales	R&D Invest	Adver-tising Exp	Global Employ ment	Global Capital	Stock Market Value	Book Value	Debt	100 × (ΔEBIT >0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					I. Exposure Period 1991-2007					
Δ U.S. Industry Exposure to Chinese Imports	-1.14	-0.81 *	-0.83 **	-0.96 *	-0.71 *	-1.25 **	-1.67 *	-1.31 *	-0.37	-0.43 *
	(0.76)	(0.36)	(0.32)	(0.47)	(0.28)	(0.49)	(0.67)	(0.62)	(0.76)	(0.18)
Mean Outcome Variable	31.56	53.35	49.76	29.11	18.43	54.33	39.72	-15.62	6.73	76.17
No. Observations	1731	2404	1888	425	2198	2406	2125	2307	2199	2405
					II. Pre Period 1975-1991					
Δ U.S. Industry Exposure to Chinese Imports	0.22	0.06	0.25	-0.64	0.15	0.48	0.62	0.09	-0.05	0.27
	(0.31)	(0.26)	(0.33)	(0.89)	(0.22)	(0.39)	(0.54)	(0.38)	(0.59)	(0.30)
Mean Outcome Variable	44.68	59.91	72.23	74.32	2.44	57.48	58.48	-5.57	72.71	70.25
No. Observations	1508	1672	1181	592	1597	1670	1456	1656	1634	1644

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from column 3 model (h) in table 2. All outcomes except US sales in column 1 refer to a company's global operations. The relative change of an outcome variable in columns 1-9 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 tests 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. Standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

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 influential analysis in Dasgupta and Stiglitz (1980). In panel I of Table 5, we examine the impact of trade exposure on ten alternative measures of firm outcomes: total sales in the U.S. market (column 1), total sales in the global market (column 2), total R&D spending in the firm's global operations (column 3), total advertising spending in the firm's global operations (column 4), total employment in the firm's global operations (column 5), the firm's global capital stock (column 6), stock market valuation of the firm (column 7), book value of the firm's global assets (column 8), total debt of the firm (column 9), and an indicator for whether the firm had an increase in the value of debt over the same period (column 10).[34] In parallel to the preceding analysis for patents, the outcome variables in columns (1) to (9) are defined as the first difference of the outcome, divided by the average of the start-of-period and end-of-period values, a statistic that approximates a log change.[35] In all ten specifications, the estimated impact of a

[34]Firms' U.S. employment or R&D spending would also be of interest for this analysis, but are not observed in Compustat except for a very small number of firms over a short time period. To be included in the analysis of firm outcomes in Table 5, a firm needs to be included in Compustat both at the start and end of a period, and the respective outcome variable must not be missing. The latter restriction leads to smaller sample sizes especially for the outcomes U.S. sales and global R&D spending.

[35]In very rare cases, Compustat records negative values such variables as sales, capital or R&D expenditure, which

change in industry import penetration on the change in firm activity is negative; the impact coefficient is statistically significant for eight of the ten outcomes (global sales, R&D spending, advertising spending, global employment, global capital, stock market value, book value, and the likelihood that debt increases). 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. Aggregate firm sales revenues, employment, available capital, market valuation, and investments in new technology have diminished as competitive conditions have tightened, thereby contributing to diminished profitability. Importantly, the impacts we uncover of how import competition affects firm outcomes are not a byproduct of long-running trends in firm performance. In panel II of Table 5, we repeat the panel I regression but now using as outcomes changes in firm performance over the pre-sample period of 1975 to 1991. Estimated coefficients are all small, mostly positive (in eight of the ten cases), and imprecisely estimated. Whereas trade exposure over 1991 to 2007 negatively affects contemporaneous firm performance, it has no predictive power for firm performance in the pre-sample period.

We next explore whether the impact of import competition on firm innovation is uniform across companies or whether these impacts are concentrated among a subset of firms differentiated by initial sales per worker, capital intensity, or return on investment. In the Melitz (2003) model, for instance, more productive firms are better positioned to take advantage of opportunities created by globalization. In response to lower trade barriers, they expand their operations both at home and abroad. Their less productive domestic counterparts, however, fair less well. Greater openness makes them relatively likely to shut down their operations and among those that remain in business to cut back on their production. A similar mechanism is at work in the model of Aghion, Bloom, Blundell, Griffith, and Howitt (2005), where greater competition dampens a laggard's incentives to innovate in industries with technological gaps.

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we winsorize at zero.

Table 6: Effect of Chinese Import Competition on Patenting 1991-2007: Splitting Sample According to Initial Firm Sales, Sales/Worker, Capital/Worker, and Return on Investment. Dependent Variable: Change in Patents by US-Based Inventors (% pts).

	A. Labor Productivity and Capital Intensity				B. Profitability and Leverage			
	I. Firm Sales/Worker		II. Firm Capital/Worker		III. Firm Profit/Capital (ROI)		IV. Firm Debt/Equity	
	> Ind Mean	≤ Ind Mean	> Ind Mean	≤ Ind Mean	> Ind Mean	≤ Ind Mean	> Ind Mean	≤ Ind Mean
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ U.S. Industry Exposure to Chinese Imports	-1.11	-2.32 ~	0.04	-2.47 **	-0.98	-2.01 **	-3.18 ~	-0.95 *
	(0.79)	(1.38)	(1.04)	(0.58)	(0.63)	(0.74)	(1.72)	(0.42)
Mean Outcome Variable	27.27	3.29	25.48	3.16	17.16	0.69	12.76	11.34
No. Observations	1348	2738	1270	2068	1492	2078	638	2555

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from column 3 model (h) in table 2, with firm-level controls aggregated to the industry level. Columns 1-2, 3-4, 5-6 and 7-8 split the firm sample into firms whose global sales, sales per employee, capital per employee, or return on investment is above/below the patent-weighted industry average in the start-of-period year. All models are weighted by the number of matched patents in a firm, averaged over patents at the start and end of a period. Standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In Table 6, we examine the impacts of exposure to import competition on firm patenting when we separate firms into subsamples based on whether they fall above or below the patent-weighted sample mean among firms in the same industry for various indicators of firm performance in the initial time period. By construction, each of the resulting subsamples comprises approximately half of the patents of each industry. All four sample splits convey that import competition leads to a larger contraction of innovation for the less productive or less profitable firms of each industry. Firms with lower initial global sales per employee (panel A.I), lower initial capital per employee (panel A.II), a low initial rate of return on investment (panel B.I), or a lower initial debt/equity ratio (panel B.II) experience larger reductions in patenting for a comparable increase in exposure to import competition when compared to their initially better-performing industry counterparts.

Though the difference in impacts for firms above versus below the mean is statistically significant for only one of the four cases—the separation of firms by capital intensity—the results are indicative of how weaker firms tend to experience larger reductions in patenting in response to adverse trade shocks. Consider the separation of firms based on sales per worker in panel A.I. A one-standard-deviation increase in import competition produces a 26.3 (-2.32×11.34) percentage-point decrease in patenting among firms with below mean initial labor productivity, while generating a 12.6 (-1.11×11.34) percentage-point decrease for firms above the industry mean; the coefficient for the first effect is statistically significant at the 10% level and for the second coefficient is insignificant. The difference is yet more stark when separating firms by capital intensity. Whereas firms with above-mean capital per worker see a positive though very small and highly insignificant impact of trade exposure on patenting, firms with below-mean capital per worker see a 28.0 (-2.47×11.34) percentage decrease in patenting from a one standard deviation increase in import competition. The finding of more severe effects of negative trade shocks on less productive, less capital intensive and less profitable firms is broadly consistent with the reasoning in Melitz (2003) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005).

4.2 Publicly Listed and Non-Publicly Listed Corporations

Since there is evidence that import competition has heterogeneous effects based on firms' initial conditions, a natural question is whether our results extend to small firms that never cross the threshold into being publicly listed and are thus not covered by Compustat. While we cannot directly test this question as we do not observe the industry affiliations of non-publicly listed firms, we provide suggestive evidence based on detailed technology classes, which we observe for all patents. Using the sample of patents that are matched to Compustat firms, we impute the trade shock to which a technology class is exposed as the average industry trade shock of Compustat firms in that technology class, weighted by firms' shares of patents in the class. We then examine how these imputed trade shocks at the technology-class level affect patenting by corporate entities, whether or not they appear in Compustat. Table 7 presents these results.

Table 7: Effect of Chinese Import Competition on Patenting 1991-2007: Technology Class-Level Analysis. Dependent Variable: Change in Patents within Technology Class (% pts).

	All Corporate Patents			CompuStat-Matched Corporate Only			All Non-Corporate Patents		Corporate + Non-Corporate Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ U.S. Industry Exposure to Chinese Imports	-3.33 *	-3.37 *	-3.25 *	-3.06 *	-3.56 **	-3.35 *	0.63	2.01	-3.11 *	-2.64 *
	(1.33)	(1.34)	(1.33)	(1.49)	(1.37)	(1.34)	(1.29)	(1.43)	(1.25)	(1.30)
Two Sectors (Comp, Chem)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Eleven Sectors		yes	yes		yes	yes		yes		yes
Six Tech Categories			yes			yes		yes		yes

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007. N=819, based on 184,262/130,611/52,084/236,346 patents in columns 1-4/5-6/7-8/9-10. The mean of the outcome variable is 29.57/21.88/9.04/25.93 in columns 1-4/5-6/7-8/9-10. The control vector in column 1 includes a period dummy, the start-of-period fraction of Compustat-matched patents in a technology class that have an assignee in either the computer or chemical sector. Subsequent models also control for the distribution of Compustat-matched patents across 11 sectors, dummies for 6 major technology categories, and two 8-year lags of the dependent variable. All models are weighted by the number of matched patents in a technology class, averaged over patents at the start and end of a period. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

The unit of analysis in Table 7 is a detailed patent technology class, rather than the firm.

Columns 1 to 3 show results for the change in patenting by all corporate entities, where across the columns we expand the set of controls included in the analysis. As in our earlier results, the impact of exposure to import competition on patenting is negative and precisely estimated. The impact changes little, while retaining statistical significance, as we move from controls for the share of Compustat firms in the class that are active in the computer or chemical sectors (column 1) to controlling for the 11 major industry sectors (column 2), and dummy variables for the six major technology-class categories (column 3). Since the imputed import shock for a technology class is a weighted average of the original industry-level trade shocks, the import exposure measure in Table 7 has a notably smaller standard deviation (4.38) than the import shock used in column 3 of Table 2 (11.34). The absolute size of the estimated regression coefficients in the two tables is inversely proportional to that dispersion of the exposure variable. If we take the coefficient estimate from column 3 in Table 7, a one standard deviation increase in trade exposure over the 1991 to 2007 period would lead to a 14.2 percentage-point decrease in patenting in a technology class, whereas in column 3i of Table 2, we had found a 15.3 percentage-point reduction in firm-level patents associated with a one standard deviation in import exposure. In columns 4 to 6, we limit the patents included in the analysis to those that can be matched to Compustat firms, such that the patents represented are the same as in Table 2 but now aggregated to the technology class level. The coefficient estimates are similar to those for all corporate patents, showing a smaller negative effect in the specification with minimal controls (columns 4 vs. 1) and a larger negative effect in the specification with full controls (columns 6 vs. 3).

Another benefit of doing the analysis at the technology class level is that we can estimate the impact of import competition on patents by non-corporate entities—which include universities, hospitals, other non-profit institutions, and private individuals. Since these entities are not directly subject to manufacturing-industry market forces, we would expect their patenting activities to reflect underlying availabilities of technological opportunities or tendencies to disclose innovations—which presumably apply to all types of invention—more so than responses to import competition. In columns 7 and 8, we find that the negative impact of trade shocks on patenting disappears when we use patents by non-corporate entities; the impact coefficients of import competition on non-corporate patenting are now positive but imprecisely estimated. That import competition does not inhibit patenting by non-corporate entities suggests that our results on how trade shocks affect corporate patenting are not the result of a failure to control sufficiently for the exhaustion of technological opportunities or rising non-disclosure of innovations. Finally, in columns 9 and 10, we include in the analysis both corporate and non-corporate patents, which constitutes the universe of patenting in the U.S. For this combined sample, the impact of trade shocks on patenting is negative, though smaller than for the sample of corporate patents (i.e., when comparing columns 1 and 4 with columns 9 and 10). We conclude that adverse trade shocks reduce in patenting for all types of corporate entities, whether or not these firms are publicly listed.

4.3 Heterogeneity by Firm Headquarters and Inventor Locations

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 located abroad.[36] 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 8, 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 application. In its worldwide operations, IBM, for instance, has 12 R&D labs located in 10 different countries.[37] 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 used in the analysis so far, 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.

[36] All firms in Compustat are publicly listed in the U.S., whereas some have parent firms located in the U.S. and others have parent firms located in other countries.

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

Table 8: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007: Alternative Firm and Inventor Samples. Dependent Variable: Relative Change of Number of Patents.

	All Firms, Invent-ors	All Firms, US Invent-or	All Firms, Foreign Invent-or	US Firm	US Firm, US Invent-or	US Firm, Foreign Invent-or	Foreign Firm	Foreign Firm, US Invent-or	Foreign Firm, Foreign Inven-tor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ U.S. Industry Exposure to Chinese Imports	-1.28 **	-1.35 **	-1.37 **	-1.15 *	-1.17 ~	-1.03 ~	-1.70 **	-2.23 **	-1.51 **
	(0.40)	(0.50)	(0.42)	(0.56)	(0.64)	(0.63)	(0.48)	(0.47)	(0.55)
Mean Outcome Variable	27.56	24.42	32.26	25.07	22.50	44.39	31.49	41.81	29.62
No. Observations	9381	8271	3168	7996	7596	2003	1385	675	1165
No. Patents Used	217,498	129,585	87,913	133,151	117,190	15,961	84,347	12,395	71,952

Notes: Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from column 3 model (h) 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 in 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. 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 8, 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 (-1.37, column 3) is negative and precisely estimated, and almost equal to the the baseline specification for U.S. inventors (-1.35, column 2). Innovation in import-exposed industries does not appear to shift from the U.S. to other countries; instead, patenting declines both domestically and abroad. A similar pattern holds when the sample is constrained to firms that are headquartered in the U.S. according to Compustat. Again, patenting falls overall (column 4) and both for patents with a U.S.-based or a foreign-based lead inventor (columns 5 and 6), although the effects are slightly smaller in magnitude and less precisely estimated than in samples of columns 1 to 3. The innovation by foreign companies is covered in our data only to a limited extent, namely for foreign firms that both patent their innovations in the U.S. and have a listing at a U.S. stock market. For this select sample of foreign firms, there is again a negative impact of Chinese import competition in the U.S. market on the patent production of both foreign-based and domestically-based inventors (columns 7 to 9).

5 Discussion

Does escalating import competition from China induce U.S. manufacturing firms to innovate? Our analysis suggests that the answer is no. Publicly listed 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 operations. 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 or when expanding the sample to include patenting by corporations that are not publicly listed. Our finding that trade shocks do not inhibit patenting by non-corporate entities suggests that our results are not a byproduct of the exhaustion of technological opportunities or rising non-disclosure of innovations.

Another 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 sales, employment, capital, and R&D spending. In whatever manner U.S. manufacturers manage to survive the competitive threat from China, innovating their way out does not appear to be a prevalent strategy.

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 possible 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. The literature provides some suggestive evidence that this may be the case.[38] Europe differs also from the U.S. in terms of its industry structure, and by having a more balanced trade relationship with China. It is thus possible that the negative demand

[38]Hashmi (2013) documents that U.S. industries display larger gaps in the technological capabilities of leading and lagging firms when compared to firms in Europe, and Bartelsman, Haltiwanger, and Scarpetta (2013) find that the correlation between firm productivity and firm size is stronger in the U.S. than in Europe. Both sets of results suggest that there is more competition among U.S. firms than among their European counterparts. This is consistent with the operation of the Aghion et al. (2005) model in which more intense industry-level competition encourages continuous innovation and thus increase the technology gap within an industry.

shock from Chinese trade competition was less pronounced in Europe. Indeed, the manufacturing employment share in Germany—the largest European manufacturer—has declined more modestly than its counterpart in the U.S., and Dauth, Findeisen and Südekum (2014) estimate that the labor market effects of China trade have been less severe.

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-Fiber Arrangement in 2005, is best suited for apparel and textiles, two sectors that are important in terms of labor-intensive production but that account for only a small fraction of overall U.S. patenting. 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.

The decline of innovation in the face of Chinese import competition suggests that R&D and manufacturing tend to be complements, rather than substitutes. That is, when faced with intensifying rivalry in the manufacturing stage of industry production, firms tend not to substitute effort in manufacturing with effort in R&D. There are a number of reasons this may happen. First, greater competition in manufacturing could portend a more general decline in the profitability of an industry, thereby reducing incentives to invest in R&D (Dasgupta and Stiglitz, 1980). Second, intensified competition from low cost Chinese suppliers may have shifted American consumer preferences from more innovative intensive offerings to lower cost products. To the extent the presence of significantly lower cost alternatives impacts demand with respect to "quality", the incentive of firms to invest in quality enhancing innovations may have been reduced (Bena and Simintzi, 2016). Finally, to the extent greater import competition from China was also associated with a shift in the locus of production from the US to China, it likely increased the geographic distance between R&D (in the US) and manufacturing. Such geographic separation may have made it more difficult for US companies with R&D operations in the US to engage in the coordination between R&D and manufacturing often required for successful innovation (Pisano and Shih, 2012). Our data do not allow us to distinguish between these alternative explanations. Because each explanation has important implications for both policy and our understanding of the impact of trade on economic performance, further analysis to explore them would be fruitful.

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Appendix Tables

Table A1: Patents matched to IBM by NBER-PDP and ADHPS

Assignee Name	Number of Patents Granted 1975-2013	Any Patent Granted by 2006	Matched to IBM by Name Matching Only	Matched to IBM by NBER-PDP	Matched to IBM by ADHPS Web Matching	Matched to IBM by ADHPS (Consolidated)
	(1)	(2)	(3)	(4)	(5)	(6)
INTERNATIONAL BUSINESS MACHINES CORPORATION	74489	x	x	x	x	x
INTERNATIONAL BUSINESS MACHINES CORP	766	x	x	x	x	x
INTERNATIONAL BUSINESS MACHINE CORPORATION	90	x		x	x	x
IBM CORPORATION	85	x		x	x	x
INTERNATIONAL BUSINESS MACHINES	71	x		x	x	x
INTERNATIONAL BUISNESS MACHINES CORPORATION	29	x		x	x	x
INTERNATIONAL BUSINESS MACHINE CORP	27	x		x	x	x
INTERNATIONAL BUSINESS MACHINES COPORATION	26	x		x	x	x
INTERNATIONAL BUSINES MACHINES CORPORATION	19	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORAITON	18	x		x	x	x
INTERNATIONAL BUSINESS MACHIENS CORPORATION	15	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORTION	15	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPROATION	14	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORATIONS	12	x		x	x	x
INTERNATIONAL BUSINESSS MACHINES CORPORATION	12	x		x	x	x
INTERNATIONAL BUSINESS MACHINES INC	11	x		x	x	x
INTERNATINAL BUSINESS MACHINES CORPORATION	11	x		x	x	x
INTERNATIONAL BUSNIESS MACHINES CORPORATION	11	x			x	x
INTENATIONAL BUSINESS MACHINES CORPORATION	10	x		x	x	x
INTERNATIONL BUSINESS MACHINES CORPORATION	9	x		x	x	x
INTERNATION BUSINESS MACHINES CORPORATION	9	x		x	x	x
INTERNATIOANL BUSINESS MACHINES CORPORATION	9	x		x	x	x
INTERNATIONAL BUSINESS MACHINES COMPANY	8	x		x	x	x
INTERNATIONAL BUSINESS MACHINESS CORPORATION	8	x		x	x	x
INTERNATIONAL BUSINESS MACINES CORPORATION	7	x		x	x	x
INERNATIONAL BUSINESS MACHINES CORPORATION	7	x		x	x	x
INTERNATIONAL MACHINES CORPORATION	7	x		x	x	x
INTERNAITONAL BUSINESS MACHINES CORPORATION	6	x		x	x	x
INTERNATIONAL BUSSINESS MACHINES CORPORATION	6	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORATON	6	x		x	x	x
INTERNTIONAL BUSINESS MACHINES CORPORATION	6	x		x	x	x
INTERNATIONAL BUSINESS MACHINES INCORPORATED	6	x		x		x
INTERNATIONAL BUSINESS MACHINES COPRORATION	5	x		x	x	x
INTERNATIOAL BUSINESS MACHINES CORPORATION	5	x		x	x	x
INTERNATIONAL BUINESS MACHINES CORPORATION	5	x		x	x	x
INTERNATIONAL BUSINESS MACHINCES CORPORATION	4	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORAION	4	x			x	x
IBM JAPAN LTD	4	x			x	x
INTERNATIONAL BUSINESS MAHINES CORPORATION	4	x		x	x	x
INTERNATONAL BUSINESS MACHINES CORPORATION	4	x		x	x	x
INTERNATIONAL BSUINESS MACHINES CORPORATION	4				x	x
INTERNATIONAL BUSINESS MACHINES CORPORARTION	4	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORATIION	3	x		x	x	x
INTERNATIONANL BUSINESS MACHINES CORPORATION	3				x	x
INTERNATIONAL BUSIENSS MACHINES CORPORATION	3	x		x	x	x
INTERANTIONAL BUSINESS MACHINES CORPORATION	3	x		x	x	x
IBM	3	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORATIOIN	3	x		x	x	x
INTERNATIONAL BUSINESS MACHNIES CORPORATION	3	x		x	x	x
INTERNATIONAL BUSINESS MAHCINES CORPORATION	3	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORATOIN	3	x		x	x	x
INTERNATIONAL BUSINSS MACHINES CORPORATION	3	x		x	x	x
INTERNATIOANAL BUSINESS MACHINES CORPORATION	3	x		x	x	x
INTERNATIONAL BUSINESS MACHINES INCORPORATION	2	x		x		x
INTERNATIONAL BUSNINESS MACHINES CORPORATION	2	x			x	x
INNTERNATIONAL BUSINESS MACHINES CORPORATION	2				x	x
INTERNATIONAL BUSINESS MACHINES CORPOATION	2	x		x	x	x
INTERNATIONAL BUSINESS MACHNINES CORPORATION	2	x		x	x	x
INTERNATIIONAL BUSINESS MACHINES CORPORATION	2	x		x	x	x
INTRANATIONAL BUSINESS MACHINES CORPORATION	2				x	x
INTERNATIONAL BUISINESS MACHINES CORPORATION	2	x			x	x
INTERNATIONAL BUSINESS MACHINES CORPOARTION	2				x	x
INTERNATIONAL BUSINESS MACHINES CORPORATIONAL	2				x	x
INTERNATIONAL BUSINESS MACHINES CORPRATION	2				x	x
INTERNATIONA BUSINESS MACHINES CORPORATION	2				x	x
INTERNATIONAL BUSINESS MACHINES COPROATION	2	x		x	x	x
INFORMATION BUSINESS MACHINES CORPORATION	2	x		x		x
INTERNATIONAL BUSINESS MACHINES COROPORATION	2	x		x	x	x
INTERNATIONAL BUSINESS MACHINES CORPORATIN	2	x		x	x	x
LNTERNATIONAL BUSINESS MACHINES CORPORATION	2	x		x	x	x

Notes: The table comprises all patent assignees with at least two granted patents during 1975-2013 which have been matched to IBM by either name matching (column 3), through the NBER-PDP project (column 4) or by the ADHPS (our own) web match algorithm (column 5). The NBER-PDP is only updated through 2006, and thus by construction fails to match patent assignees that only appear after 2006. The consolidated ADHPS match (column 6) appends the ADHPS name+web match with assignee names that were matched only through NBER-PDP. In addition to the assignee names with at least 2 patents that are shown in the table, there are a further 77 assignee names with one patent each that are matched to IBM. NBER-PDP matches 51 of these assignees, while ADHPS name+web match matches 67. The listed assignee names have been subject to minimal cleaning, including standardizing cases, removing of accents, and cleaning of non-alphabetic and non-numeric characters.

Table A2: Sample Construction.

	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	239,110	76%
and Matched to Compustat Firm	171,838	72%
and with Valid Industry Code	170,788	99%
Main Patent Sample	170,788	

Table A3: Matching of Corporate Patents to Compustat

	Sequential Matching of Patents to Compustat								
	Total Sample	Via Name Matching	% Final Sample	Via Web Matching	% Final Sample	Via NBER-PDP	% Final Sample	Via Manual Matching	% Final Sample
	(1)	(2)		(3)		(4)		(5)	
				I. Number of Patents					
1975 Patents	22,531	17,630	78%	2,758	12%	1,990	9%	153	1%
1983 Patents	18,696	14,704	79%	2,135	11%	1,785	10%	72	0%
1991 Patents	27,094	20,324	75%	3,827	14%	2,713	10%	230	1%
1999 Patents	53,617	36,671	68%	12,111	23%	3,619	7%	1,216	2%
2007 Patents	49,900	31,254	63%	13,664	27%	1,393	3%	3,589	7%
All Years	171,838	120,583	70%	34,495	20%	11,500	7%	5,260	3%
				II. Number of Assignee-Years					
1975 Patents	1,942	1,131	58%	403	21%	401	21%	7	0%
1983 Patents	2,010	1,149	57%	419	21%	429	21%	13	1%
1991 Patents	2,904	1,592	55%	735	25%	550	19%	27	1%
1999 Patents	6,493	3,190	49%	2,332	36%	858	13%	113	2%
2007 Patents	4,275	2,023	47%	1,907	45%	219	5%	126	3%
All Years	17,624	9,085	52%	5,796	33%	2,457	14%	286	2%
				III. Avg. Number of Patents per Assignee-Year					
All Years	9.8	13.3		6.0		8.3		18.4	

Notes: Patents are sequentially matched to Compustat based on name strings (column 1), based on our novel web search algorithm (column 2), and based on manual matching by the NBER-PDP project (column 3) or done by ourselves (column 4). While the NBER-PDP does not cover patents granted after 2006, there are some name strings on patents with application year 2007 that were already linked by NBER-PDP in preceding years.

Table A4: Patent Applications by Sectors and Technology Classes, US-Based Inventors

	Patent Application Year				
	1975	1983	1991	1999	2007
			I. Sectors		
Chem., Petrol., Rubber	27.0%	27.0%	23.9%	14.2%	9.5%
Computers, Electronics	10.0%	13.6%	21.5%	35.1%	35.3%
Machinery, Equipment	21.3%	21.3%	19.3%	15.5%	13.0%
Transportation	8.8%	7.9%	8.0%	6.2%	8.0%
Paper, Print	2.6%	2.6%	3.0%	2.1%	1.4%
Metal, Metal Products	4.7%	3.5%	2.5%	1.4%	1.1%
Food, Tobacco	1.5%	1.6%	1.4%	0.6%	0.3%
Clay, Stone, Glass	3.4%	2.3%	1.4%	1.2%	1.0%
Wood, Furniture	0.5%	0.5%	0.7%	0.5%	0.5%
Other Manufacturing	0.6%	0.5%	0.4%	0.5%	0.8%
Textile, Apparel, Leather	0.4%	0.5%	0.2%	0.2%	0.1%
Non Manufacturing	19.3%	18.7%	17.8%	22.7%	29.0%
			II. Technology Classes		
Chemical	30.0%	29.3%	23.7%	12.6%	8.4%
Electrical, Electronic	18.2%	19.2%	20.1%	20.1%	21.3%
Computers, Communic.	8.0%	12.0%	17.1%	36.8%	44.0%
Mechanical	22.1%	17.2%	16.7%	10.7%	10.2%
Drugs, Medical	5.4%	6.3%	9.0%	11.6%	8.8%
Other	16.4%	16.0%	13.5%	8.3%	7.3%

Notes: The Computer and Electronics sector comprises the SIC industries that correspond to NAICS sector 334, while the Machinery and Equipment sector comprises all other industries belonging to the 2-digit SIC codes 35, 36 and 38. Statistics are based on corporate patents with U.S. inventor that are matched to Compustat firms with valid industry information.

Table A5: Average Characteristics for Compustat Firms with and without Patenting Activity

	Average Characteristics for Firms with Patents	Average Characteristics for Firms w/o Patents	Contribution of Patenting Firms to Overall Volume
	(1)	(2)	(3)
		I. Firms in All Sectors	
Number of Firms 1975-2014	6,754	29,519	18.6%
% Manufacturing Firms	71.7%	22.8%	n/a
% Non-Manufacturing Firms	28.3%	77.2%	n/a
Number of Firms in 1991	2,513	5,520	31.3%
US Sales 1991 (m$)	2,611	1,404	59.2%
Global Sales 1991 (m$)	5,962	1,485	64.0%
Global Employment 1991	14,537	5,347	57.6%
Global Capital 1991 (m$)	5,696	2,238	52.9%
Global R&D 1991 (m$)	204	7	97.1%
		II. Firms in Manufacturing Sector	
Number of Firms 1975-2014	4,840	6,716	41.9%
Mach/Equip/Transp/Metal Firm	33.7%	26.5%	n/a
Computer/Electronics Firm	29.4%	19.2%	n/a
Chemical/Petrol/Rubber Firm	21.0%	20.2%	n/a
Food/Textile/Apparel Firm	4.9%	15.3%	n/a
Wood/Furnit/Paper/Print Firm	4.9%	10.4%	n/a
Other Manufacturing Firm	6.1%	8.4%	n/a
Number of Firms in 1991	1,816	1,361	57.2%
US Sales 1991 (m$)	1,729	703	85.9%
Global Sales 1991 (m$)	5,039	866	89.6%
Global Employment 1991	11,608	2,901	86.6%
Global Capital 1991 (m$)	3,360	776	86.6%
Global R&D 1991 (m$)	224	9	98.2%

Notes: Column 1 summarizes the average characteristics of firms that are covered by Compustat in at least one year between 1975 and 2014, and that have at least one patent included in our analysis (patent application years 1975/1983/1991/1999/2007). Column 2 summarizes the average characteristics of Compustat-covered firms without any such patent. Column 3 indicates the contribution of firms in the patenting sample to the overall total of the indicated variable. Firms are assigned to sectors based on the time-invariant main Compustat industry code. Employment and financial variables are provided for the indicated subset of firms that were covered by Compustat in 1991.