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David Autor
David Dorn
Gordon H. Hanson
Gary Pisano
Pian Shu

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ABSTRACT

The competitive shock to the U.S. manufacturing sector spurred by rising China import competition could either catalyze or stifle innovation. Using three distinct sources of variation to identify rising trade exposure, we provide a causal analysis of the effect of surging import competition on U.S. innovative activities. Applying a novel internet-based matching algorithm to map all U.S. utility patents granted by 2013 to firm-level data, and carefully accounting for the shifting concentration of patenting activity across sectors, we document a robust, negative impact of rising Chinese competition on firm-level and technology class-level patent production. Accompanying this fall in innovation, global employment, sales, profitability, and R&D expenditure all decline within trade-exposed firms. The trade-induced contraction along all margins of adjustment and for all measures of valuation suggest that the primary response of firms to greater import competition is to scale back their global operations.

David Autor
Department of Economics, E52-438
MIT
77 Massachusetts Avenue
Cambridge, MA 02139
and NBER
dautor@mit.edu

David Dorn
University of Zurich
Department of Economics
Schoenberggasse 1
CH-8001 Zurich - Switzerland
and CEPR
david.dorn@econ.uzh.ch

Gordon H. Hanson
IR/PS 0519
University of California, San Diego
9500 Gilman Drive
La Jolla, CA 92093-0519
and NBER
gohanson@ucsd.edu

Gary Pisano
Harvard Business School
Morgan Hall
Soldiers Field Road
Boston, MA 02163
gpisano@hbs.edu

Pian Shu
800 West Peachtree Street N.W.
Scheller College of Business
Georgia Institute of Technology
Atlanta, GA 30308-1149
pian.shu@scheller.gatech.edu

1 Introduction

What impact does foreign competition have on innovation by domestic firms? 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.[1] 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 18.3% of the world total in 2014 (Autor, Dorn, and Hanson, 2016). While a substantial literature evaluates the impact of China's rise on 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), 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 corporate patents despite accounting for less than one-tenth of U.S. private non-farm employment.[2] 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.[3] 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. 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 where competition is close to perfect and there is 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), then an increase in product-market competition lowers the cost of redeploying these factors from production to innovation. Greater import competition may, consequently, lead to accelerated productivity growth.

Further ambiguity arises when one allows for global production networks. If product design interacts with the production process, then a firm's capacity to innovate may be compromised when offshoring relocates factories away from R&D labs (Pisano and Shih, 2012). Compounding disincentives for innovation, firms may find investing in cutting-edge technologies less enticing once they

[1] General-equilibrium trade theory suggests that expanded trade with low-wage countries raises innovation in high-wage countries (e.g., Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1993). Industry-specific models, by contrast, suggest that impacts of global integration on high-wage-country innovation may be more complex.

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

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

have moved production to countries where wages are low and workers have limited technical skills (Fuchs and Kirchain, 2010).[4] At the same time, offshoring could raise the productivity of factors in the home market (Grossman and Rossi-Hansberg, 2008), improve access to imported intermediate inputs (Halpern, Koren, and Szeidl, 2015), and deepen specialization (Arkolakis, Ramondo, Rodriguez-Clare, and Yeaple, 2016), all of which could enhance prospects for innovation. How import competition and innovation are related remains intrinsically an empirical question, and the relationship may differ across countries and competitive structures.

In this paper, we study how import competition affects U.S. innovation by estimating the impact of greater exposure to trade on patenting by U.S. firms. As in recent literature, we measure trade exposure using the change in industry import penetration resulting from increased U.S. trade with China. 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 through 2014. We address the common problem of inconsistent or misspelled names of firms in patent records by developing an algorithm that harnesses the machine-learning capabilities of Internet search engines.[5] 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. We assign 72% of all corporate patents by U.S. inventors to a known entity in Compustat, and we find patents for nearly all Compustat firms that report positive R&D expenditure.[6]

Our empirical strategy isolates 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), which instruments import penetration from China in the U.S. using import penetration in other high-income countries. As a robustness check, we also follow Pierce and Schott's (2016) identification strategy, which exploits the reduction in trade policy uncertainty associated with China's WTO accession. Our analysis demonstrates the importance of accounting for differential pre-trends in technology creation across sectors. We control for underlying technology trends using an extensive vector of sectoral fixed effects, start-of-period firm and industry characteristics, start-of-period firm technology mix, and lags on firm-level patenting. As a further checks on technology trends, we incorporate detailed industry fixed effects into the analysis, such that the impact of trade exposure on patenting is identified based solely on the differential growth in import penetration within an industry in the 2000s relative to the 1990s.

We find that U.S. industries or firms that are subject to larger increases in trade exposure show *smaller* increases in patenting. This finding emerges once we control for the broad sector of

[4]Branstetter, Chen, Glennon, Yang, and Zolas (2017) find that increased opportunities to offshore production to mainland China have reduced patenting by high-tech companies in Taiwan. Hémous and Olsen (2016) describe theoretically how automation reacts to changing wage levels in a model of endogenous growth.

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

[6]Relative to string matching on firm names alone, our search-engine-based algorithm increases the number of patents that are matched to Compustat records by 29% over all years in our sample, and by 44% in the final application year of 2007.

production. Since we analyze patenting over the long time window of 1975 to 2007, which commences well before China's rise as an export powerhouse, we are able to detect a secular growth in patenting in electronics and a secular stagnation of patenting in chemicals, which are the two most patent-intensive sectors. Both of these trends predate the Chinese import competition of the 1990s and 2000s, which was much stronger in electronics than in the chemical sector. Given these countervailing patterns, 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 electronics, the impact of trade exposure on changes in patenting becomes strongly negative and precisely estimated. This negative impact remains when we add the extensive set of further controls and (or) use the alternative measures of trade exposure. Our analysis that includes industry fixed effects suggests that accelerating import competition from China during the 2000s can explain about 40% of the slowdown in patenting in 1999–2007 relative to 1991–1999.

In extended analysis, we provide evidence that the negative impact of Chinese import competition on U.S. innovative activity is not limited to the publicly listed companies that populate Compustat. Using imputed import penetration ratios at the detailed technology-class level, which allows us to include the universe of patents by corporate entities, we find that technology classes with larger growth in import penetration have a smaller growth in total corporate patents. By contrast, import competition has small and insignificant effects on non-corporate patents, which further suggests that our key result is driven by the market forces of import competition rather than a spurious correlations between trends in technological opportunities and trade.

Greater import exposure also has negative impacts on a range of additional firm outcomes, including global sales, profit growth, global employment, and global R&D spending.[7] 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. Together, our results suggest that the China trade shock reduces firm profitability in U.S. manufacturing, leading firms to contract operations along multiple margins of activity, including innovation.

The contribution of our paper is to provide a causal analysis of how the surge in import competition from China affects both the inputs and outputs of U.S. innovative activities.[8] Our work is contemporaneous to a body of emerging evidence on the impacts of import competition on innovation-related outcomes for firms in North America. Bena and Simintzi (2016) find that U.S. firms with easier access to offshoring in China are less likely to invest in process innovations; Gong and Xu (2017) show that R&D is reallocated towards the more productive firms in the U.S., and R&D talent is flowing from manufacturing to services; Gutierrez and Philippon (2017) document that the current capital stock of U.S. manufacturing firms is negatively correlated with previous industry exposure

[7]For related findings on import exposure and firm sales and employment, see Hombert and Matray (2016).

[8]On using patents to measure innovation, see Jaffe and Trajtenberg (2002) and Moser (2016). On the economic value of patents, see Hall, Jaffe, and Trajtenberg (2005) and Kogan, Papanikolaou, Seru, and Stoffman (2016).

to import competition, where this relationship is weaker for the largest firms in an industry; and Kueng, Li, and Yang (2016) find that Canadian firms in more trade-exposed industries experience a strong decline in self-reported innovation outcomes, especially in process innovations. Relative to existing work on trade and innovation, our paper significantly improves the matching of patents to firms, more completely accounts for the contaminating effects of industry pre-trends, evaluates the impact of trade shocks on innovation using the complete set of identification strategies deployed in the literature, and demonstrates that the negative impacts of trade shocks on firm and industry-level outcomes are consistent across the full range of observable adjustment margins.

Our results differ substantively from the results of Bloom, Draca, and Van Reenen (2016) for Europe, where greater import competition from China is associated with higher firm patenting, expanded investment in information technology, and higher TFP growth conditional on survival.[9] These diverging empirical findings for North America and Europe highlight the underlying theoretical ambiguity in the relationships examined. Prior literature suggests that the European markets are less competitive than the U.S. ones, which would reconcile the differential impacts in North America versus Europe through the lens of Aghion, Bloom, Blundell, Griffith, and Howitt (2005).[10] Europe also appears to differ from the U.S. in terms the rigidity of its labor markets. It is thus possible that European firms have more "trapped" productive factors (e.g., labor) that end up being redeployed towards innovation, as suggested in the model of Bloom, Romer, Terry, and Van Reenen (2014). It is further possible that the shock from Chinese trade competition may be less pronounced in Europe due to a more balanced trade relationship with China. 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 for Germany have been much less severe.

In section 2, we discuss our data and methods, along with descriptive analyses of trends in industry innovation and trade exposure. Section 3 presents our baseline estimation results on firm-level patenting and documents their robustness to different specification and identification choices. Section 4 studies patterns of heterogeneity and expands the analysis to other firm-level outcomes. Section 5 concludes with a discussion of our results.

[9] Our paper also connects 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), 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, 2017), on export-demand shocks and innovation (Aghion, Bergeaud, Lequien, and Melitz, 2017), and on the declining propensity of U.S. corporations to invest in basic science (Arora, Belenzon, and Patacconi, 2017).

[10] 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 model in Aghion, Bloom, Blundell, Griffith, and Howitt (2005) where more intense industry-level competition encourages continuous innovation and thus increase the technology gap within an industry. In this interpretation, 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.

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.[11] 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 the 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.[12] The year 1991 also coincides with the rapid acceleration of export growth in China. Between 1984 and 1990, China's share of world manufacturing exports had only ticked up modestly, rising from 1.2% to 1.9%. It began its rapid ascent in 1991, doubling to 4.0% by 1999, and subsequently more than quadrupling to 18.8% by 2013. The literature associates China's post-1990 export surge with the relaxation of barriers to foreign investment (Yu and Tian, 2012), the progressive dismantling of state-owned enterprises (Hsieh and Song, 2015), and the reduction of trade barriers associated with

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

[12] 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.

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.

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.[13] 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 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.[14] 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.[15]

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,

[13]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, 2017).

[14]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.

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

Modeling, Simulation, and Emulation), which does not indicate that the invention originated from the apparel sector and will most directly affect production there. 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 with regular filing of financial reports.[16] In addition to industry, Compustat contains information on firms' annual sales, employment, R&D expenditure and other outcomes of interest, which we use to link firm patenting to industry-level trade shocks 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 also by the technology deployed (e.g., software). Following Hall, Jaffe, and Trajtenberg (2001), we categorize patents into six main technology fields based on their primary technology class: Chemical; Computers and Communications; Drugs and Medical; Electrical and Electronics; Mechanical; and Others.

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 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 are an officially recognized spelling of IBM. The researcher is then faced with the unpalatable choice of either throwing away observations for unmatched patents or making subjective manual 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 patents granted by 2006.

We improve on existing methods and extend the match to 2013 by developing a fully automated approach that corrects 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 the assignee

[16] The data includes foreign companies that use American Depository Receipts (ADRs).

company 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 from internet searches eliminates the need for the extensive manual work that was previously required to deal with different spellings, abbreviations and typos in firm names. Appendix Table A1 in Appendix A illustrates the success of our data strategy for the case of IBM. A simple matching on name strings links only the two most frequent name variations of IBM, but misses dozens of alternative spellings. Our fully automated algorithm greatly improves the matching success by detecting 142 additional variations of the IBM name in U.S. patent records.[17] In each year from 1994 to 2012, the number of patents that our algorithm matches to IBM corresponds to between 99.5% and 100.0% of the patent output that IBM states in its annual company reports.[18] Our approach is readily scalable and generalizable to the matching between any two firm-level datasets, and many other applications in which string matching is complicated by variations in spellings and abbreviations. Appendix A discusses the specifics of our matching procedure.

Our Compustat data cover public firms that were listed on the North American stock markets between 1950 and 2014. 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 estimation 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. 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. Our results are robust to these various schemes for assigning industry codes to firms.

[17]Extensive hand-coding in the NBER-PDP found 106 additional name variations for IBM.

[18]IBM company reports indicate how many patents were granted in each year, but not how many eventually successful patents were applied for. Since our data contain both the application and the grant data of each patent, we can sort patents by grant year in order to compare patent totals with those indicated in company reports, while the subsequent empirical analysis will aggregate patents by application year to capture the precise timing of innovation.

Table 1: Firm Characteristics

	In-Sample Firms (1)	Compustat Firms (2)	Contribution of In-Sample Firms to Overall Volume (3)
		I. Firms in All Sectors	
Number of Firms	6,081	36,273	16.8%
Number of Patenting Firms in 1975	1,682	n/a	n/a
Number of Patenting Firms in 1983	1,671	n/a	n/a
Number of Patenting Firms in 1991	2,270	n/a	n/a
Number of Patenting Firms in 1999	3,153	n/a	n/a
Number of Patenting Firms in 2007	2,389	n/a	n/a
Avg US Sales in 1991 (millions)	$1,189.2	$617.4	62.8%
Avg Global Sales in 1991 (millions)	$2,093.3	$985.9	63.1%
Avg Global Employment in 1991	11,404.6	6,104.5	59.4%
Avg Global Capital in 1991 (millions)	$1,400.5	$759.1	54.2%
Avg Global R&D in 1991 (millions)	$74.2	$36.3	95.0%
		II. Firms in Manufacturing Sectors	
Number of Firms	4,413	11,556	38.2%
Number of Patenting Firms in 1975	1,393	n/a	n/a
Number of Patenting Firms in 1983	1,364	n/a	n/a
Number of Patenting Firms in 1991	1,827	n/a	n/a
Number of Patenting Firms in 1999	2,399	n/a	n/a
Number of Patenting Firms in 2007	1,758	n/a	n/a
Avg US Sales in 1991 (millions)	$945.8	$599.6	89.7%
Avg Global Sales in 1991 (millions)	$1,908.4	$1,204.8	86.6%
Avg Global Employment in 1991	9,944.8	6,510.1	86.5%
Avg Global Capital in 1991 (millions)	$1,091.9	$699.5	85.1%
Avg Global R&D in 1991 (millions)	$73.3	$49.7	97.0%

Notes: The sample in column 1 consists of Compustat firms that have at least one patent included in our analysis (corporate patents with U.S.-based primary inventors and application years 1975/1983/1991/1999/2007). The sample in column 2 consists of all Compustat firms with a valid industry code. Our coverage of Compustat is from 1950 to 2014. Patenting years are determined by patent applications. Firms are assigned to sectors based on the time-invariant main Compustat industry code. Average firm characteristics in 1991 are calculated for firms that were covered by Compustat in 1991, regardless of whether they applied for patents that year.

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.[19] Of these U.S.-based innovations, 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.[20] This group includes publicly held companies, which appear in Compustat, and privately held companies, which do not. Of these corporate patents, we match 72% to Compustat, which provides 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 (Table A3). 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 typically belong to smaller firms that never went public and are thus missing from Compustat.[21] Our sample comprises 170,788 corporate patents with U.S. inventors that are matched to Compustat firms with valid industry codes.

Table 1 indicates that the matched patents originate from 6,081 firms. This implies that 17% of all firms that were covered by Compustat at any time between 1950 and 2014—and 38% of the manufacturing firms—had at least one patent in one of the five sample years (1975, 1983, 1991, 1999, and 2007). These firms with matched patents account for 95% of all R&D expenditure that Compustat records in the year 1991, and for 97% of R&D expenditure in manufacturing. Conversely, firms without patents contribute very little to overall R&D. This pattern suggests that it is unusual for firms to spend on R&D while not patenting the resulting innovation. It also confirms that our strategy of matching patents to firms successfully avoids false negative matches that would result in a frequent observation of firms that have large R&D expenditures but no matched patents. In addition to accounting for almost all of the recorded R&D expenditure, patenting firms are also larger than the average Compustat firm in terms of sales, employment, and capital.[22] Patenting firms comprise between 85% and 90% of Compustat-recorded sales, employment and capital in manufacturing.

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 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: a sharp rise between 1983 and 1999 and a modest decline between 1999 and 2007.[23] The

[19] Patents with a U.S. primary inventor make up 98% of all patents with at least one U.S. inventor. The physical location of the inventor is of natural interest as we study the impact of imports to the U.S. on innovation in the U.S. in our main analysis. However, we later also expand the analysis to patenting by foreign-based inventors who work for companies that are listed in U.S. stock markets.

[20] 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.

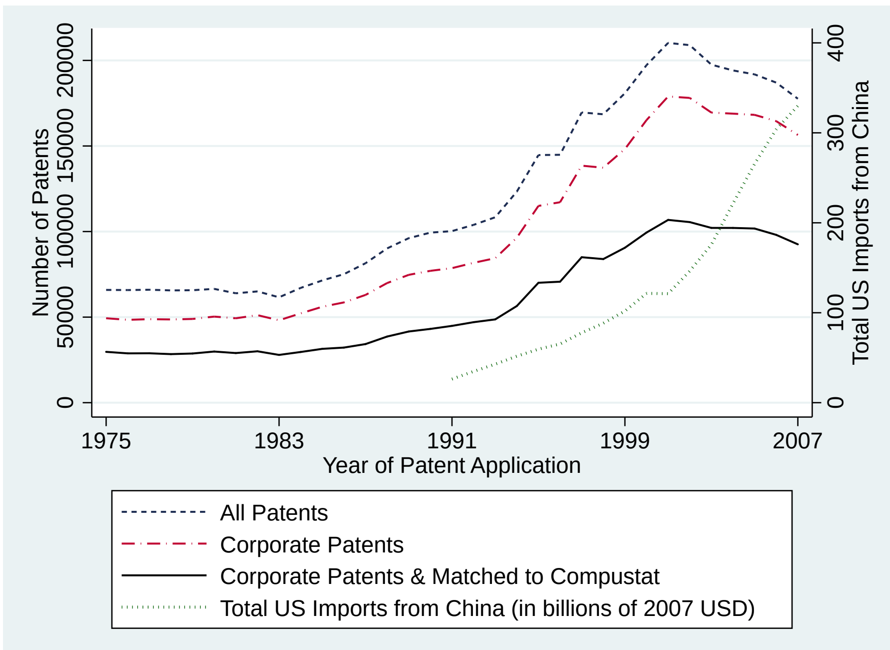
[21] For comparison, Compustat firms accounted for 62% of R&D in the U.S. in 1995 (Bloom, Schankerman, and Van Reenen, 2013).

[22] Table 1 reports firm data for the year 1991. Using other years yields highly similar results.

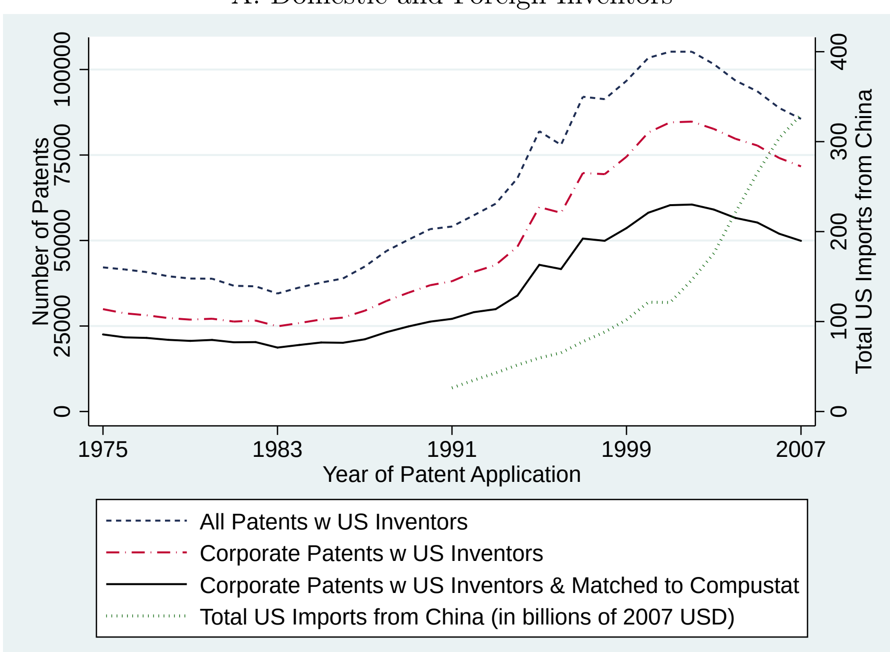
[23] The literature provides various explanations for the slowdown in patenting in the early 2000s. These include the exhaustion of technological opportunities (Gordon, 2012), the lasting effects of the post-2001 dot-com bust (Jorgenson, Mun, and Stiroh, 2008), strategic non-disclosure of patents by firms so as not to reveal their intellectual property (Boldrin and Levine, 2013), the increasing stringency of patent examiners (Carley, Hegde, and Marco, 2015), and the decline of corporate investments in basic science (Arora, Belenzon, and Patacconi, 2017).

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 declines modestly over time, from 75.3% in 1975 to 71.1% in 1991 and 69.6% in 2007 (Appendix Table A3), most likely because the share of privately held firms among U.S. corporations has risen in recent decades (Doidge, Karolyi, Stulz, 2015).

Figure 1: Number of Patents by Application Year



A. Domestic and Foreign Inventors



B. Domestic Inventors

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. Panel I of Table 2 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 that year, just two sectors, chemicals and petroleum and computers and electronics, comprised 45.4% of all patents and 55.2% of patents by manufacturing companies.[24] 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. Computers and electronics, buoyed by the IT revolution, 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; in 2007, the computers sector was responsible for half (49.8%) of all patents by manufacturing firms in Compustat.

The number of patents in other manufacturing sectors, and their contribution to total patents, changed more modestly over time. Panel I of Table 2 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.[25] 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 slightly higher shares of patents.

Panel II of Table 2 breaks down patenting by the technology categories that are indicated on the patents. The share of drug and medical patents in total patents remained largely unchanged between 1991 and 2007 (declining from 9.0% to 8.8%), suggesting that the reduced patenting in the chemicals sector is not primarily the result of a slowdown in breakthroughs in drugs or medical devices. Rather, it follows from a reduction in patenting in other parts of the chemical sector, as the chemical technology class sees its share fall precipitously from 23.7% of patents in 1991 to 8.4% in 2007. Patents in the computers and communications technology class rose from 8.0% of all patents

[24] Chemicals and petroleum include the two-digit SIC industries 28 and 29. Computers and electronics track the 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).

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

in 1975 to 44.0% in 2007, while the patent share of electric and electronic technologies also expanded.

Table 2: Patent Applications by Sectors and Technology Classes, US-Based Inventors

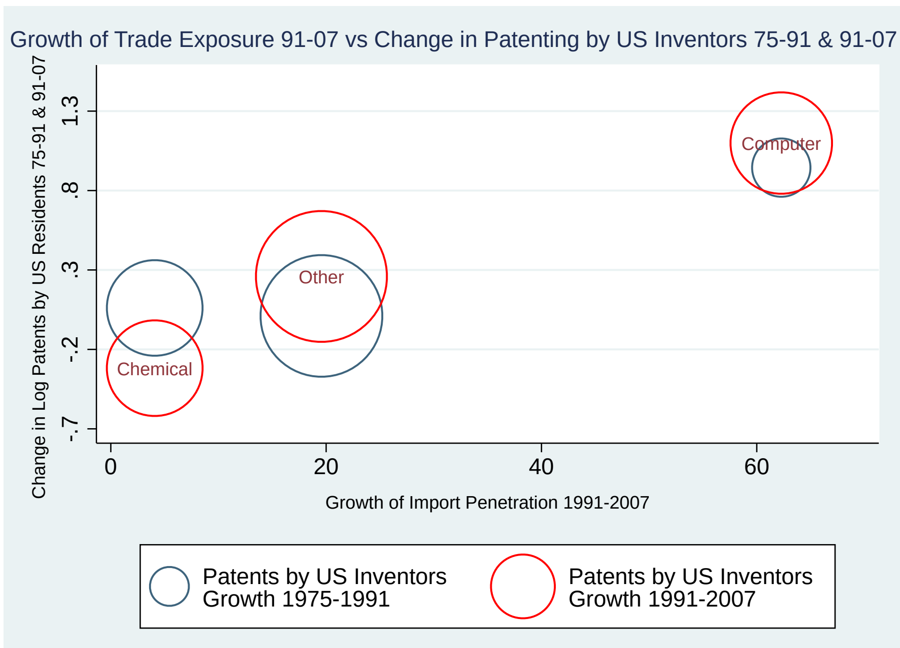
	Patent Application Year				
	1975	1983	1991	1999	2007
			I. Sectors		
Chem., Petrol., Rubber	27.0%	27.0%	23.9%	14.2%	9.5%
Computers, Electronics	10.0%	13.6%	21.5%	35.1%	35.3%
Machinery, Equipment	21.3%	21.3%	19.3%	15.5%	13.0%
Transportation	8.8%	7.9%	8.0%	6.2%	8.0%
Paper, Print	2.6%	2.6%	3.0%	2.1%	1.4%
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.

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). Moreover, the broadening and strengthening of intellectual property protection for computer software patents has played an important role in the rise of computer patents, with there being little evidence that strategic patenting (e.g., to deter entry) has lowered the quality of computer patents or harmed firm performance (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 2 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.

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



As suggested by Table 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 2 also plots the change in sectoral log patent applications for the pre-sample period of 1975 to 1991 against the sectoral change in import penetration from China for 1991 to 2007. Here again, the raw correlation is positive. The stagnation in chemical patenting and the acceleration in computer and electronic patenting that took place in the 1990s and 2000s was already well underway in the late 1970s and 1980s. We certainly would not want to attribute changes in innovation in the decades before 1990 to changes in import exposure that occurred in later decades. Yet, because of the strong secular patterns in industry patenting, we would be in danger of making just such an attribution if we failed to adequately account for these sectoral trends.[26]

[26]The same sectoral patterns are also observed when we examine patenting by both US-based and foreign inventors.

3 Empirical Strategies and Main Results

3.1 Empirical Strategies

We estimate the impact of changes in industry exposure to import competition from China on patenting at the firm level. We approximate the timing of innovation using the application years of eventually successful patent applications. The baseline regression specification is of the form,

$$\Delta P_{ij\tau} = \alpha_\tau + \beta_1 \Delta IP_{j\tau} + \gamma X_{ij0} + e_{ij\tau}, \tag{2}$$

where $\Delta P_{ij\tau}$ is the relative 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) in Section 2.1; 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.[27]

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 or 1999; similarly, it appears in the second time period if it had any patents in 1999 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. We assign a firm to an industry based on its main industry code in Compustat, which is generally the most recent code. In Section 3.4, we experiment with using historical industry codes for firms whose main code changes over time, and we analyze whether trade shocks affect a firm's industry affiliation itself. Observations are weighted by the number of firm patents, averaged over the start and end year of period τ; standard errors are clustered on four-digit SIC industries.

There are several concerns about estimating equation (2) in OLS and interpreting the coefficient on $\Delta IP_{j\tau}$ as causal. First, observed changes in the import penetration ratio may in part reflect domestic shocks to U.S. industries that determine both U.S. import demand and innovative activity. 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,

$$\Delta IPO_{j\tau} = \frac{\Delta M^{OC}_{j,\tau}}{Y_{j,88} + M_{j,88} - X_{j,88}} \tag{3}$$

where $\Delta M^{OC}_{j,\tau}$ is the growth in imports from China in industry j during the period τ.[28] The denominator in (3) is initial absorption in the industry in 1988. The motivation for the instrument

[27] The specification of the outcome variable is a standard approximation of a log change that is also defined for firms whose patent output was zero at the start or end of a period.

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

in (3) is that high-income economies are similarly exposed to growth in imports from China that is driven by supply shocks such as expanding product variety, falling prices, rising quality, and diminishing trade and tariff costs in China's surging sectors. The identifying assumption is that industry import demand shocks are uncorrelated across high-income economies.[29]

Autor, Dorn, and Hanson (2013) and Autor, Dorn, Hanson, and Song (2014) provide ample discussions and evidence on the robustness of this instrumentation approach in studying the employment effects of the China trade shock. In analyzing the effect on innovative activity, however, instrumenting for the trade shock from China is arguably less critical. Autor, Dorn, and Hanson (2013) show that unmeasured domestic demand shocks cause Chinese imports and U.S. production to rise or fall in parallel, generating an upward bias to the OLS estimates of the impact of trade shocks on domestic employment. 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 innovating; alternatively, a rise in demand may reflect diminished needs for innovation. 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.

Another empirical concern is the presence of confounding industry pre-trends in technology creation which could be incidentally related to trade with China. Figure 2 offers suggestive evidence as to why it is crucial, at the very least, to control for trends in the major patent-producing sectors of chemicals & petroleum and computers & electronics. Very simply, trade exposure appears to be positively correlated with patenting pre-trends in these two sectors. Furthermore, characteristics such as industry factor intensity, earnings, and propensity to invest in information technology could all drive systematic differences across firms and industries in the potential for successful innovation. We account for these potentially confounding factors by including an extensive set of controls: dummy variables for the 11 manufacturing sectors shown in Table 2; 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); and 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).[30] To absorb changes in patenting that are driven by diverging trends across technology classes, we add controls for the technology mix of firm patents (the fraction of a firm's patents that fall into each of the six major technology classes shown in Table 2, averaged over the start and end of period). We also control for

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

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

a firm's previous history of patenting using the 8-year and 16-year lags of the outcome variable. In alternative specifications, we include fixed effects for each detailed industry, such that identification is based on within-industry variation over time in the growth of import exposure and patenting.

Our main analysis thus compares the change in patenting by firms across industries that face differential increases in import penetration by China, while other sources of firm and industry heterogeneity in changes in innovative potential are absorbed by a rich set of control variables. A remaining potential source of simultaneity bias is correlation between the acceleration of growth in industry trade exposure and of the residual industry propensity to innovate, which firm-level controls may not fully account for. For instance, an unanticipated exhaustion of technological opportunities in certain industries may be a global phenomenon, rendering these industries particularly vulnerable to competition from China not only in the U.S. but also in other high-income economies. Such patterns could be problematic for our identification strategy.

To address other such sources of simultaneity bias, we follow Pierce and Schott's (2016) strategy of exploiting implicit changes in trade-policy uncertainty related to China's World Trade Organization (WTO) accession in 2001 to instrument for the acceleration of the growth in U.S. industry import competition in the 2000s versus the 1990s. U.S. imports from WTO member nations are subject to MFN ("Most Favored Nation") tariffs, which are much lower than the otherwise applicable non-MFN tariffs, the current levels for many of which were established in the 1930s following the Smoot-Hawley Tariff Act. Between 1989 and 2001, the U.S. granted China temporary MFN access to the U.S. market, which required annual reauthorization by Congress. If in some year Congress *had not* reauthorized China's MFN status, U.S. tariffs on Chinese imports would have jumped from U.S. MFN rates, which averaged 3.4% in 1999, to U.S. non-MFN rates, which averaged 37.0% in 1999. Uncertainty over congressional reauthorization may have dissuaded firms from investing in China for the purpose of exporting to the United States. Pierce and Schott (2016) and Handley and Limao (2017) find that industries with higher gaps between non-MFN and MFN tariffs experienced more rapid acceleration in Chinese imports after China's 2001 WTO accession removed this uncertainty. Because U.S. non-MFN tariffs were largely determined in the 1930s and U.S. MFN tariffs are small, the difference between them is due primarily to the historic non-MFN tariff levels, which plausibly are weakly connected to changes in industry innovation potential in the 1990s and 2000s.

For completeness, we also consider the phase-out of import quotas from the Multi-Fiber Agreement (MFA) between 1999 and 2005 as an additional instrument for within-industry changes in import exposure, which follows the approach of Bloom, Draca and Van Reenen (2016). MFA quotas applied primarily to products from the textile, apparel and leather sectors. In the U.S., these sectors however account for a negligible share of total patent output, as indicated in Table 2.

3.2 Baseline Estimates

Table 3 gives estimation results for equation (2). 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). Consistent with our reasoning in Section 3.1, the modest difference between OLS and IV estimates for growth in patenting stands in contrast to the application to employment changes in Autor, Dorn, and Hanson (2013), suggesting that the multiple sources of OLS bias may offset each other here.

Moving beyond the univariate regressions in panel A, panel B adds controls to address differences across sectors in patenting trends. In rows (c) and (d) of Table 3, we add dummy variables for the two most technology-intensive sectors, which also have divergent long-term trends of patenting: chemicals—in which patenting has been decelerating over time—and computers, in which patenting has been sharply accelerating. The negative impact of industry import penetration on firm patenting becomes larger and statistically significant, both in OLS (column 3, row c) and 2SLS (column 3, row d) specifications. The change in results from panel A to panel B illustrates the importance of controlling for industry trends in innovation, a finding that our subsequent analysis reinforces.

In columns 4 to 6 of panel A in Table 3, 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 correlation becomes close to zero and statistically insignificant once we control for the two sectoral dummies for computers and chemicals, as seen in rows (c) and (d) of Table 3. Failure to control for patenting pre-trends across sectors thus introduces a source of confounding variation that imparts upward bias to estimates of the impact of import competition on patenting.

Column 7 of Table 3 indicates the difference between the coefficient estimates of column 3 versus column 6, obtained from a stacked version of the column 3 and 6 models. The significant negative point estimates in rows (a) to (d) indicate that industries facing 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 in all these specifications. The role of the sectoral dummies for computers and chemicals is to absorb the differential secular trends in patenting for these sectors that predate the growth of Chinese import competition. Therefore, the coefficients in rows (c) and (d) of column 3 for the 1991-2007 period are very similar to the coefficients in rows (c) and (d) of column 7, as the latter evaluates the 1991-2007 impact of imports on patenting relative to a pre-trend that is close to zero conditional on controlling for patenting trends in computers and chemicals.

Table 3: 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. +	-1.16	-0.52	-1.17 *	0.62	0.33	0.48	-1.65 **
industry/firm controls	(1.06)	(0.34)	(0.48)	(0.42)	(0.58)	(0.43)	(0.54)
h. 2SLS, 11 mfg d. +	-1.13	-0.72 *	-1.35 **	0.31	0.27	0.27	-1.63 **
industry/firm controls +	(1.31)	(0.35)	(0.50)	(0.34)	(0.62)	(0.39)	(0.55)
i. 2SLS, 11 mfg d. +ind/firm	-1.29	-0.80 *	-1.39 **	n/a	n/a	n/a	n/a
cntrls +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. Import penetration increased by a mean of 2.07 (s.e. 4.37) percentage points in 1991-1999, by 6.46 (s.e. 14.34) in 1999-2007, and by 4.54 (s.e. 11.34) pooled over both periods. 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 and 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 3 successively add further controls to account for other potentially confounding factors that may affect industry or firm incentives to innovate, as discussed in Section 3.1. 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. In fact, when adding controls for industry and firm characteristics, including lagged patenting, the impact coefficient of trade exposure on patenting slightly *increases* in absolute value, though parameter differences across rows in panel B of column 3 are not statistically significant. 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 approximately a 15.3 log-point decrease in patents.

We conduct a variety of robustness tests on our main specification and discuss the results in Appendix B. In short, our finding of a significant negative impact of import competition on patenting is robust to using different samples, such as including only patents granted within six years of the application date, excluding patents from the computer sector, excluding patents from the chemical sector, and using only subsets of patents matched during the different steps of our matching algorithm. It is also robust to using alternative firm weights, which include patent citations, firm R&D expenditure, firm global sales, or an unweighted sample of firms.

3.3 Alternative Identification Strategies

Table 4 reports results using the alternative instruments for trade exposure as discussed in Section 3.1. To start, column 1 presents an OLS regression of the change in patenting on the growth of import penetration and the full vector of control variables from Table 3. This regression does not rely on any of the instruments considered. It finds a highly significant negative correlation between import competition and innovation that is comparable in magnitude to the corresponding 2SLS estimate of Table 3 (column 3, row h). Column 2 of Table 4 augments this specification with a full set of fixed effects for 4-digit industries that would absorb any secular technology trend at the level of detailed industries. The coefficient estimate on the interaction term between import exposure and an indicator for the 1999-2007 period in column 2 derives from a comparison of import exposure and patenting within 4-digit industries over time. The coefficient is smaller and less precisely estimated than the correlation in column 1, but remains significantly negative. It implies that industries in which import growth accelerated more in the 1999-2007 period relative to 1991-1999 also experienced a greater slowdown in patent production in the 2000s relative to the 1990s.

The subsequent columns in Table 4 show the results of regressions without and with industry fixed effects that exploit the alternative instruments for growth in import competition. Following Pierce and Schott (2016), we report these results using the OLS reduced form, in which the instrument for U.S. import growth from China is included directly as a regressor, in place of the endogenous change in U.S. imports. Columns 3 and 4 of Table 4 regress the change in patenting on the instrument from equation (3) that draws on Chinese exports to developed countries other than the U.S.. The estimated coefficients are significantly negative and of similar magnitude both in the specifications without and with industry fixed effects.

Table 4: Response of Patenting to Alternative Measures of Trade Exposure, 1991-2007. Dependent Variable: Relative Change of Number of Patents by US-Based Inventors: OLS and OLS Reduced Form Estimates.

	Exposure Variable							
	A. US Imports from China (OLS)		*B. Third Country Imports from China (OLS Reduced Form)*		*C. Normalized Trade Relations Tariff Gap (OLS Reduced Form)*		*D. Multi-Fiber Agreement Quotas (OLS Reduced Form)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Regression Estimates							
Exposure Variable	-1.17 **		-1.81 **		1.95 **		-3.28	
	(0.16)		(0.69)		(0.43)		(2.22)	
Exposure Variable x		-0.71 *		-1.63 *	-1.85 **	-0.92 ~	-2.70 ~	-2.27
1999-2007 Period		(0.33)		(0.74)	(0.59)	(0.56)	(1.39)	(2.11)
Full Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry Fixed Effects		yes		yes		yes		yes
	Descriptives for Exposure Variable in 1999-2007 Period							
Mean		6.46		5.62		30.00		1.47
Std Dev		(14.34)		(9.17)		(14.31)		(4.49)
Impact of 1σ Exposure		-10.15		-14.91		-13.11		-10.21
	Share of Manufacturing Patents in 4-Digit Industries with Non-Zero Exposure, 1999							
Exposure Rate	100.0%		100.0%		100.0%		4.9%	

Notes: N=8271 except N=495 in columns 7-8 which include only the 3-digit sectors that comprise at least one MFA-affected 4-digit industry. Every regression comprises two stacked first differences 1991-1999 and 1999-2007, and includes the full set of controls from model 3h in table 2. Data on average fill rates of MFA quotas in 1999 and on NTR tariff gaps are based on Pierce and Schott (2016), and are measured in percentage points. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In column 5 and 6 of Table 4, we incorporate as an alternative instrument the gap between non-MFN and MFN tariffs based on data from Pierce and Schott (2016). This variable should have different impacts during the 1990s, when China's future access to favorable U.S. MFN rates was uncertain, and the 2000s, when that uncertainty was eliminated following China's accession to the WTO. We therefore include in column 5 both a main effect of the instrument, and an interaction of the instrument with the 1999-2007 period.[31] The tariff gap is positively correlated with the change in patenting in the 1990s (first row, column 5), but relative to this positive trend, industries with higher tariff gaps experience a slowdown in patenting in the 2000s (second row, column 5). This pattern suggests that in the 2000s, innovation fell by more in industries subject to larger reductions in trade policy uncertainty. When we introduce industry fixed effects in column 6, the coefficient on

[31] Similar to the non-MFN versus MFN tariff gap, the expected economic effect of the MFA quotas in column 7 differs across the 1991-1999 period (when quotas were in place) versus the 1999-2007 period (during which the quotas were removed). By contrast, the expected impact of rising predicted Chinese import competition as captured by the instrument of equation (3) does not differ across periods. When an interaction term with the 1999-2007 period is added to the regression in column 3 of Table 4, then the coefficient of the interaction term is very small and imprecisely estimated (coefficient 0.04, s.e. 1.75), which suggests that a unit increase in the column 3 instrument has the same impact on patenting in both periods.

the interaction between tariff gap and second period indicator remains negative and is marginally statistically significant. The alternative instrument used in columns 3-4 and 5-6 yield not only qualitatively but also quantitatively comparable estimates. As indicated in the lower half of the table, a one standard deviation increase of the column 4 instrument reduces growth in patenting by 15 log points, whereas a one standard deviation greater value of the column 6 instrument is associated with a 13 log point decline.

Columns 7 and 8 of Table 4 incorporate the instrument for import competition used by Bloom, Draca, and Van Reenen (2016), which is the share of industry imports subject to MFA quotas prior to the elimination of these quotas in 2005.[32] As for the tariff gap in columns 5 and 6, the focus is on the contrast between the 1991-1999 period when the quotas were in place, and the 1999-2007 period during which the quotas were removed. A major limitation of the MFA instrument is that sectors subject to import quotas produce a very small share of patents, accounting for just 4.9% of manufacturing patenting in 1999 (bottom row, Table 4). The patent output in industries with an average MFA quota fill rate of at least 20% combined for just 17 total patents in 1999, or 0.05% of the manufacturing total in our sample. The MFA instrument thus provides identifying variation only across a limited subset of industries, and hence differs substantially from the instruments used in columns 3-6, which have non-zero values across the full range of manufacturing industries.[33] Following Bloom, Draca and Van Reenen (2016), we thus analyze the impact of the removal of MFA quotas for the subsample of firms from sectors that contain MFA-affected industries. Most of these industries are located in the textile, apparel and leather sectors.[34]

Column 7 of Table 4 indicates a negative association between MFA quotas and U.S. patent growth during the 1990s that becomes more negative in the 1999-2007 period during which the import quotas were phased out. While the interaction term between the MFA instrument and the 1999-2007 period is marginally significant in the column 7 model, the corresponding estimate in the industry fixed effects model of column 8 is of similar magnitude but less precisely estimated. These negative estimates stand in contrast to the results in Bloom, Draca, and Van Reenen (2016), who find a positive impact of exposure to the removal of MFA quotas on patenting by European firms.

Table 4 shows quite powerfully that whether we relate the change in patenting to the observed growth in U.S. imports from China, to the surge in China's exports to the U.S. using the country's export performance in other high-income countries, as in Autor, Dorn, Hanson, and Song (2004), to implicit changes in trade-policy uncertainty in the United States, as in Pierce and Schott (2016), or to the removal of import quotas in a narrow set of MFA-affected industries, as in Bloom, Draca and Van Reenen's (2016), we find that firms subject to larger increases in industry trade exposure suffer larger decreases in patenting. Since import exposure grew more rapidly in the 2000s than in the 1990s, its negative impact on innovation contributed to the slowdown in U.S. patent production

[32] Our data for the fill rate of MFA quotas in the U.S. is from Pierce and Schott (2016).

[33] In 1999, all manufacturing patents in our sample originated from industries in which both the U.S. and other developed countries obtained imports from China during the subsequent 1999-2007 period, and all of these industries faced a positive gap between non-MFN and MFN tariffs.

[34] Our sample includes all 3-digit sectors that include at least one 4-digit industry with MFA-affected products. Out of 54 industries with MFA exposure, 42 belong to the textile, apparel and leather sectors.

that is apparent in Figure 1. Based on the estimate of column 4 in Table 4, we estimate that rising import competition since 1999 explains 41% of the slowdown in the growth of U.S. manufacturing patenting in the 1999-2007 period relative to the 1991-1999 period.[35]

3.4 Alternative Industry Classifications

In the sample used for the estimation results in Table 3, we classify firms according to their main industry code, as reported in Compustat. This code generally corresponds to industry affiliation during the most recent period. It is however 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.

In Table 5, we compare our baseline results in column 1, taken from column 3 and row (h) of Table 3, to those obtained from alternative definitions of a firm's industry affiliation. In column 2, we designate a firm's primary industry to be that at the start of the respective period, when available, or else from the earliest available subsequent 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 across industries, 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

[35] The number of annual manufacturing patents in our sample grew by 18,966 in the 1991-1999 period (from 22,215 to 41,181) and then declined by 6,161 from 1999 to 2007 (from 41,181 to 35,020). We recalculate each firm's patent growth during the 1999-2007 period for a counterfactual scenario with no import growth by subtracting from each firm's outcome variable the actual growth of import penetration in its industry times the regression coefficient of -1.63 in column 4 in Table 4, and constraining the resulting values to the admissible range of -200 to 200 over which the outcome variable is defined. The counterfactual number of 2007 patents of the firm can then be directly backed of the adjusted outcome variable, which is (counterfactual 2007 patents - actual 1999 patents)/(average of counterfactual 2007 and actual 1999 patents). Summing up over the entire manufacturing sector, we calculate that absent growing import competition in the 2000s, patent output would have modestly increased by 4,173 patents (from 41,181 to 45,354) over the 1999-2007 period. In this counterfactual, the slowdown in patent growth across the two periods would have been -14,793 (4,173-18,966) instead of -25,127 (-6,161-18,966), which implies that import competition can explain 100-(-14,793/-25,127)=41.1% of the observed deceleration in patent growth.

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.

Table 5: 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 in Patenting					*Probability Δ Industry or Segment*		
						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	-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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

These estimation results suggest that changes in import competition may have little impact on firm industry representation. In columns 6 to 8 of Table 5, 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.[36] 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,

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

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.

3.5 Analysis at the Technology-Class Level

One limitation of using the Compustat firm data is that we do not observe smaller firms that never cross the threshold into being publicly listed. These firms likely account for the bulk of the 28% of corporate patents that our algorithm did not match to firms that have ever been covered by Compustat. However, while we do not know the industry of these unmatched firms, we do observe detailed technology classes 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. This allows us to examine how these imputed trade shocks at the technology-class level affect patenting by corporate entities, whether or not they appear in Compustat and thereby expand our analysis to include both public and non-public companies. Similarly, we also estimate the impact of import competition on patents by non-corporate entities—which include universities, hospitals, other non-profit institutions, and private individuals. Table 6 presents these results.

Table 6: 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	-3.33 *	-3.25 *	-3.25 *	-3.06 *	-3.35 *	-3.35 *	0.63	2.01	-3.11 *	-2.64 *
Chinese Imports	(1.33)	(1.33)	(1.33)	(1.49)	(1.34)	(1.34)	(1.29)	(1.43)	(1.25)	(1.30)
Two Sectors (Comp, Chem)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
11 Sectors, Six Tech		yes	yes		yes	yes		yes		yes
2 Lags of Outcome			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, and dummies for 6 major technology categories. 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 6 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 6 has a notably smaller standard deviation (4.38) than the import shock used in column 3 of Table 3 (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 6, 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 3, we had found a 15.3 percentage-point reduction in firm-level patents associated with a one standard deviation in import exposure. The firm- and technology-class level regressions thus find comparable sizes of effects of import competition on U.S. corporate patenting.

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 3 but now aggregated to the technology class level. The coefficient estimates are similar to those for all corporate patents, showing a modestly 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).

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. Since non-corporate entities such as universities and hospitals are not directly subject to manufacturing-industry market forces, we would expect their patenting activities to reflect underlying availabilities of technological opportunities—which presumably apply to all types of invention—more so than responses to import competition. That import competition does not inhibit patenting by non-corporate entities suggests that the trade-exposed industries do not suffer from an exhaustion of technological opportunities.

Finally, in columns 9 and 10, we include in the analysis both corporate and non-corporate patents, which constitutes the universe of patenting by U.S.-based inventors. 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, but has no such effect on non-corporate entities.

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 extend our main analysis. First, we examine whether greater import competition may have had differential effects by geography. Second, 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. Third, we explore the heterogeneity of the impact of trade shocks by firms' initial conditions to further inform the interpretation of our results.

4.1 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.[37] 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). In Table 7, we examine whether greater import competition may have had differential effects on innovation at home versus innovation abroad in a manner analogous to the impacts of trade on the global location of employment engaged in production.

The data allow us to track the location of innovation via the address of the lead inventor listed in the patent application. In its worldwide operations, IBM, for instance, has 12 R&D labs located in 10 different countries.[38] 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, Israel, 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 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, and thus captures innovation within the U.S. 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.

In column 1 of Table 7, we expand the set of firm patents to include all inventors, whether based in the U.S. or abroad; in column 2, we repeat the baseline result for U.S.-based inventors; and in column 3, we limit patents to those created by foreign-based inventors. The impact of import competition on patenting by foreign inventors (-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

[37] 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.

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

and domestically-based inventors (columns 7 to 9). Overall, we find a uniformly negative effect of Chinese import competition on firm patenting, regardless of firm and inventor locations.

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

	A. US Inventors			*B. US Firms*			*C. All Firms, Inventors*
	All	US Firms	Foreign Firms	All	US Inventors	Foreign Inventors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ U.S. Industry Exposure to Chinese Imports	-1.35 **	-1.17 ~	-2.23 **	-1.15 *	-1.17 ~	-1.03 ~	-1.28 **
	(0.50)	(0.64)	(0.47)	(0.56)	(0.64)	(0.63)	(0.40)
Mean Outcome Variable	24.42	22.50	41.81	25.07	22.50	44.39	27.56
No. Observations	8271	7596	675	7996	7596	2003	9381
No. Patents Used	129,585	117,190	12,395	133,151	117,190	15,961	217,489

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. Panel A uses only patents whose main inventor is based in the US (as observed in the patent), while Panel B uses only firms that are headquartered in the US (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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

Not observing patents filed outside of the U.S. is unlikely to be an issue for the interpretation of our analysis as it relates to U.S. firms. Given the importance of the U.S. market and its well-developed intellectual property protection system, it is highly unlikely U.S. firms would patent elsewhere, such as in China, without patenting in the U.S., regardless of where the inventions originate from. However, the scarcity of U.S. patents from China-based inventors and firms makes it difficult to examine the potential growth in innovations originating from China. Across the five sample years, there are only 2,055 corporate patents with China-based primary inventors, nearly 94% of which are from application-year 2007.[39]

4.2 Additional Firm-Level Outcomes

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 8, 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

[39] There is a similar surge in patent filings at the State Intellectual Property Office of China during the 2000s, but the quality of these inventions appears to be low (Hu and Jefferson, 2009; Boeing and Mueller, 2016).

the firm had an increase in profit over the same period (column 10).[40] 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.[41]

Table 8: 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	Advertising Exp	Global Employment	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	-1.14	-0.81 *	-0.83 **	-0.96 *	-0.71 *	-1.25 **	-1.67 *	-1.31 *	-0.37	-0.43 *
Exposure to Chinese	(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	0.22	0.06	0.25	-0.64	0.15	0.48	0.62	0.09	-0.05	0.27
Exposure to Chinese	(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	1,508	1,672	1,181	592	1,597	1,670	1,456	1,656	1,634	1,644

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. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

In all ten specifications, the estimated impact of a 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 profit increases). These results drive home the breadth of the competitive consequences that import growth from China has meant for manufacturing firms in the U.S. market. It is not simply that U.S. production employment has contracted. The largest relative change across the outcome variables in columns (1) to (9) is a decline in stock market valuations, which fall as sales, profitability, and investment into future business development through R&D and advertising expenditure contract. By contrast, the lowest adjustment is seen for debt, which falls by much less than book value or equity. Of particular interest for our analysis is that we observe a negative impact of import competition on both innovation inputs

[40] 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 8, 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 negative or missing. The latter restriction leads to smaller sample sizes especially for the outcomes R&D spending and advertising expenditure, which are not reported by all firms. Since EBIT (earnings before interest and taxes) can be negative, the corresponding outcome variable in column (10) is defined as a dummy for growth in the outcome rather than a relative change.

[41] In very rare cases, Compustat records negative values such variables as sales, capital or R&D expenditure, which we winsorize at zero.

(R&D spending) and observed innovation outputs (patenting), which suggests that firms facing fierce import competition are not simply holding back from patenting while still investing in innovation.

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 8, 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.

4.3 Heterogeneity by Initial Conditions

The results of Table 8 imply that import-exposed firms may be forced to reduce their investments in R&D as falling sales, lower profits and a higher debt ratio reduces their financial action space. We next explore whether the impact of import competition on firm innovation is particularly negative for firms that were already less productive, less profitable and more indebted prior to the import shock. The Melitz (2003) model predicts that 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.

Table 9: 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. Firm Labor Productivity and Capital Intensity				*B. Firm Profitability and Leverage*			
	Sales/Worker		Capital/Worker		Profit/Capital (ROI)		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	-1.11 (0.79)	-2.32 ~ (1.38)	0.04 (1.04)	-2.47 ** (0.58)	-0.98 (0.63)	-2.01 ** (0.74)	-3.18 ~ (1.72)	-0.95 * (0.42)
Mean Outcome Variable	27.27	3.29	25.48	3.16	17.16	0.69	12.76	11.34
No. Observations	1,348	2,738	1,270	2,068	1,492	2,078	638	2,555

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 9, 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 (column 2), lower initial capital per employee (column 4), a low initial rate of return on investment (column 7), or a higher initial debt/equity ratio (column 7) 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, 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). In complementary analyses, Gutierrez and Philippon (2017) find that the sensitivity of capital investment to changes in industry import competition is greater in smaller relative to larger U.S. manufacturing enterprises, and Aghion, Bergeaud, Lequien, and Melitz (2017) find that patenting by French manufacturing firms responds more positively to export-demand shocks in more-productive relative to less-productive establishments.

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 or when expanding the sample to include patenting by corporations that are not publicly listed. We provide a variety of robustness tests to show 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. Greater import competition also causes U.S. firms to contract along every margin of activity that we observe, including sales, profits, stock market valuation, 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.

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 U.S. to China, it likely increased the geographic distance between R&D (in the U.S.) and manufacturing. Such geographic separation may have made it more difficult for US companies with domestic R&D operations to coordinate successfully between R&D and manufacturing (Pisano and Shih, 2012) or to keep investing in advanced production technologies (Fushs and Kirchain, 2010). Among these explanations, our results are most consistent with the simple profitability mechanism of Dasgupta and Stiglitz (1980). The trade-induced contraction along all margins of adjustment and for all measures of valuation suggest that the primary response of firms to greater import competition is to scale back their global operations.

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Appendix A: Matching Patent Assignees to Firms

We utilize a four-step matching procedure to assign patents to firms in the Compustat data. First, following NBER-PDP, we clean the firm names (e.g., removing punctuation and accents) and standardize commonly used words in firm names in both the patent and Compustat data (e.g., Corp./Corporation). This allows us to perform an initial matching based on standardized names.[42] Columns (4a-b) of Table A3 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. However, the performance of name matching deteriorates over time, with a match rate that falls from 59% of corporate patents in 1975 to just 44% of patents in 2007, perhaps due to an increasing variety of inconsistent and misspelled firm names over time. Next, we conduct an internet search of 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

[42]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.

if the top search results for the patent assignee contain the company website listed in Compustat (e.g., ibm.com). 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 A3 show that web-based matching alone allows us to match 64% of corporate patents to Compustat firms, with 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 match less frequently used variations of a firm's name in the patent records. In the final two steps of our matching procedure, we append 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. Our final sample links 72% of all corporate patents to Compustat (column 2b of Table A3), compared to a match rate of 65% in the NBER-PDP up to the application year 1999 (column 3b).

Table A4 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 final sample), while web-based matching adds 34,495 patents that would have been missed by name matching (20% of the sample). 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).

Because our matching algorithm is easily scalable, we have also executed the matching of patents to Compustat records for all other patent application years. Table A1 provides an illustration of the quality 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 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)
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	*Cumulative %*
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: 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. Avgerage 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.

Table A4: Matching of Corporate 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	

Sequential Matching of Patents to Compustat (columns 2–5)

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.

Appendix B: Alternative Samples and Weighting Methods

Table B1 provides additional robustness tests on our primary results and compares them to the estimates from our baseline specification (taken from column 3, row h of Table 3 and reported in column 1 of Table B1).We first 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 B1, we examine the robustness of our results to imposing a uniform time to approval for all patents considered in the analysis. We restrict the sample to patents granted within six years of the time of application. Because the vast majority of patents are granted within a few years after an application is submitted, the impact of this restriction on the sample size is small. The number of firm-years included in the analysis falls from $8,271$ 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 B1: 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	No Grant Lag >6 Years	No Comp / Comm Tech	No Chem/ Drug Tech	No Manual Matches	No Manual or NBER Matches	Compustat Balanced Panel	Patent Citations	Global R&D	No Weights
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ U.S. Industry Exposure to Chinese Imports	-1.35 **	-1.37 **	-1.83 **	-1.52 **	-1.32 **	-1.09 *	-1.60 **	-1.30 *	-1.26 **	-0.39 **
	(0.50)	(0.50)	(0.54)	(0.54)	(0.44)	(0.45)	(0.58)	(0.59)	(0.38)	(0.14)
No. Observations	8,271	8,167	6,837	6,566	8,257	7,795	3,262	7,150	14,371	44,615
No. Patents Used	129,585	127,654	83,690	99,440	125,533	117,847	104,510	126,855	116,162	129,585

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 retains only firms that are observed in Compustat both at the start and end of a period. Column 8 weights firms by the share of its patents among all patent citations, averaged over the start and end of the period. Column 9 weights firms by R&D expenditures, averaged over the start and end of the period. Column 10 does not use weights. 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 3, we have already explored such sensitivity by incorporating controls for the technology mix of patenting by the firm, as measured by the average shares of firm patents that fall into the six major patent classes shown in panel II of Table 2. The results in Table 3 reveal that after adding controls for the firm's broad sector of activity, controlling for the technology mix of the firm's patents has little extra effect. In columns 3 and 4 of Table B1, 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 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 B1 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 modestly 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 order to match a patent to a Compustat firm, it is required that the firm appears in Compustat data at least once during the 1950 to 2014 period. It is not necessary, however, that Compustat lists the firm in the year of the patent application, as we can for instance match a firm's patents prior to its listing in the stock market to the Compustat record that was created after the firm went public. As a further robustness check, column 7 of Table B1 restricts the sample to a balanced panel of those firms that are covered by Compustat both at the start and at the end of an outcome period. The firms in this balanced panel account for 104,510 out of the 129,585 patents that we use in the baseline specification, and the coefficient estimate from the corresponding regression is slightly larger.

In Table 3, 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 8 of Table B1 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 very similar estimated impact of trade exposure on firm patenting (-1.30). 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. Moreover, weighting by firm global R&D spending extends the sample to include firms for which we observe positive R&D spending but no patents in the sample period. The resulting regression estimate in column 9 of Table B1 again indicates a similar impact of trade exposure on firm patenting (-1.26), when compared to patent-citation weighting in column 7 or patent-count weighting in column 1. Each of the weighting schemes based on patents, patent citations or R&D expenditure allocate greater weight to firms whose contribution to U.S. innovation is larger. In column 10 of Table B1, we instead consider an unweighted sample of Compustat firms which also comprises non-innovative firms that do neither patent nor report R&D spending in a given time period, and that would hence have a zero weight in the previous specification. The estimated impact of import penetration on patenting in the unweighted firm sample is smaller in magnitude (-0.39) than in the baseline specification, but it remains significantly negative (t-statistic 2.7).