

Introduction

Despite accounting for less than one-tenth of U.S. private non-farm employment, U.S. manufacturing still generates more than two-thirds of U.S. R&D spending and corporate patents.¹ In light of China’s spectacular growth in manufacturing exports, the potential impact of import competition on innovation by domestic firms has gained relevance.² In this paper, we study the effect of rising import competition on U.S. innovation at the firm level.

How product-market competition affects innovation is of longstanding theoretical interest.³ Schumpeterian models posit that a more competitive product market reduces firm profit margins, resulting in lower investments in innovative activity (e.g., Dasgupta and Stiglitz, 1980). But as Arrow (1962) noted, when competitive pressure is low and pre-innovation rents are high, firms may have little incentive to invest in innovation. Aghion et al. (2005) formalize these competing insights, showing how differences between pre-innovation and post-innovation rents determine a firm’s response to competition. This response depends on the dispersion in technological advancement across firms. When dispersion is low, intensified competition encourages firms to innovate to “escape competition.” When dispersion is high, more competition may stifle innovation among laggard enterprises.⁴

Following a large literature (Cohen, 2010), we measure innovation using firm patenting and R&D expenditure, which we supplement with firm-level data on sales, investment, and profitability.⁵ We match the assignees of all U.S. patents granted between 1975 and 2013 to publicly held firms listed in Compustat through 2014 using a search-engine-based algorithm that disambiguates inconsistently spelled and abbreviated renditions of firm names on patent applications. Following Autor et al. (2014), we isolate the industry-specific component of U.S. import growth that is driven by export-supply growth in China by instrumenting rising U.S. import competition with contemporaneous changes in industry-level import penetration in other high-income countries. Using alternative identification strategies (Bloom et al., 2016; Pierce and Schott, 2016), we obtain comparable results.

We first show that increased imports from China ramped up competitive pressure on publicly listed U.S. firms: reducing U.S. and global sales, diminishing book and stock values, curtailing

¹Helper et al. (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.

²A substantial literature shows that import competition from China has contributed to job loss in U.S. manufacturing (e.g., Bernard et al., 2006; Autor et al., 2013, 2014; Pierce and Schott, 2016; Acemoglu et al., 2015).

³See Gilbert (2006) and Cohen (2010).

⁴The prediction is unclear for firms that are technological leaders. Additional causal mechanisms raise further ambiguity. See Hart (1983), Chen and Steinwender (2017), and Bloom et al. (2018), as well as Shu and Steinwender (2018) for a synthesis of this literature.

⁵On using patents to measure innovation, see Jaffe and Trajtenberg (2002) and Moser (2016). On the economic value of patents, see Hall et al. (2005) and Kogan et al. (2017).

purchases of labor and capital inputs, and proportionally reducing R&D investment. We next show that this increase in competitive pressure led U.S. firms to *decrease* their output of innovations as measured by patent grants. These negative effects are confirmed when using two alternative measures of trade exposure based on changes in trade policy, neither of which is likely to be driven by technology trends: the U.S. grant of Permanent Normal Trade Relations to China in 2000; and the scheduled elimination of the Multi-Fiber Agreement tariffs in 2005. Notably, the induced fall in patents is roughly proportional to the contraction of sales, employment, capital, and R&D expenditure at import-competing firms.

To overcome the fact that our firm-level analysis necessarily excludes patents granted to firms that are *not* listed in Compustat, we exploit the fact that all patents are assigned a technology class regardless of corporate ownership, which allows us to estimate the effect of import competition on patenting at the *technology class* level. Consistent with the firm-level results, we find that technology classes with greater growth in import penetration saw a substantial relative decline in *corporate* patents during our analytic window of 1991-2007. We find no similar decline in patenting by non-corporate entities (e.g., governments and universities), indicating that our key findings are specific to private-sector innovation and do not reflect underlying correlations between contracting innovation opportunities and rising trade exposure.

Our results stand in contrast to those of Bloom et al. (2016) for European firms and highlight the underlying theoretical ambiguity in the relationships between competition and innovation. We speculate that the differential impacts of foreign competition on domestic innovation in the U.S. versus Europe may be reconciled through the lens of Aghion et al. (2005): U.S. industries have been found to display larger gaps in the technological capabilities of leading and lagging firms when compared to firms in Europe (Bartelsman et al., 2013; Hashmi, 2013). We provide suggestive evidence in support of the Aghion et al. (2005) model by showing that within the U.S., the negative effects of import competition concentrate on firms that are initially less productive and less profitable.

Our work is contemporaneous to emerging evidence on the impacts of import competition on innovation-related outcomes in North America.⁶ Xu and Gong (2017) and Hombert and Matray (2018) also use Compustat data to show that import competition has a negative impact on firms' R&D expenditure and financial outcomes. Xu and Gong (2017) further show that R&D is reallocated toward more productive firms, and Hombert and Matray (2018) find that firms with large R&D stocks mitigate the negative impact of import competition through product differentiation. Kueng et al. (2016) find that more trade-exposed Canadian firms experience strong declines in self-reported innovation outcomes. We contribute to this literature by providing a comprehensive analysis of the impact of Chinese import competition on both output (patenting) and input (R&D

⁶An extended set of results are available in our earlier working paper, Autor et al. (2016).

expenditure) of firm innovation in the U.S. Our analysis accounts for industry pre-trends and establishes robustness to a wide range of identification strategies. Consistent with a competitive market response, we find that Chinese import competition reduces innovation at both the firm and technology-class levels in the U.S. private sector.

1 Measuring Trade Exposure

To measure import penetration, we match trade data to U.S. manufacturing industries. In a second step, we match industry-level trade exposure to firm-level data, which we then match to patent records. The Online Appendix provides further details.

To create measures of changing import penetration, we match trade data to four-digit SIC U.S. manufacturing industries using the UN Comtrade Database and the crosswalk in Pierce and Schott (2012). 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

$$\Delta IP_{j\tau} = \frac{\Delta M_{j,\tau}^{UC}}{Y_{j,91} + M_{j,91} - E_{j,91}}, \quad (1)$$

where for U.S. industry j , $\Delta M_{j,\tau}^{UC}$ is the change in imports from China over two sub-periods, 1991 to 1999 and 1999 to 2007, and $Y_{j,91} + M_{j,91} - E_{j,91}$ is initial absorption (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 starting year for the analysis as it is the earliest period for which we have disaggregated bilateral trade data to match to U.S. manufacturing industries.⁷

Observed changes in import penetration 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 et al. (2014) and instrument for trade exposure in (1) with the variable,

$$\Delta IPO_{j\tau} = \frac{\Delta M_{j,\tau}^{OC}}{Y_{j,88} + M_{j,88} - X_{j,88}} \quad (2)$$

where $\Delta M_{j,\tau}^{OC}$ is the growth in imports from China in industry j during the period τ for a group of eight industrialized countries that does not include the U.S.⁸ The denominator in (2) is initial

⁷Our empirical approach requires 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.

⁸These 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.

absorption in the industry in 1988. The motivation for the instrument in (2) is that high-income economies are similarly exposed to growth in imports from China that is driven by supply shocks 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. Autor et al. (2013) and Autor et al. (2014) provide evidence on the robustness of this instrumentation approach in studying the China trade shock. We complement this strategy by also using the identification approaches of Pierce and Schott (2016) and Bloom et al. (2016), as discussed in Section 3.3.

2 Evidence of Increased Competitive Pressure from Imports

Prior to assessing the impact of rising Chinese import competition on *realized* innovation outcomes, we verify that this force exerts significant competitive pressure on import-competing firms, measured by sales, profitability, and R&D investment.⁹ For our analysis, we match industry-level trade exposure to Compustat North America, which provides industry affiliation and financial statement data on companies whose shares are traded at a North American stock exchange.¹⁰ We estimate the following regression model using these matched data:

$$\Delta Y_{ij\tau} = \alpha_{\tau} + \beta_1 \Delta IP_{j\tau} + \gamma X_{ij0} + e_{ij\tau}, \quad (3)$$

where $\Delta Y_{ij\tau}$ is the change in a firm outcome, for firm i in industry j over time period τ , defined as $100 \times (Y_{ij,t1} - Y_{ij,t0}) / (0.5Y_{ij,t1} + 0.5Y_{ij,t0})$, and $\Delta IP_{j\tau}$ is growth of import exposure (in percentage points) for industry j over period τ , as defined in equation (1) and instrumented by $\Delta IPO_{j\tau}$, as defined in equation (2)).¹¹ The control vector X_{ij0} comprises time trends for eleven U.S. manufacturing sectors. For consistency with the analysis of firms’ patenting activity, observations are weighted by the number of firm patents, averaged over the start and end year of period τ , though we obtain similar results when observations are weighted by firms’ U.S. sales.

Table 1 reports results. The first two columns of panel I indicate that firms facing an exogenous rise in Chinese import competition exhibit a relative decline in both U.S. and global sales between 1991 and 2007. The former effect is imprecisely measured, while the latter estimate implies that global sales contract by eight-tenths of a percent for each percentage point increase in Chinese

⁹These results corroborate literature on the consequences of the China trade shock. See footnote 2, Xu and Gong (2017), and Hombert and Matray (2018).

¹⁰Compustat covers companies that have at least one regularly, actively, and publicly traded issue listed on a US or Canadian exchange and that provide a regular filing of financial reports. The data includes foreign companies that use American Depository Receipts (ADRs). The coverage of our data ends in 2014.

¹¹We use the proportional change scaling of the outcome variable rather than the log change because some values of Y are equal to zero.

import penetration. Columns 3 and 4 report a corresponding decline in firm utilization of labor and capital, suggesting an overall decrease in firms' scale of operation. Consistent with these contractions, the book and stock market value of exposed firms falls by approximately 1.5 percent for every percentage point rise in import competition (columns 5 and 6). Column 7 indicates that R&D investment at import-competing firms drops roughly one-for-one with rising import exposure, indicating a fall in *inputs* used in innovation.

Could these patterns merely reflect firm-level trends that pre-date the “China Shock?” Panel II of Table 1 indicates otherwise. When we regress firm outcomes during the *pre-period* of 1975-1991 on *future* change in Chinese imports occurring between 1991 and 2007, we find that in seven of eight cases, the point estimates are insignificant, and in all cases the coefficients are opposite signed to those in Panel I.

Table 1: Effect of Chinese Import Competition on Firm Outcomes, 1991-2007 and 1975-1991 (for Falsification Test). Dependent Variable: Change in Sales, Inputs, Firm Value, and R&D (in % pts).

	<i>Firm Sales</i>		<i>Firm Global Inputs</i>		<i>Firm Value</i>		<i>R&D</i>
	U.S.	Global	Workers	Capital	Book	Market	Investment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>I. Exposure Period 1991-2007</i>							
Δ U.S. Industry Exposure to Chinese Imports	-1.29 (1.07)	-0.79 (0.41)	~ -0.75 (0.41)	~ -1.28 (0.55)	* -1.42 (0.71)	* -1.65 (0.76)	* -0.95 (0.39)
Mean Outcome Variable	32.94	54.42	19.92	55.55	-14.80	41.38	50.77
No. Observations	2200	3098	2803	3104	2965	2679	2279
<i>II. Pre Period 1975-1991</i>							
Δ U.S. Industry Exposure to Chinese Imports	0.47 (0.31)	0.48 (0.40)	0.21 (0.27)	0.80 (0.49)	0.54 (0.58)	0.28 (0.50)	0.79 (0.41) ~
Mean Outcome Variable	45.44	60.63	3.55	58.19	-4.84	58.73	72.87
No. Observations	1,971	2,188	2,084	2,178	2,162	1,872	1,453

Notes: Every regression in Panel I comprises two stacked first differences 1991-1999 and 1999-2007, and includes a period dummy and eleven indicator variables for broad sectors of manufacturing. The data includes all U.S. firms for whom the indicated outcome variable is reported in Compustat at the start and end of a given period. The relative change of an outcome variable is defined as the first difference in the outcome over a period $t, t+1$, divided by the average of the outcome across the two periods t and $t+1$. Panel II provides falsification tests that regress the change in outcomes during the periods 1975-1983 and 1983-1991 on the future increase in Chinese import penetration, which is averaged over the 1991-1999 and 1999-2007 periods. All models are weighted by a firm's U.S.-inventor patents, averaged over the start and end of a period. Standard errors are clustered on 4-digit SIC industries. ~ $p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

3 The Effect of Industry-Level Import Competition on Firm-Level Patenting

3.1 Firm-Level Data and Patent Matching

We combine Compustat data with utility patents from the U.S. Patent and Inventor Database, which covers all patents granted by the U.S. Patent and Trademark Office (USPTO) between 1975 and

March 2013.¹² A longstanding limitation of patent records is that the firm names entered on patents frequently contain unusual abbreviations or misspellings, which inhibit machine matching. We overcome this problem with an algorithm that leverages the fact that internet search algorithms function as repositories of information on common spelling variations of company names.¹³ If “International Bussiness Machines” is a common misspelling of IBM, an internet search engine will suggest IBM.com or IBM’s Wikipedia page as its top search results. Our algorithm enters the firm names appearing on patents and Compustat records into the Bing.com search engine and harvests the URLs of the search results. This procedure allows us to match patents to firms based on shared web search URLs in cases where the name strings on patents and firm records do not match exactly.¹⁴ Compared to the traditional string matching and manual inspection used in the NBER Patent Data Project, our procedure significantly improves efficiency without sacrificing accuracy. Since our search-engine-based algorithm minimizes the need for manual intervention, it is readily scalable. Our approach is generalizable to the matching between any two firm-level datasets, and to many other applications in which string matching is complicated by spelling variations. Section A of the Online Appendix discusses our matching procedure in detail.

Our analysis uses utility patents *applied* for in the years 1975, 1983, 1991, 1999, and 2007. The 1991-1999 and 1999-2007 periods coincide with the surge in Chinese import competition; the 1975-1983 and 1983-1991 periods enable us to account for industry pre-trends. Since the mean difference between the patent application and grant dates is 2.5 years in our data (standard deviation 1.5 years), right censoring due to not observing patents granted after March 2013 is unlikely to pose a serious problem. We use inventors’ addresses listed on patents to determine the location of invention, and restrict our patent sample to corporate patents with a U.S.-based primary inventor. We match 72% of these corporate patents to firms that appear in Compustat.¹⁵ Our patent sample consists of more than 170k patents that originate at 6,081 firms, which jointly accounted for 95% of all R&D expenditure that Compustat records in 1991.

Panel A of Figure 1 plots by year of patent application the total number of patents with U.S.-based primary inventors, corporate patents with U.S. inventors, and corporate patents with U.S. inventors matched to Compustat. All three series show a sharp rise between 1983 and 1999 and a modest decline between 1999 and 2007.¹⁶ The fourth series in the figure shows that the decline of patenting in the early 2000s coincides with a strong acceleration in U.S. imports from China.

The aggregate trends in patenting shown in Panel A mask important heterogeneity in the shifting

¹²The data are available at <https://github.com/funginstitute/downloads>. See Li et al. (2014) for a description.

¹³On supervised approaches to matching patents to disambiguating patent assignees, see also Ventura et al. (2015), Morrison et al. (2017), and Balsmeier et al. (2018).

¹⁴In case of IBM, we identify 147 name variations on its patents (Online Appendix, Table A1).

¹⁵Unmatched corporate patents were likely granted to firms that were never public and thus lack a Compustat record.

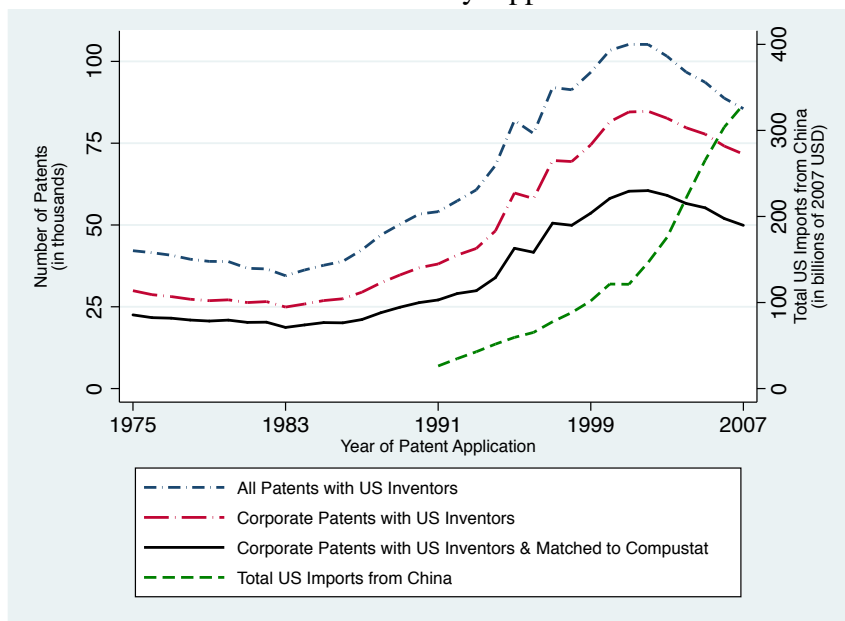
¹⁶The literature offers several possible explanations for the slowdown in patenting in the early 2000s. See Jorgenson et al. (2008), Gordon (2012), Boldrin and Levine (2013), and Arora et al. (2018).

concentration of patenting across sectors. Between 1975 and 2007, patenting in computers and electronics expanded rapidly while patenting in chemicals and petroleum was stagnant. As a result, computers overtook chemicals as the sector that produces most patents in the early 1990s (Online Appendix, Table A4).¹⁷ Panel B of Figure 1 plots the change in log patents for 1991-2007 against the contemporaneous change in import penetration for computers and electronics, chemicals and petroleum, and all other manufacturing industries. Since the growth in Chinese imports was much stronger in computers than in chemicals, the raw correlation between patenting and trade exposure at the broad sectoral level is *positive*. However, Panel B of Figure 1 also indicates a positive raw correlation between sectoral patent growth in the *pre-period* of 1975-1991 and the *subsequent* growth in Chinese import competition between 1991 and 2007. The acceleration of patenting in the computer sector and the stagnation in the chemical thus each predate the rise in Chinese imports. Accounting for these secular (pre-)trends will be critical to our identification.

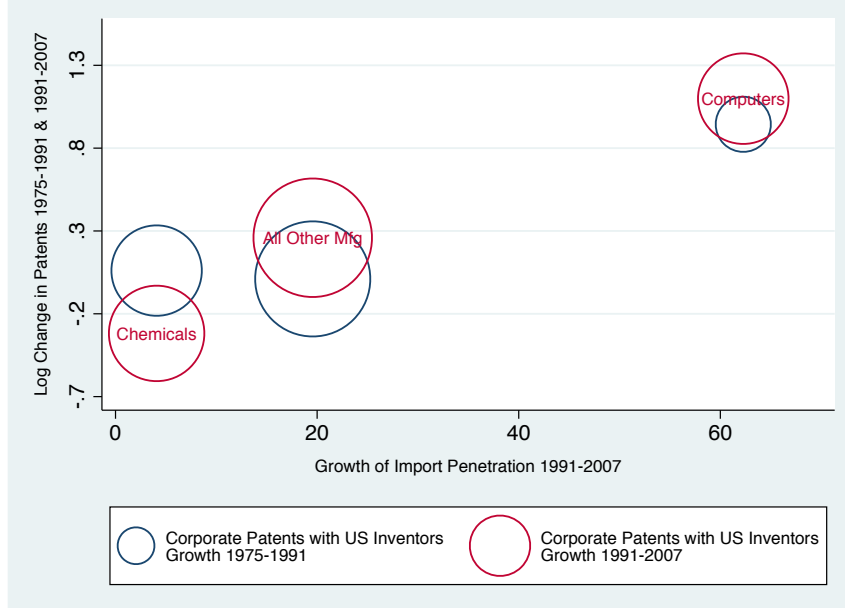
¹⁷On the growth of information technology and software patents, see Jorgenson (2001) and Bessen and Hunt (2007).

Figure 1: Trends in Patenting

A. Number of Patents by Application Year



B. Growth in Sectoral Patenting and Import Penetration from China



3.2 Import Competition and Patent Production: Baseline Estimates

Following equation (3), we estimate the impact of rising Chinese import competition on patent production at the firm level. Panel I of Table 2 applies a bare-bones specification that includes no

covariates beyond the change in import penetration and a year-specific constant.¹⁸ The conditional correlation between the change in firm patents and the change in industry import penetration is positive for 1991-1999 (column 1), negative for 1999-2007 (column 2), and negative for the stacked first-difference model that include both periods with a separate time effect for each period (column 3). The difference between the OLS and IV estimates reported in rows (a) and (b) is modest.

Panel II of the Table confronts the pre-trends in patenting in the computers and chemical sectors documented in Figure 1 Panel B. Merely including indicator variables for these two trending sectors (computers and chemicals) reveals a robust negative relationship between changes in industry import penetration and changes in firm patenting. Specifically, both OLS and IV models (rows c and d) detect a statistically significant negative effect of Chinese import competition on firm-level domestic patent production in both sub-periods and in the stacked first-difference specification. IV estimates are uniformly larger (more negative) than their OLS counterparts, suggesting that the IV models purge simultaneity or measurement error (or both).

We document the importance of pre-trends in columns 4 to 6 of Table 2, where we regress changes in firm-level patenting in the *preceding* 16-year (pre-China Shock) period of 1975 to 1991 (in two eight-year intervals) on the change in industry-level import penetration over the subsequent 1991-2007 period. In both eight-year time intervals as well as in the stacked model, and for both the OLS (row a) and 2SLS (row b) specifications, we find a positive, statistically significant relationship between changes in firm-level patenting and China import growth 16 years later. Notably, simply adding sector dummies for computers and chemicals reduces this correlation to near zero and renders it statistically insignificant across all columns (rows c and d). Column 7 shows that we can also eliminate the influence of these pre-trends by double-differencing the post and pre-China shock outcomes to estimate the effect of China import competition on the change in firm-level patenting in 1991-2007 relative to 1975-1991. This approach requires no sectoral level dummies (rows a and b) and is little affected by their inclusion (rows c and d).

Panel III of Table 2 introduces additional controls that might mitigate the relationships detected in Panel II, including: (row e) dummy variables for 11 manufacturing sectors; (row f) measures of 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);¹⁹ (row g) firm start-of-period characteristics (a dummy for U.S. headquartered firms, log U.S. sales, and firm global R&D spending as a share of firm global sales); (row h) the technology mix of a firm's patents

¹⁸The sample in Table 2 includes all firms that applied for at least one patent at the start or end of a given period. Continuous coverage in Compustat during the period is not required. Table A5 in the Online Appendix alternatively considers a balanced panel of Compustat-covered firms, which is also used for the analysis in Table 1.

¹⁹The first three variables are based on the NBER productivity database and the latter two on Feenstra and Hanson (1999).

(the fractions of a firm's patents that fall into each of six major technology fields); and (row i) the firm's prior patent growth using the 8-year and 16-year lags of the outcome variable.²⁰ Results from these specifications are comparable in magnitude to the parsimonious 2SLS model in row (d) that includes only sectoral dummies to absorb patenting trends in computers and chemicals.

²⁰Following Hall, Jaffe, and Trajtenberg (2001), we group patents in six technology fields based on their primary technology class: chemical; computers and communications; drugs and medical; electrical and electronics; mechanical; and others. To maintain a constant sample size across 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.

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

	<i>Exposure Period: 1991-2007</i>			<i>Pre-Period: 1975-1991</i>			Δ 1991-07
	1991-1999	1999-2007	1991-2007	1975-1983	1983-1991	1975-1991	-1975-91
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>I. Models without Controls</i>							
a. OLS, no controls	1.37 (1.14)	-0.45 * (0.22)	-0.32 (0.26)	0.91 ** (0.33)	1.09 ~ (0.61)	1.02 * (0.45)	-1.34 * (0.57)
b. 2SLS, no controls	0.40 (1.39)	-0.29 (0.40)	-0.26 (0.40)	1.06 * (0.43)	1.70 * (0.68)	1.44 ** (0.54)	-1.70 * (0.67)
<i>II. Controlling for Computer and Chemical Sector Main Effects</i>							
c. OLS, 2 mfg sector dummies (computers, chemicals)	-0.87 (1.02)	-0.63 ** (0.12)	-0.91 ** (0.15)	0.36 (0.25)	-0.30 (0.64)	0.00 (0.38)	-0.92 * (0.38)
d. 2SLS, 2 mfg sector dummies (computers, chemicals)	-2.36 ~ (1.40)	-0.57 ~ (0.31)	-1.25 * (0.53)	0.36 (0.33)	0.17 (0.61)	0.27 (0.40)	-1.53 ** (0.56)
<i>III. Adding Detailed Controls</i>							
e. 2SLS, 11 mfg sector dummies	-1.77 (1.16)	-0.46 (0.34)	-1.10 * (0.51)	0.54 (0.41)	0.47 (0.68)	0.52 (0.49)	-1.62 ** (0.62)
f. 2SLS, 11 mfg sector dummies + industry controls	-1.10 (1.26)	-0.50 (0.34)	-1.11 * (0.48)	0.60 (0.44)	0.38 (0.55)	0.50 (0.43)	-1.61 ** (0.55)
g. 2SLS, 11 mfg d. + industry/firm controls	-1.16 (1.06)	-0.52 (0.34)	-1.17 * (0.48)	0.62 (0.42)	0.33 (0.58)	0.48 (0.43)	-1.65 ** (0.54)
h. 2SLS, 11 mfg d. + industry/firm controls + technology mix	-1.13 (1.31)	-0.72 * (0.35)	-1.35 ** (0.50)	0.31 (0.34)	0.27 (0.62)	0.27 (0.39)	-1.63 ** (0.55)
i. 2SLS, 11 mfg d. + industry/firm controls + technology mix + 2 lags	-1.29 (1.27)	-0.80 * (0.39)	-1.39 ** (0.47)	n/a	n/a	n/a	n/a
Mean Outcome Variable	65.37	-7.61	24.42	-18.65	36.46	10.33	19.88
No. Observations	4,157	4,114	8,271	2,437	3,035	5,472	13,743

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 1991-1999 and 1999-2007 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) include 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 a firm's U.S.-inventor patents, averaged over the start and end of a period. Standard errors are clustered on 4-digit SIC industries. $\sim p \leq 0.10$, * $p \leq 0.05$, ** $p \leq 0.01$.

3.3 Alternative Identification Strategies

We obtain causal identification by exploiting the external, supply-driven component of rising Chinese exports to the U.S, identified by the industry-level covariance between rising Chinese import penetration to the U.S. and other high income countries. This interpretation would be threatened if an exhaustion of technological opportunities in specific industries occurring worldwide rendered these ‘mined out’ industries vulnerable to Chinese competition. To address this concern, we implement Pierce and Schott’s (2016) strategy of leveraging changes in trade-policy uncertainty related to China’s attainment of Permanent Normal Trade Relations (PNTR) with the U.S. in 2000 to instrument for the acceleration of the growth in U.S. industry import competition in the 2000s versus the 1990s.²¹ As a second strategy, we exploit the phase-out of import quotas from the Multi-Fiber Agreement (MFA) between 1999 and 2005 as an additional source of within-industry changes in import exposure, following the approach of Bloom et al. (2016). These MFA quotas applied primarily to imports from the textile, apparel and leather sectors.

Table 3: Response of Patenting to Alternative Measures of Trade Exposure, 1991-2007. Dependent Variable: Relative Change of Number of Corporate Patents by US-Based Inventors: OLS and OLS Reduced Form Estimates.

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

Notes: N=8,271 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 3b 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. All models are weighted by a firm’s U.S.-inventor patents, averaged over 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.

Table 3 reports side-by-side estimates of the impact of import competition on firm-level patent-

²¹Had China’s Most Favored Nation (MFN) trading status not been reauthorized in any year after 1980, its U.S. tariff rates would have risen to the far-higher Smoot-Hawley rates set in the 1930s. Pierce and Schott (2016) and Handley and Limao (2017) show that U.S. industries with higher gaps between non-MFN and MFN tariffs experienced more rapid acceleration in Chinese imports after 2000.

ing, estimated first by OLS and then with each of our three instrumentation strategies. Column 1 presents an OLS regression of the change in firm-level patenting on the change in import penetration and the full vector of control variables from Table 2. This estimate detects a highly significant negative relationship between import competition and innovation that is comparable in magnitude to the corresponding 2SLS estimate in Table 2 (column 3, row h). Column 2 adds a full set of 4-digit industry fixed effects, which absorb any secular trend in patenting at the detailed industry level. The coefficient on the interaction term between import exposure and the the 1999-2007 indicator variable in column 2 is now identified by *within-industry, over-time* changes in import exposure and patenting. The significant negative point estimate of -0.71 means that industries that saw a greater increase in import penetration in 1999-2007 relative to 1991-1999 saw a larger fall in the patent production in the latter relative to the former period.

Columns 3 and 4 apply our baseline China exposure instrument to this exercise.²² These estimates are negative and highly significant, as expected. This reduced-form IV inference is also robust to the inclusion of four-digit industry main effects (column 4), so that identification comes from within-industry changes in import exposure during 1999-2007 versus 1991-1999.

We next implement the Pierce and Schott (2016) identification strategy by exploiting the gap between non-MFN and MFN tariffs as a shock to industry-level China import competition facing U.S. firms after 2000. Since the elimination of the non-MFN, Smoot-Hawley tariff threat improved the competitive position of Chinese exporters to the U.S. market, this gap measure should have a negative impact on domestic U.S. patenting following China's attainment of PNTR in 2000. Because we have no strong prior on the relationship between the tariff gap and U.S. domestic innovation during the *pre-2000* period, we include both a main effect for the tariff-gap instrument and an interaction of that instrument with the 1999-2007 dummy.²³ Column 5 shows that the tariff gap is positively correlated with industry-level patenting growth during the 1990s, prior to China's WTO accession. Relative to this trend, however, industries with higher tariff gaps experienced a statistically significant slowdown in patenting in the 2000s (second row, column 5). Paralleling earlier estimates, column 6 introduces industry fixed effects into the model. The coefficient of interest in this demanding specification (tariff-gap \times post) remains negative and is marginally statistically significant.

In columns 7 and 8, we employ the instruments of Bloom et al. (2016), which correspond to the share of industry imports subject to MFA quotas prior to the 2005 MFA termination.²⁴ As with the tariff gap instrument, we focus on the contrast between the pre-removal period of 1991-1999, and

²²For comparability with subsequent columns, we report these models as reduced-form rather than 2SLS regressions.

²³By contrast, the expected impact of rising predicted Chinese import competition using our primary strategy does not differ across periods. When an interaction term with the 1999-2007 period is added to the regression in column 3 of Table 3, its coefficient is very small and imprecisely estimated (coefficient 0.04, s.e. 1.75), suggesting that the causal effect is comparable across the two periods.

²⁴The MFA quota fill rate data come from Pierce and Schott (2016).

the removal period of 1999-2007. Following Bloom et al. (2016), we analyze the impact of the removal of MFA quotas exclusively for the subsample of firms operating in MFA-affected industries. This reduces our sample from 8,271 to 495 observations, and the affected sectors account for just 4.9% of manufacturing patenting in 1999 (bottom row of Table 3). Nevertheless, the column 7 estimate finds a negative association between MFA quotas and U.S. patent growth during 19991-1999, which becomes (marginally) significantly more negative in the 1999-2007 period when import quotas are phased out. When four-digit industry fixed effects are added in column 8, the point estimate remains comparable but it is less precisely estimated.

The second to last row of Table 3 shows that for all three sets of instruments employed, a one standard deviation increase in the trade exposure instrument is estimated to reduce patenting by 10 to 15 log points. Thus, whether we exploit the observed growth in U.S. imports from China, the supply-driven surge in China's exports to the U.S. and other high income countries, the reduction in China-U.S. trade-policy uncertainty following the grant of PNTR, or the removal of import quotas in MFA-affected industries, we find qualitatively and quantitatively similar deterrent effects on patenting by import-competing U.S. firms.

As detailed in the Online Appendix Tables A5 and A6, our key finding that rising import competition reduces patenting by U.S. firms is robust to variations of our basic approach, including: restricting the analysis to only patents granted within six years of the application date; excluding patents from the computer or chemical technology classes; using alternative firm weights (patent citations, R&D expenditure, sales, no weights); and assigning Compustat firms to corresponding industries based on historical industry codes or using fractional industry assignments according to firms' sales shares across the industries in which they operate.²⁵

A limitation of our firm-level analysis is that the analytic sample excludes patents granted to firms that are *not* listed in Compustat. We overcome this limitation by estimating the effect of import competition on patenting at the *technology class* level. Exploiting the fact that every patent is assigned to a specific technology class, we calculate the import exposure facing each technology class by using the implicit mapping of patent classes to industries provided by our Compustat-patent matched data. Fitting (3) to patent counts at the technology class level, we find that technology classes with greater growth in import penetration during our window of 1991-2007 experienced a substantial relative decline in total *corporate* patents (see Appendix Table A7). Yet, no such negative effect is detected for patenting by non-corporate entities (e.g., government and universities). Our findings are thus specific to private-sector innovation and are unlikely to reflect a spurious correlation between declining innovation opportunities and rising trade exposure.

²⁵We also find that import competition has little impact on firm industry representation: conditional on survival, Compustat firms do not appear to change industry in response to rising China competition.

3.4 Which Firms are Most Affected?

Our findings contrast with Bloom et al. (2016), who report a positive effect of exposure to the removal of MFA quotas on patenting by European firms. These opposite-signed effects for the U.S. and Europe are not intrinsically at odds: as Aghion et al. (2005) emphasize, a marginal increase in competition may either spur or hinder innovation depending on the initial competitiveness of a market.²⁶ Our findings could imply that U.S. manufacturing industries largely locate on the downward sloping leg of the Aghion et al. (2005) inverted U-shaped locus, where greater competition diminishes innovation.

Table 4: Effect of Chinese Import Competition on Patenting 1991-2007: Splitting Sample According to Initial Sales/Worker, Capital/Worker, Return on Investment, and Debt/Equity. Dependent Variable: Change in Corporate Patents by US-Based Inventors (% pts).

	<i>Firm Labor Productivity and Capital Intensity</i>				<i>Profitability and Leverage</i>			
	Sales/Worker		Capital/Worker		Profit/Capital (ROI)		Debt/Equity	
	>Avg	≤Avg	>Avg	≤Avg	>Avg	≤Avg	≤Avg	>Avg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ U.S. Industry Exposure to Chinese Imports	-1.11 (0.79)	-2.32 (1.38)	~ -0.01 (1.01)	-2.41 ** (0.55)	-0.86 (0.57)	-2.06 ** (0.72)	-0.86 * (0.40)	-2.92 * (1.47)
Test for Equal Coeff.	p=0.274		p=0.001		p=0.036		p=0.426	
Mean Outcome Variable	27.27	3.29	29.80	7.83	20.03	7.58	19.18	14.23
No. Observations	1,348	2,738	1,529	2,560	1,887	2,493	3,154	766

Notes: 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. Columns 1-2, 3-4, 5-6 and 7-8 split the firm sample into firms whose sales per employee, capital per employee, return on investment, or debt to equity ratio is above/below the patent-weighted industry average in the start-of-period year. All models are weighted by a firm's U.S.-inventor patents, averaged over the start and end of a period. Standard errors are clustered on 4-digit SIC industries. ~ p ≤ 0.10, * p ≤ 0.05, ** p ≤ 0.01.

To explore heterogeneous effects of competition on firm patenting, Table 4 splits U.S. firms within detailed industries into groups according to four metrics: sales per worker, capital per work, profit over capital (ROI), and debt to equity. The odd-numbered columns estimate the effect of import competition on patenting for firms that outperform their respective industry's mean in terms of higher productivity, capital intensity, profitability, and lower indebtedness. The even-numbered columns present analogous regressions for the complementary samples. All four sample splits qualitatively confirm that firms with an initially weaker competitive position are more likely to be hurt by foreign competition, and this heterogeneity in treatment effects is statistically significant for the two sample splits by capital intensity and profitability. In Table A9 of the Online Appendix, we extend the results in Table 4 by redefining the dependent variable to be the change in patents relative to the change in firm size (measured as sales or employment, either for the U.S.

²⁶It 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. Dauth et al. (2014) estimate that the labor market effects of China trade for Germany, for instance, have been much less severe.

or globally). We find that for the initially weaker firms—when measured by capital intensity or profitability—the trade-induced contraction in patenting is *not* simply a byproduct of a reduction in firm scale. Instead, these firms experience a significant decline in patenting relative to sales and relative to employment. Our analysis of firm heterogeneity suggests that rising import competition could, by culling the ranks of weaker incumbents, catalyze the reallocation of sales and profits to the stronger firms that remain. While it does not definitively explain why results differ between the U.S. and Europe, it does support the notion that the effect of increased competition on innovation depends on initial conditions.²⁷

4 Discussion

We provide a comprehensive analysis of how the surge in import competition from China affects both the inputs and outputs of U.S. innovative activities. Accounting for the important confounding effects of industry pre-trends, we demonstrate that the negative impact of Chinese import competition on innovation at the firm and technology-class level is robust to a wide range of regression specifications and identification strategies; that it is evident on both output (patenting) and input (R&D expenditure) margins; and that it applies to private-sector patent production but not to patenting by universities or government, consistent with a competitive market response. These findings do not constitute a welfare analysis of the impact of competition on domestic innovation since they do not capture, for example, dynamic responses that may ultimately include the culling of weaker firms and the entry of robust new innovators. Nevertheless, they demonstrate that the innovation response of U.S. firms more exposed to rising market competition from China has been substantially and unambiguously negative.

²⁷In 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 et al. (2018) find that patenting by French manufacturing firms responds more positively to *export* demand shocks in more-productive relative to less-productive establishments.

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