Escaping from Chinese Import Competition? Evidence from U.S. Firm Innovation (Job Market Paper)

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Abstract

This paper examines the impact of competition from Chinese imports on innovation by U.S. public manufacturing firms. Exploiting cross-industry and over-time trade variations from 1991 to 2004, I find that when Chinese imports surged onto the U.S. market, U.S. public manufacturing firms increased their number of patents as a response. In addition, U.S. public manufacturing firms appeared to adopt horizontal differentiation as a new strategy to escape Chinese competition; they were more likely to patent in new technology classes and to enter new product markets. I also document large and small firms' differential responses to Chinese import competition. While large firms were responsible for the increase in patents and horizontal differentiation, small firms significantly reduced their R&D expenditures and were more likely to exit. Such heterogeneity may help reconcile different findings in the literature. Finally, I provide novel evidence on the channel of adjustment: new inventors at large firms contributed to almost all of the new innovation. When Chinese import penetration intensified, inventors were more likely to leave small firms and go to large firms.

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1 Introduction

China's rapid rise in the global economy has sparked heated discussions about its economic impact on other countries, including the United States, for which Chinese imports quadrupled between the early 1990s and 2007. Surging Chinese imports not only provided American consumers with cheaper manufactured products (Schott, 2008; Amiti et al., 2017), but also raised competitive pressure on U.S. manufacturing firms. In response, U.S. manufacturing firms have the option to either simply shut down (Bernard et al., 2006; Autor et al., 2013, 2014; Pierce and Schott, 2016; Acemoglu et al., 2016), or to survive through innovation, and possibly differentiate themselves from entrants. This paper studies the innovation margin and its heterogeneity across U.S. manufacturing firms.

In theory, the impact of competition on innovation is ambiguous. Firms might increase their innovation to differentiate themselves vertically from low-cost competitors and thus escape fierce competition (Aghion et al., 2005). Firms might also decrease their innovation because they don't have the "deep pockets" to pursue risky and costly innovative activities in highly competitive environments (Schumpeter, 1942; Galbraith, 1952; Hall and Lerner, 2010). In fact, depending on the modeling framework, a multitude of often contradictory relationships, which I review in Section 2, could arise (Kamien and Schwartz, 1975; Gilbert, 2006; De Bondt and Vandekerckhove, 2012; Gomellini, 2013). How Chinese import competition affects firm innovation is thus an empirical question. A growing stream of empirical literature investigates how firm innovation responds to import competition (Iacovone et al., 2011; Bloom et al., 2016; Autor et al., 2016), but presents mixed and seemingly contradictory evidence. Bloom et al. (2016) find that China's trade shock has led European textile and apparel manufacturing firms to create more patents, expand investment in IT, and increase their overall level of TFP. Autor et al. (2016), on the other hand, find the opposite in the United States. This paper examines firms' nuanced responses, which may help reconcile different findings in prior work while developing new dimensions in firm innovation response, particularly the strategy of horizontal differentiation and the acquisition of new inventors.

I focus on U.S. Compustat manufacturing firms between 1991 and 2004, and use an empirical strategy as follows Autor et al. (2013). I measure Chinese import penetration with annual Chinese imports in each 4-digit SIC industry normalized by its U.S. domestic demand from 1991. To isolate China's supply shock from U.S.-specific demand and productivity shocks, I instrument China's import penetration into the United States with China's import penetration into other high-income economies. I also control for year by three-digit

SIC industry fixed effects to account for differential time trends across industries. The identifying assumption is that China's own economic development and falling trade costs drive the surge of Chinese exports to the economies of the developed world.

I present four core findings: 1) firms increased their number of patents on average; 2) firms differentiated themselves horizontally from Chinese competitors by shifting to new technical fields and entering new markets; 3) large firms were responsible for the increase in patents and horizontal differentiation, while small firms reduced their R&D expenditures and suffered from a higher probability of exit; and 4) new inventors at large firms contributed to almost all increase in innovation, and inventors were more likely to move from small firms to large firms. Next, I document each of these findings in detail.

First, I examine how firms' rate of patenting responded to rising Chinese import penetration. I find that a one-standard-deviation increase in Chinese import penetration stimulated firm innovation by 39.2% or roughly 5 additional patents.[1] Such results are robust to 1) using an alternative dataset for patents linked to firms from 1991 to 2007 (Kogan et al., 2017); 2) employing an alternative identification strategy that exploits the United States' granting of permanent normal trade relations (PNTR) to China in 2000 (Pierce and Schott, 2016); and 3) using a sales-weighted import penetration measure. I also rule out any pre-trends, anticipation effects, and offshoring as alternative explanations for increased firm innovation.

Second, I investigate horizontal differentiation as a novel strategy for firms to escape competition. In particular, I look at changes in firm innovation direction and firm entry into new markets. I find that a one-standard-deviation increase in Chinese import penetration induced firms on average to be 13.4 percentage points (33.7%) more likely to patent in new technology classes, and 7 percentage points (37.2%) more likely to enter new product markets.[2]

Third, I document large and small firms' heterogenous responses to Chinese import penetration. Large firms were responsible for the increase in innovation and horizontal differentiation. Small firms, in contrast, significantly reduced their R&D expenditures, exhibited no increase in innovation, and had a higher probability of exit. A one-standard-deviation

[1] These results are different from Autor et al. (2016), due partly to a different time frame and partly to different firm coverage. I present and discuss my reconciliation analyses in both Section 7 and Appendix D.

[2] I obtained the complete patenting history of each firm that was already public in 1991, going back as early as 1975. Based on this patenting history (1975-1991), I estimate a firm's propensity to patent in new technology classes in each subsequent year (1992-2004). In a similar fashion, I use firms' historical sales across different 4-digit SIC industries to estimate firms' propensity for entering new markets.

increase in Chinese import penetration raised large firms' innovation by 42.5% or roughly 8 additional patents, made large firms 18 percentage points (45%) more likely to patent in new technology classes, and 8 percentage points (36.9%) more likely to enter new markets. Small firms, on the other hand, were 8 percentage points (10.58%) more likely to exit the market and reduced their R&D expenditures by 49.5%.

Finally, I identify patenting by new inventors as a channel through which firms increased innovation. At the firm level, I find that a one-standard-deviation increase in Chinese import penetration induced firms on average to have 4 additional new inventors or an increase of 75%. This increase came entirely from large firms, and new inventors at large firms contributed to almost all of the new innovation. At the inventor level, I find that a one-standard-deviation increase in Chinese import penetration made inventors initially working at small firms 6 percentage points (146%) more likely to leave. Conditional on leaving, those inventors had a higher propensity for joining large firms.[3]

One potential concern with my study is that my analyses are limited to Compustat firms, and the aggregate impact of Chinese import competition on U.S. innovation may turn negative once private firms are included. To address this concern, I construct Chinese import penetration at the technology class level and estimate its impact on total U.S. corporate patents. I find that a one-standard-deviation increase in Chinese import competition spurred 17.5% more innovation, or roughly 27 additional corporate patents in a technology class, consistent with the increase in innovation among Compustat firms.[4]

This paper relates to several strands of literature. First, it contributes to the literature on Chinese trade and firm innovation by providing a more nuanced picture of firms' responses that may help reconcile contradictory findings in prior work. The overall positive results are consistent with the European evidence (Bloom et al., 2016), while the heterogeneity between large and small firms helps explain opposite findings in the United States (Autor et al., 2016). When Chinese imports came in as strong competitors, firms of different sizes responded differently. Large firms were able to escape fierce competition by innovating

[3] I use Harvard Patent Network Dataverse to study inventor mobility. An appealing feature of this dataset is that it creates a unique ID number for each inventor, and thus enables me to track inventors over time and across different entities.

[4] For all patents filed by Compustat firms between 1975 and 1991, I calculate the share of patents of each 4-digit SIC industry for a given technology class. Using these shares as initial weights, I then construct China's annual trade shock in each technology class by taking a weighted average of industry level import penetration. The overall positive results are not surprising because Compustat firms produce the majority (over 60%) of all U.S. corporate patents.

more in new technical fields and thus differentiating themselves horizontally; small firms, in contrast, significantly reduced their R&D expenditures and suffered from a higher probability of exit. The data Autor et al. (2016) used included not only U.S. public manufacturing firms, but also those firms when they were still private. Their sample is therefore a mixture of public and private firms, with the number of private observations far exceeding that of public ones. Thus their negative results may better represent private firms' response.

Second, this paper provides complementary U.S. evidence to the heterogenous firms' responses identified in the emerging trade and innovation literature. A series of papers have examined innovative responses by firms to trade liberalization from either the exporter's (Bustos, 2011; Aghion et al., 2017) or the importer's (Iacovone et al., 2011; Branstetter et al., 2017; Bloom et al., 2016) perspective in non-U.S. contexts. All these studies find that larger/more productive firms are better at adapting to the changing environment and increasing their innovation, while smaller/less productive firms are less able to do so. Consistent with their findings, this paper obtains similar heterogeneity among U.S. manufacturing firms, suggesting that such heterogeneity may be a global phenomenon.

Third, this paper informs the theory debate over competition and innovation by providing new empirical findings on horizontal differentiation as firms' specific strategies for escaping competition. Current theories mainly focus on vertical differentiation as a way for firms to escape competition (Aghion et al., 2001, 2005), but relatively little has been said on horizontal differentiation. This paper shows that, in addition to providing higher-quality products, firms can steer away from their increasingly competitive current market, patent in new technology classes, and enter new but less competitive markets. Moreover, this paper adds to the literature on direction of innovation, and presents empirical evidence consistent with the theoretical prediction of Bryan and Lemus (2016) that increased competition from trade can force firms to switch their research lines. [5]

Finally, this paper contributes to the literature on trade and firm productivity. To the best of the author's knowledge, this is the first paper to present the reallocation of talents between firms at the individual level in the wake of import competition. Existing literature has found that trade liberalization increases aggregate industry productivity (Pavcnik, 2002; Trefler, 2004; Dunne et al., 2008) by reallocating output from less productive firms to more efficient ones (Melitz, 2003; Melitz and Redding, 2013). Besides finding similar

[5] The change in innovation direction and entry into new product markets can also be explained from the perspective of the "Resource View" in corporate diversification literature, which I review in Section 2 and discuss in Section 7.

reallocation effects at the firm level, this paper provides direct micro evidence of inventors moving from small firms to large ones.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 describes the data and the empirical strategy. Section 4 presents baseline results on the rate of innovation and the direction of innovation. Section 5 examines heterogeneous responses between large and small firms. Section 6 studies inventor mobility as one important channel of firm adjustment. Section 7 discusses the results, and Section 8 concludes.

2 Literature Review

2.1 Competition and Innovation

The theoretical relationship between market competition and firm innovation has been discussed extensively. However, depending on the modeling framework, a multitude of relationships could arise(Kamien and Schwartz, 1975; Gilbert, 2006; De Bondt and Vandekerckhove, 2012; Gomellini, 2013). For instance, several theories predict that high competition is detrimental to innovation: the "Discouragement Effect" (Schumpeter, 1942) argues that high competition significantly reduces a firm's post-innovation rents and thus discourages innovation; the "Pre-emptive Effect" (Gilbert and Newbery, 1982) emphasizes monopoly's strong incentive to prevent new entry via pre-emptive innovation; the "Deep Pockets Effect" (Schumpeter, 1942; Galbraith, 1952; Hall and Lerner, 2010) contends that firms have to rely on internal resources for innovation due to capital market imperfections, and big firms with market power are more likely to have the "deep pockets" to pursue such risky and costly activities. The "Replacement Effect" (Arrow, 1962) predicts the opposite: high competition spurs more innovation. A monopolist has less incentive to innovate because new innovation replaces its current monopoly rents, while a competitive entrant would not displace its own profits and could therefore capture the full return of new innovation. The "Escape Competition Effect" (Aghion et al., 2001) states that when a firm is in neck-and-neck competition with a technologically equal rival, it has a larger incentive to innovate and thus escape competition by becoming a technological leader. However, Aghion et al. (2005) propose an inverted-U relationship between competition and innovation, which depends on firms' technological position and initial market structure. The empirical findings in my paper are in line with the "Escape Competition Effect" (Aghion et al., 2001, 2005), but emphasize horizontal differentiation rather than vertical differentiation as a way for firms to escape competition.

On the empirical side, the relationship between industry concentration and R&D expenditures is the second most tested hypothesis in industrial organization, after the relationship between profits and firm size/concentration (Aghion and Tirole, 1994). In general, papers before the mid-1990s find either a weakly positive or no correlation between market concentration and R&D expenditures (see Table 6.2 in Gilbert (2006)). However, most of the earlier empirical studies document correlation, not causation. Beginning in the mid-1990s, a new wave of empirical researchers attempt to establish causality by using arguably exogenous policy changes (Carlin et al., 2004; MacDonald, 1994; Aghion et al., 2004), and they find either a positive or inverted-U relationship between market competition and firm innovation. In a similar spirit, this paper uses changes in Chinese import penetration to approximate a natural experiment in which market competition increased significantly due to external forces.

2.2 Trade and Innovation

In the emerging trade and innovation literature, a series of papers investigate the impact of trade liberalization on firm innovation from either the exporter's (Bustos, 2011; Aghion et al., 2017) or the importer's (Iacovone et al., 2011; Branstetter et al., 2017; Bloom et al., 2016) perspective in non-U.S. contexts. These studies all find that larger/more productive firms are better at adapting to the changing environment and producing more innovation while smaller/less productive firms are less able to do so. Looking at the impact of Chinese imports on developed economies' innovation per se, the evidence is mixed and seemingly contradictory. In Europe, Bloom et al. (2016) find that China's trade shock has led textile and apparel manufacturing firms to create more patents, expand investment in IT, and increase their overall level of TFP.[6] In the United States, Hombert and Matray (2016) find that public firms with a larger R&D stock significantly reduce the adverse impact of China's trade shock on a number of firm performance measures (sales growth, profitability, etc.). They also find suggestive evidence that firms with a higher level of R&D stock react to import penetration by differentiating their products from Chinese competitors.[7] Autor et al. (2016), however, find that after accounting for secular trends in two broad sectors–

[6]Bloom et al. (2016) actually present positive correlations between Chinese imports and firm innovation for all European manufacturing industries, but their key identification applies only to the textile and apparel industry.

[7]They develop a model of competition with vertical differentiation, and employ textual analysis of firms' 10-K files to show that firms with a higher level of R&D stock have product descriptions different from their competitors.

chemicals, and computers and electronics–U.S. firms significantly reduced their innovation. Relatedly, Schott (2008) looks at the relative sophistication of Chinese imports. He finds that Chinese imports are significantly cheaper than their OECD counterparts, and firms in developed countries seem to avoid direct Chinese competition by dropping their least sophisticated offerings and climbing up the quality ladder. Such evidence hints at vertical differentiation as an escape from Chinese competition. Freeman and Kleiner (2005) find a similar story for an American shoe manufacturer, and Bartel et al. (2007) for U.S. valve manufacturers.[8] My paper's contribution to this strand of literature is twofold: 1) it reconciles different findings on Chinese import competition and firm innovation in Europe and the United States by providing a more nuanced picture of firms' responses; and 2) it adds complementary U.S. evidence to the heterogenous firms' responses identified in the literature, implying that such heterogeneity may be a global phenomenon.

Moreover, existing literature on trade and firm productivity finds that trade liberalization promotes aggregate industry productivity(Pavcnik, 2002; Trefler, 2004; Dunne et al., 2008) by reallocating output from less productive firms to more efficient ones (Melitz, 2003; Melitz and Redding, 2013). In addition to finding similar reallocation effects at the firm level, this paper also presents the reallocation of inventors from small firms to large ones in the wake of import competition.

2.3 Other Related Literature

Direction of Innovation On a macro level, several papers investigate the directed technical change induced by international trade and its implications on the relative demand of skilled versus unskilled workers (Acemoglu, 2002; Acemoglu et al., 2015). This paper offers firm-level evidence of such a technical change by showing that large firms had more skilled labor i.e., inventors. Recent endogenous growth models (Klette and Kortum, 2004; Akcigit and Kerr, 2016) have also explicitly incorporated firm innovation choices into their

[8] Anecdotal evidence also suggests that innovation is a popular strategy adopted by surviving firms. As the *New York Times* article "If You Can Make It Here..." documents, "Innovation is often compulsively pursued at the manufacturing companies that stay in America. The engineers and designers at Harley and Haas–they constitute more than 10 % of each work force– are constantly altering the companies' products in ways that are not easily imitated by lower-priced foreign competitors. The resulting cachet helps to sustain demand." (http://www.nytimes.com/2005/09/04/business/if-you-can-make-it-here.html) The examples mentioned are two leading manufacturing firms: Harley-Davidson, Inc., and Haas Automation, Inc. Harley produces iconic American motorcycles, and Haas is a renowned machine tool builder. Both companies survived fierce Chinese competition via product innovation. However, without systematic study on a more representative sample, it is hard to tell whether Harley and Haas are the norms or the exceptions.

framework to confront firm-level evidence. In particular, Akcigit and Kerr (2016) predict that in steady state, large incumbents are more likely to make innovations that improve their existing product lines while small firms contribute disproportionately to creating new products and capturing markets from others. My paper, in contrast, suggests that when the market becomes more competitive and thus drifts away from steady state, firms may be pressured to pursue innovations in new technical fields and new markets. And, large firms seem to be the ones making such rapid changes to adapt to the competitive environment. On a micro level, several studies focus on the inefficiencies in firm research lines under current research regimes (Acemoglu, 2011; Bryan and Lemus, 2016; Squintani and Hopenhayn, 2016). In particular, Bryan and Lemus (2016) predict, in one of their theoretical applications that a decrease in trade barriers can force firms to switch to research projects that are either more immediately lucrative or quicker to complete. Those newly pursued research lines, however, may not be socially optimal. My paper presents empirical evidence consistent with the theoretical prediction of Bryan and Lemus (2016), but does not address the welfare implications of such directional changes.

Firm Diversification Strategy Literature on corporate diversification has made three main arguments about why firms diversify (Montgomery, 1994). The first, called "The Market-Power View" (Edwards, 1955; Hill, 1985; Gribbin, 1976) argues that diversification would grant a firm access to *conglomerate power*, which enables the firm to thrive at the expense of nondiversified firms via cross-subsidization (Edwards, 1955), mutual forbearance (Bernheim and Whinston, 1990), and/or reciprocal buying (Montgomery, 1994). This view stresses the anti-competitive consequences of diversification, not necessarily the motivation of diversification. The second, called "The Agency View" (Mueller, 1969; Jensen, 1986; Shleifer and Vishny, 1989) states that managers might pursue excessive expansion out of the pleasures of empire-building (Jensen, 1986), the intent to increase the firm's demands for their particular skills (Shleifer and Vishny, 1989), or to diversify their employment risk (Amihud and Lev, 1981). The last one, called "The Resource View" (Penrose, 2009; Teece, 1980; Montgomery and Wernerfelt, 1992) contends that rent-seeking firms diversify to more profitably employ their underused resources; thus, a firm's level of profit and breath of diversification are a function of its resource stock. "The Market-Power View" receives little empirical support and seems less plausible (Rhoades, 1974; Utton, 1977; Montgomery, 1985; Palepu, 1985). The other two views are consistent with empirical findings that diversification built around a core organizational capability is on average more profitable than single line businesses or highly diversified firms (Rumelt, 1982; Christensen and Montgomery, 1981; Lecraw, 1984; Varadarajan and Ramanujam, 1987). "The Resource View" has additional merit in explaining the direction of firm expansion. Numerous empirical studies highlight that existing organizational capabilities, particularly in R&D and marketing, often guide diversified expansion (Lemelin, 1982; MacDonald, 1985; Montgomery and Hariharan, 1991; Collis, 1988; Collis and Stuart, 1991; Collis and Noda, 1993; Itami and Roehl, 1991; Silverman, 1999; Neffke and Henning, 2013). My paper also provides empirical evidence consistent with "The Resource View." In particular, when market rivalry becomes intense, large firms have the capability/resource to steer away from the currently competitive environment, and expand into new areas via product innovation. Moreover, the empirical evidence that firms have more new inventors and more inventions in new technical fields when entering new product markets seems to suggest that firms' direction of market expansion revolves around their core human capital–inventors.

3 Data and Empirical Strategy

3.1 Data

In this paper, firm innovation is measured by its number of granted patents. I use the NBER patent database (Hall et al., 2001) to link utility patents to U.S. public manufacturing firms for years 1991 to 2004. The database itself covers the entire universe of utility patents filed in the U.S. from 1975 to 2006 along with a wide range of information, such as patent application and grant dates, technology classes, citations and assignees. I focus on patents by U.S. public manufacturing firms[9] and date them by application year. On average, it takes about two years for a patent to be granted. To mitigate the right censored problem, I only use patent data up to 2004.[10] The manufacturing sector is the engine of U.S. innovation accounting for 68% of total U.S. R&D spending (Helper et al., 2012) and 71% of all U.S. corporate patents (Autor et al., 2016). Compustat firms, meanwhile, represent 62% of total U.S. R&D spending (Bloom et al., 2013) and 61% of all U.S. corporate patents.[11] Therefore, by looking at the innovation response of Compustat manufacturing firms, I capture a significant share of U.S. innovation. I also use the Harvard Patent Network Dataverse (Lai et al., 2015) for inventor-level analysis. An appealing feature of this dataset is that it creates a unique ID number for each inventor, and thus enables me to track inventors over

[9]All public manufacturing firms' information comes from Compustat. I limit my attention to public manufacturing firms that are headquartered in the United States and have patented at least once between 1991 and 2004. The latter is to ensure that the firms are potential patenting-responsive entities during the sample period and constitute 80% of the original sample.

[10]As long as time to grant is randomly distributed across different patents, year fixed effects in main regressions could sweep out the time lag effect.

[11]This is from author's own calculation.

time and across entities.

Bilateral trade data is readily available from Acemoglu et al. (2016), which originally comes from the UN Comtrade database. I use Chinese manufacturing imports to both the United States and a group of eight high-income economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) aggregated at the 4-digit SIC level for years between 1991 and 2004. I start with 1991, the first year when aggregating imports at the 4-digit SIC level became possible.

3.2 Import Penetration Measure

Adapting from Acemoglu et al. (2016), I define import penetration as follows:

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

where for U.S. industry j (by 4-digit SIC code), $M^{UC}_{j,t}$ is imports from China each year, 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, $E_{j,91}$) in year 1991, the start of the period.

For fear that rising Chinese imports are driven by U.S.-specific (negative) productivity and (positive) demand shocks, I follow Autor et al. (2013) and use China's import penetration to other developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) as an IV:

$$IPW\_OTH_{j,t} = \frac{M^{OC}_{j,t}}{Y_{j,88} + M_{j,88} - E_{j,88}}. \tag{2}$$

Here $M^{OC}_{j,t}$ is imports from China to other developed countries in industry j year t. The denominator is U.S. initial absorption in the industry in 1988.

The identifying assumption is that rising Chinese imports to the United States and eight other high-income economies are primarily driven by China's own economic development and trade comparative advantage. In other words, China's internal supply shock generates a surge of its imports to these economies. A possible threat to such an identification strategy is that demand and productivity shocks may be correlated across high-income countries. If there were a universal demand boom across the developed world, I would be underestimating the true import competition effect.[12] This is because booming demand mitigates the

[12] However, given that many U.S. plants shut down and employment fell during this period, the demand boom scenario didn't seem very likely.

adverse impact of rising import competition and makes it easier for firms to survive without innovation. A common negative productivity shock in high-income economies also works against my finding any positive impact because it is now even harder for firms to innovate.

3.3 Empirical Specification

The baseline specification is of the form:

$$E[Y_{fjt}] = exp(\alpha IPW_{jt-l} + \beta_f + \gamma_t) \tag{3}$$

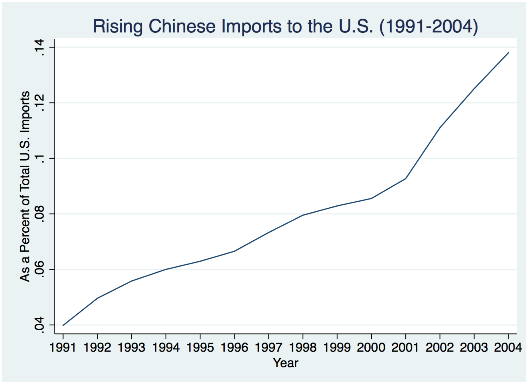
where Y_{fjt} is the number of (granted) patents of firm f in industry j applied in year t. IPW_{jt-l} is import penetration in industry j of year t-l, and l represents years of lag; I take up to five years of lag to capture firms' dynamic response. β_f is firm fixed effect, γ_t is year fixed effect, and $exp(.)$ is an exponential operator. I estimate a Poisson regression because the dependent variable is count data. I also include Negative Binomial results in Appendix E, and the two specifications deliver very similar results. α is key variable of interest and is expected to be positive: U.S. public manufacturing firms innovated more (and thus introduced more new products to markets) to escape competition from Chinese imports. I use IPW_OTH_{jt-l} as an IV.

4 Baseline Results

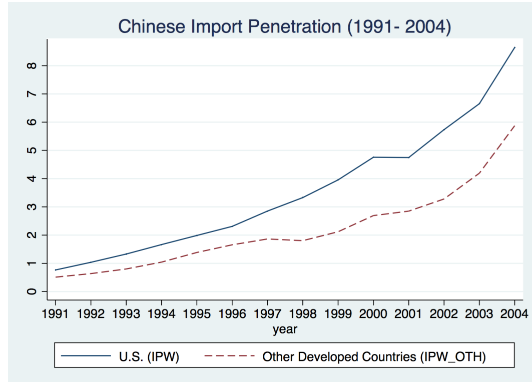
4.1 Summary Statistics

In this section, I present some simple summary statistics to display basic patterns of the data. In Figure (a), we can see that Chinese imports have been rising steadily over the sample period (1991-2004). Here, Chinese imports are normalized by U.S. total imports. In 1991, Chinese imports accounted for only 4% of U.S. total imports, but almost quadrupled by the end of 2004. Moreover, there was an apparent acceleration after 2001, when China joined the WTO.

Figure (b) paints the same story using import penetration measures defined in Section 3.2. The measures capture important dynamics of rising Chinese imports over the years, both to the United States and to other developed countries. In addition, the two measures are highly correlated, suggesting that China's internal supply shock and falling trade barriers are driving the import surge.



(a) Rising Chinese Imports to the U.S. (1991-2004)



(b) Chinese Import Penetration to the U.S. and Other Developed Countries (1991-2004)

Which industries were most affected by rising Chinese imports? Table A.1 provides the top 10 list by 2-digit SIC code, which was calculated as the change of Chinese import penetration between 1991 and 2004. The top three industries are leather and leather products (e.g., footwear, except rubber); miscellaneous manufacturing industries (e.g., dolls, toys, games, and sporting and athletic goods); and apparel and other textile products (e.g., Schiffli machine embroideries). Going down the list, one can imagine that firms in these industries could innovate their way out when facing fierce Chinese import competition.

Table 1 shows summary statistics of key variables. PatCount is each firm's annual number of patents. On average, a firm has roughly 12 patents each year. However, the median number of patents is only one, indicating a distribution with high skewness and wide dispersion. Given the nature of the dependent variable, I mainly use Poisson specification and include Negative Binomial results in Appendix E. Both specifications show very similar results.

Table 1: Summary Statistics of Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Median
PatCount	27740	12.54	68.994	0	2353	1
IPW	27659	3.41	8.865	0	102.647	.676
IPW_OTH	27659	2.1	5.222	0	96.28	.483

Notes: First row reports summary statistics of firm annual patent counts; second and third rows show summary statistics of pooled Chinese import penetration to the United States and other eight high-income economies respectively.

4.2 Rate of Innovation

4.2.1 Industry-Level Results

Before delving into firm-level analysis, I first examine industry-level response to rising Chinese imports, which gives us an idea of the aggregate effects. Here, industry is at 4-digit SIC level. The dependent variable is industry's annual number of patents, and up to five-years' lag of import penetration is used. First-stage F-statistics for IV estimates are also included.

Table 2: Import Penetration and Industry Innovation (IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0389***				
	(0.0094)				
L2.IPW		0.0478***			
		(0.0183)			
L3.IPW			0.0571**		
			(0.0227)		
L4.IPW				0.0463**	
				(0.0228)	
L5.IPW					0.0326*
					(0.0184)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
IndustryFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	15.82	13.60	12.77	11.45	10.04
Observations	2467	2273	2078	1885	1691

Notes: This table shows industry-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Industry is defined at 4-digit SIC level. The dependent variable is each industry's annual number of patents (dated by application year). Both year fixed effects and industry fixed effects are included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The across-the-board positive and significant coefficients suggest that Chinese import penetration spurred more innovation. For instance, in the third column with three-years' lag specification, the coefficient implies that a one-standard-deviation (8.87) increase in import penetration raised industry innovation by 65.94%; alternatively, it roughly represents 62 additional patents. This aggregate effect is sizable, but is a combination of both within and between firm effects. To better understand how individual firms responded to China's trade shock, I now turn to firm-level analysis.

4.2.2 Firm-Level Results: Unbalanced Panel

In Table 3, the dependent variable is changed to the firm's annual number of patents, and industry fixed effects are replaced by firm fixed effects. All other specifications remain the same. Firm entry and exit are allowed, so the panel is unbalanced.[13] I also include year by 3-digit SIC industry fixed effects to control for differential industrial trends. This time, although the signs are still positive, only three-years' and four-years' lag remain significant. A one-standard-deviation (8.87) increase in import penetration induced 39.2% more innovation (or five additional patents). Such results seem to imply that when Chinese import competition surged, firms needed time to respond and it generally took them about three years to generate new patent applications. This is roughly consistent with the European evidence, where Bloom et al. (2016) also find that the largest impact happened at three-years' lag. Going forward, I will always include year by 3-digit SIC industry fixed effects in regression analyses.

4.2.3 Firm-Level Results: Balanced Panel

Turning to the balanced panel (Table A.2), which only includes firms stayed alive throughout the entire period, the results are slightly stronger: starting from three-years' lag, import penetration had a positive and significant impact on firm innovation, and the largest impact happened around three to four-years' lag. The three-years' lag coefficient now implies an increase of 42.8% firm innovation, or five additional patents. The stronger effects are intuitive because I am selecting on survivors.

4.2.4 Robustness Checks

Alternative Dataset with Longer Time Span: 1991-2007 Due to data limitations, my NBER sample ends in 2004, three years after China's entry into the WTO. Because Chinese imports to the United States accelerated after the event, one might be concerned that my current time frame would not be able to capture the major influence of Chinese import competition on U.S. firm innovation. To address that concern, I use an alternative

[13] For fear that outliers would bias estimation results, I exclude observations with annual number of patents that are above 500 (less than 0.4% of the sample) in all my subsequent analyses.

Table 3: Import Penetration and Firm Innovation: Unbalanced Panel (IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0311				
	(0.0215)				
L2.IPW		0.0329			
		(0.0219)			
L3.IPW			0.0373*		
			(0.0226)		
L4.IPW				0.0389*	
				(0.0230)	
L5.IPW					0.0318
					(0.0249)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	12.58	30.45	40.71	32.21	23.23
Observations	25545	23605	21571	19495	16389

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson regressions are estimated using a control function approach, and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

dataset with a longer time span, i.e., 1991-2007, to check the robustness of my main results.

The alternative dataset comes from Kogan et al. (2017), which matches firms in the CRSP database to their annual USPTO patents from 1926 to 2010. For the purpose of my study, the main advantage of this dataset is that it allows me to extend my time frame to 2007, the year before the Great Recession. The disadvantage of this dataset is that although all firms included in CRSP are publicly listed, they are a subsample of the firms in Compustat.[14] Hence, some patenting public firms are not covered by CRSP. To maintain consistency, I use only this subsample and rerun all the baseline regressions both at the industry level (Table B.1.1) and at the firm level (Table B.1.2 -Table B.1.5). Overall, the results are very similar to those using the NBER dataset from 1991 to 2004, indicating my main findings are robust to a different time frame. This is also intuitive: facing rising Chinese import competition, firms had to take action fairly quickly. Any firm-level patenting trend that persisted into 2007 should have started years earlier, otherwise they would not have been able to survive the tougher market.

Alternative Instrument for Trade Shock In this section, I show my results are robust to an alternative instrument, which exploits changes in trade tariffs between China and the United States. Following Pierce and Schott (2016), I use the fact that the United States granted Permanent Normal Trade Relations (PNTR) to China in 2000. Since 1980, Chinese imports had enjoyed relatively low Normal Trade Relations (NTR) tariff rates. However, China had to renew its trade agreements with the United States annually to secure these low tariff rates, which was often uncertain and politically contentious. According to the Smoot-Hawley Tariff Act of 1930, Chinese imports would have been subject to the higher non-NTR tariff rates if an annual renewal had failed. PNTR permanently set U.S. duties on Chinese imports at NTR levels, removing uncertainties associated with China's annual renewals.

It is important to note that the agreement did not affect all industries the same way. The "NTR gap," defined as the difference between the non-NTR tariff rates and the NTR rates, varied widely across different industries. As shown in Pierce and Schott (2016), industries facing a larger drop in expected tariff rates experienced a larger increase in Chinese imports. I therefore adopt a generalized difference-in-difference approach that exploits this

[14] For more details on the dataset and CRSP database, please refer to Kogan et al. (2017) and `https://wrds-web.wharton.upenn.edu/wrds/support/Data/_001Manuals%20and%20Overviews/_002CRSP/_001General/_009WRDS%20Overview%20of%20CRSP%20U.S.%20Stock%20Database.cfm`

cross-sectional variation in the NTR gap to test whether firms in industries with higher NTR gaps (first difference) innovated more after the change in policy relative to innovation in the pre-PNTR era (second difference). I regress each firm's annual number of patent counts on the NTR gap interacted with a dummy variable "Post" equal to one after the year 2000, and include the same fixed effects as in the baseline regressions. Results are presented in Table B.2.1. The first two columns employ the NBER dataset that covers all Compustat patenting firms from 1991 to 2004. Columns (3) and (4) use data from Kogan et al. (2017), which includes firms in the CRSP database from 1991 to 2007. Although the two datasets come from two independent sources, they provide very similar results, with even stronger estimates from the 1991-2007 sample. Such patterns suggest that as Chinese import competition further intensified into 2007, firms had much stronger patenting incentives. Based on column (2), a one-standard-deviation (0.15) increase in the NTR gap induced 11% more firm innovation or one additional patent after the policy change.

Placebo Tests To rule out the possibility that pre-trends might be generating spurious positive correlation between import penetration and firm innovation, I also regress the firms' annual number of patents from 1975 to 1991 on future import penetration (i.e., 1991 to 2007), and find no effects (Table B.3.1).

Sales-Weighted Import Penetration In Compustat, each firm self-identifies a primary 4-digit SIC code it operates in, which I used to construct import penetration measure in my main analysis. However, some firms operate in multiple industries and using import penetration based on a single industry incurs measurement errors. In this section, I use firms' annual sales data across different 4-digit SIC industries to construct sales-weighted import penetration measure. Whenever such information is missing, I use firm's primary SIC code instead.[15] One concern is that firm sales are endogenous to Chinese import penetration. Hence, I focus on firms that were already public in 1991 (the start of the rising Chinese imports era) and employ their sales information across different industries in 1991 as the initial sales weight. The results (Table B.4.1) are even stronger than those of baseline regressions: looking at three-years' lag specification, a one-standard-deviation (7.82) increase in sales-weighted import penetration raised a firm's number of patents by 48.3% (versus 39.2% in baseline) or six additional patents (versus five additional patents in baseline). Moreover, using this alternative measure yields almost across-the-board positive and

[15]The sales information comes from firms' historical segments data in Compustat. The data dates as early as 1976; roughly 6% of the observations in my sample are missing such information.

significant results (except that of five-years' lag). This is intuitive because firms operating in multiple industries could be hit especially hard by Chinese imports, and thus had much stronger incentives to innovate their way out.

Anticipation Effects Did firms increase their innovation in anticipation of rising Chinese imports? While Chinese imports enjoyed low tariff rates under the terms of U.S. Normal Trade Relations before 2001, there was considerable uncertainty from year to year as to whether China could renew its status (Pierce and Schott, 2016). Without the renewal, China would suffer from high import tariffs. There was also a large element of surprise when China joined the WTO, which granted China low tariff rates permanently. Therefore, at least before 2001, due to the annual uncertainty, U.S. manufacturing firms were less likely to take pre-emptive innovative actions against Chinese imports. After 2001, however, it is plausible that U.S. manufacturing firms sensed the ever-increasing competitive pressure from rising Chinese imports and started innovation preemptively to cope with the tougher environment. To examine this possibility, I regress the firms' annual number of patents on future import penetration, but don't find any significant effects (Table B.5.1). Therefore, firms seemed to have limited power of taking pre-emptive actions when experiencing adverse shocks.

Offshoring An alternative explanation for the increase of firm innovation is offshoring: firms could migrate their production lines to China and focus on R&D activities at home. However, studying Taiwanese firms who offshored in mainland China, Branstetter et al. (2017) find that offshoring reduced firm innovation. If similar dynamics are at work in the United States, the presence of offshoring would bias my estimate downward and thus pose less of a concern. Looking at the United States, specifically, offshoring is less likely to take place before 2001, when there was still uncertainty around China's Most Favored Nation status. Anecdotal evidence suggests that firms delayed their investment decisions in China for fear of a sudden rise of import tariffs (Pierce and Schott, 2016). After 2001, offshoring is more prevalent. To gauge its overall importance, I look at how firm sales across different industries are affected. In essence, offshoring helps firms to better utilize global production chains for cheaper intermediates or assembled final products to profit more. Hence, rising Chinese import competition in this case would help firm sales in its respective industry. Import competition, on the other hand, works against firms. Therefore, by looking at how firm sales across different industries responded to rising Chinese import competition, one can tell which force was dominant. When Chinese imports rose in a given industry and firm sales in that particular field also rose, offshoring was more likely to be the driving force for increased firm innovation; if firm sales in that particular field declined, however, import competition would be the more plausible driver of increased firm innovation. Regression results in Table B.6.1 indicate that import competition, rather than offshoring, was mainly responsible for spurring firm innovation: a one-standard-deviation (8.87) increase in Chinese import competition reduced firm sales in that particular industry by 15.5% (taking three-years' lag specification for instance).

4.3 Direction of Innovation

When Chinese imports gathered their momentum, U.S. public manufacturing firms increased their number of patents in response. However, the number of patents represents only one dimension of firm innovation. Another important aspect is change in innovation direction. To address this dimension, I test whether firms hit harder by Chinese imports were more likely to patent in new technology classes. The U.S. Patent Office assigns one of 421 technology classes to each patent. To isolate possible trade-related confounders, I focus on firms that were already public in 1991, the beginning of the rising Chinese imports era. I was able to trace the patenting history of each firm as early as 1975. Hence, I know which technology classes a firm historically patented in.[16] This allows me to create a dummy that takes value one if a firm patented in technology classes distinct from its patenting history (1975-1991) in a subsequent year and zero otherwise. Table 4 shows that firms were more likely to patent in new technology classes when Chinese competition intensified in their respective industry. A one-standard-deviation (8.87) increase in Chinese import penetration made a firm 13.4 percentage points (33.7%) more likely to patent in new technology classes (taking three-years' lag specification as an example). Moreover, this also indicates that firms were producing true innovation, i.e., gaining new knowledge/technology, rather than filing patent applications for technology they already had but previously kept as a secret (known as "defensive patenting").

Where did firms make use of their patents in new technology fields? Did they enter new product markets as a result? Here, I examine this possibility using firms' historical sales data across different 4-digit SIC industries. Such sales data date as early as 1976. Again, I focus on firms that were public in 1991[17] and track the 4-digit SIC industries they had

[16] I also limit my analysis to firms that had been public for at least three years by 1991. This ensures the firm had enough previous patenting history that a subsequent new technology class could be reliably identified.

[17] Similarly, those firms had been public for at least three years by 1991.

Table 4: Import Penetration and Firm Patenting in New Technology Classes (1991 Subsample)

	IV1	IV2	IV3	IV4	IV5
L.IPW	0.0092**				
	(0.0046)				
L2.IPW		0.0119**			
		(0.0052)			
L3.IPW			0.0151***		
			(0.0048)		
L4.IPW				0.0152**	
				(0.0061)	
L5.IPW					0.0080
					(0.0051)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	11.82	26.97	38.59	29.40	21.88
R-squared	0.4827	0.4988	0.5124	0.5270	0.5492
Observations	13280	11872	10505	9208	7971

Notes: This table examines whether firms are more likely to patent in new technology classes when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. USPTO assigns one of 421 technology classes to each patent. I track the patenting history of each firm as early as 1975. To make sure that the firm had some patenting history to begin with, and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years by 1991. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is a dummy that takes value one if a firm patented in technology classes distinct from its patenting history (1975-1991) in a subsequent year and zero otherwise. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

historically operated in. Starting from 1992, whenever a firm had sales that constituted at least 10% of its total annual sales in an industry distinct from its historical record, I consider the firm had entered a new market. As in the previous analysis, the dependent variable is a dummy that takes value one if a firm had sales in a new industry in a given year and zero otherwise. Consistent with patenting in new technology classes, firms hit harder by Chinese imports were also more likely to enter new markets. Specifically, a one-standard-deviation (8.87) increase in Chinese import penetration (three-years' lag) made a firm's entry into new markets 7 percentage points (37.2%) more likely (Table 5).

To conclude, rising Chinese import competition not only spurred more firm innovation, but it also propelled firms to patent in new technology classes and to enter new product markets. Such empirical results are consistent with a horizontal differentiation story, where firms escaped fierce Chinese import competition by exploring new technical fields and producing products tailored to new markets.

5 Heterogenous Treatment Effects: Survival of the Fittest

Until now, all analyses investigate average treatment effects on surviving firms. But China's trade shock could have reduced firm survival probability and generated heterogeneous firms' responses. In this section, I investigate potential heterogeneity between large and small firms in detail.

5.1 Firm Survival Rate

I start with examining firm survival rate. As before, I focus on a baseline group of firms that were public in 1991 and had been public for at least three years.[18] The dependent variable is a dummy that takes value one if the firm existed in that particular year and zero otherwise. I also create a dummy called "large." It takes value one if firm size was above its industry median in 1991 and zero otherwise. As we can see from Table 6, small firms had a lower probability of survival. For example, a one-standard-deviation (8.87) increase in the three-years' lag import penetration reduced the survival rate of small firms by about 8 percentage points (10.58%). Yet, large firms were pretty much immune to such an adverse impact.

[18] Limiting the sample to firms that were public for at least three years could effectively distinguish small firms from young firms, which have very different growth dynamics.

Table 5: Import Penetration and Firm Entry in New SIC Codes (1991 Subsample)

	IV1	IV2	IV3	IV4	IV5
L.IPW	0.0052*				
	(0.0031)				
L2.IPW		0.0066**			
		(0.0033)			
L3.IPW			0.0079**		
			(0.0036)		
L4.IPW				0.0098**	
				(0.0038)	
L5.IPW					0.0112***
					(0.0039)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	11.76	26.89	38.43	29.33	21.85
R-squared	0.6118	0.6373	0.6607	0.6874	0.7160
Observations	13083	11714	10385	9121	7912

Notes: This table examines whether firms are more likely to enter new markets (by 4-digit SIC) when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. Compustat provides firms' historical sales information across different markets that date as early as 1976. I track the sales history of each firm in different markets. To make sure that the firm has some sales history to begin with, and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years by 1991. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is a dummy that takes value one if a firm has sales in a market distinct from its sales history (1975-1991) in a subsequent year and zero otherwise. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Import Penetration and Firm Survival (1991 Subsample: Large vs. Small)

	IV1	IV2	IV3	IV4	IV5
L.IPW	-0.0066*				
	(0.0039)				
L.IPW*Large	0.0057				
	(0.0035)				
L2.IPW		-0.0077*			
		(0.0045)			
L2.IPW*Large		0.0081*			
		(0.0045)			
L3.IPW			-0.0090*		
			(0.0047)		
L3.IPW*Large			0.0101*		
			(0.0052)		
L4.IPW				-0.0096**	
				(0.0043)	
L4.IPW*Large				0.0104*	
				(0.0053)	
L5.IPW					-0.0109***
					(0.0041)
L5.IPW*Large					0.0105**
					(0.0050)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	5.42	12.34	18.20	15.03	12.82
R-squared	0.6724	0.6985	0.7278	0.7572	0.7858
Observations	17277	15948	14619	13290	11961

Notes: This table investigates heterogeneous survival rate between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. "Large" is a dummy variable that takes value one if a firm's employment was above its industry median in 1991 and zero otherwise. The dependent variable is a dummy that takes value one if the firm existed in a subsequent year and zero otherwise. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 Firm Innovation

Turning to heterogenous firms' responses, I look at four outcomes sequentially: number of patents, R&D expenditures, patenting in new technology classes, and entry into new product markets.

In Table 7 we can see that increase in innovation mainly came from large firms. Starting from three-years' lag, Chinese import penetration has a positive and significant impact on large firms' innovation and the effect is slightly stronger than the baseline average treatment effects: a one-standard-deviation (8.87) increase in import penetration (three-years' lag specification) raised a large firm's number of patents by 42.5% (versus 39.2% in baseline) or roughly eight additional patents (versus five additional patents in baseline).[19] Small firms, in contrast, exhibited no increase in patents and even seemed to experience a decline in patenting over time (the coefficients drop in magnitude and that of five-years' lag turns negative, albeit insignificantly).

Table 7: Import Penetration and Firm Innovation (1991 Subsample: Large vs. Small)

	IVPois1		IVPois2		IVPois3		IVPois4		IVPois5	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
L.IPW	0.0328	0.0226								
	(0.0284)	(0.0241)								
L2.IPW			0.0299	0.0281						
			(0.0318)	(0.0230)						
L3.IPW					0.0191	0.0399*				
					(0.0350)	(0.0230)				
L4.IPW							0.0124	0.0493**		
							(0.0439)	(0.0206)		
L5.IPW									-0.0333	0.0558**
									(0.0745)	(0.0250)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	7.66	13.56	15.30	29.72	25.19	38.46	19.24	30.24	17.08	19.84
Observations	4216	8078	3763	7227	3313	6416	2888	5635	2487	4887

Notes: This table investigates heterogeneous innovation response between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. A firm is large if its employment was above the industry median in 1991 and small otherwise. Large and small firms are analyzed in separate regressions. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Looking at the input of innovation–firm R&D expenditures (in logarithm)–consistent results hold: small firms significantly reduced their R&D expenditures while large firms

[19] Negative Binomial specification shows an even larger distinction between the two groups (see F.7).

remained stable. Specifically, by three-years' lag specification, a one-standard-deviation (8.87) increase in import penetration reduced a small firm's R&D expenditures by as much as 49.5%. Large firms, on the other hand, were more resilient to rising competitive pressure and more or less maintained their normal research budget (Table A.3).

Moreover, when we examine patenting in new technology classes, large firms are again taking the lead (Table 8): based on three-years' lag specification, a one-standard-deviation (8.87) increase in import penetration made a firm 18 percentage points (45%) more likely to patent in new technology classes. For small firms, however, the impact was negative (and sometimes significant).

Table 8: Import Penetration and Firm Patenting in New Technology Classes (1991 Sub-sample: Large vs. Small)

	IV1		IV2		IV3		IV4		IV5	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
L.IPW	-0.0076*	0.0148**								
	(0.0042)	(0.0065)								
L2.IPW			-0.0112***	0.0190***						
			(0.0037)	(0.0064)						
L3.IPW					-0.0013	0.0204***				
					(0.0048)	(0.0061)				
L4.IPW							-0.0039	0.0214***		
							(0.0069)	(0.0082)		
L5.IPW									-0.0181**	0.0189**
									(0.0079)	(0.0079)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	7.66	13.56	15.30	29.72	25.19	38.46	19.24	30.24	17.08	19.84
R-squared	0.4472	0.5070	0.4710	0.5188	0.4868	0.5276	0.5005	0.5412	0.5192	0.5650
Observations	4216	8078	3763	7227	3313	6416	2888	5635	2487	4887

Notes: This table examines heterogeneous response in patenting in new technology classes between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. A firm is large if its employment was above the industry median in 1991 and small otherwise. Large and small firms are analyzed in separate regressions. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is a dummy that takes value one if in a subsequent year a firm has patented in technology classes distinct from its patenting history, and zero otherwise. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, looking at firm entry into new product markets, represented by sales in new 4-digit SIC code, we see in Table 9 that large firms managed to reorient their businesses and join new markets while small firms didn't follow suit. For instance, a one-standard-deviation (8.87) increase in import penetration (three-years' lag specification) made a large firm 8 percentage points (36.9%) more likely to enter new markets.

Table 9: Import Penetration and Firm Entry in New SIC Codes (1991 Subsample: Large vs. Small)

	IV1		IV2		IV3		IV4		IV5	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
L.IPW	0.0031	0.0065*								
	(0.0095)	(0.0035)								
L2.IPW			0.0051	0.0078*						
			(0.0096)	(0.0042)						
L3.IPW					0.0068	0.0090*				
					(0.0111)	(0.0053)				
L4.IPW							0.0097	0.0102*		
							(0.0121)	(0.0054)		
L5.IPW									0.0081	0.0118**
									(0.0133)	(0.0057)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	8.28	13.58	17.32	29.73	27.13	38.46	20.46	30.23	18.35	19.84
R-squared	0.6405	0.6298	0.6700	0.6521	0.6974	0.6723	0.7274	0.6942	0.7594	0.7185
Observations	4478	8141	4004	7278	3530	6460	3081	5675	2660	4920

Notes: This table examines heterogeneous response in entering new markets between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. A firm is large if its employment was above the industry median in 1991 and small otherwise. Large and small firms are analyzed in separate regressions. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is a dummy that takes value one if in a subsequent year a firm has sales in markets distinct from its sales history, and zero otherwise. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To sum up, large firms that faced fierce Chinese import competition were able to innovate their way out; they not only increased their number of patents, but were also more likely to patent in new technology classes and to enter new product markets. Such efforts indicate horizontal differentiation from Chinese competitors. Small firms, however, seemed to have their hands tied. Experiencing such an adverse shock, they significantly reduced their R&D expenditures and had a higher rate of exit.

6 Source of Innovation: New Inventors

The key to increasing innovation for firms is human capital. They need employees with the right talents to navigate the increasingly competitive environment. The employees themselves also have the opportunity to move for better employers. Capitalizing on inventor-patent data from Harvard Patent Network Dataverse, I show evidence of new inventors contributing to innovation at firm-level and inventor mobility at inventor-level.

6.1 At Firm-Level

Each year, a firm can have inventors both leaving and coming, and I examine whether firms facing more Chinese import competition had a greater net inflow of inventors. Because I observe an inventor only when she patented, several assumptions have to be made regarding the timing of her move. In particular, if an inventor was new to the patenting population (i.e., she has no prior patents), I assume she came to her current employer the year she filed her first patent.[20] If an inventor worked on her own or with another firm before, I assume she came to her current employer in the midpoint between the application years of her last patent and her first patent at the new firm. I define departure similarly: if an inventor filed all her subsequent patents at entities other than her current employer, she is considered to have left afterwards, and the year she left is the midpoint between the application years of her last patent at the former employer and her first patent at the new entity.[21]

Then, I compute the net number of new inventors for each manufacturing firm per year and take that as the dependent variable. Note that this variable can take negative values, which indicates a net decrease of new inventors. On average, the net number of inventors for each manufacturing firm per year is about five. Table 10 presents expected results: firms experiencing a one-standard-deviation (8.87) greater Chinese import penetration had four additional new inventors on net or an increase of 75% (three-years' lag specification). Moreover, the net increase of new inventors happened more quickly than the rise in the number of patents (starting from one-year's lag import penetration), consistent with the timing of producing new inventions.

Turning to heterogenous treatment effects, we can see that when Chinese imports soared, large firms increased their net number of new inventors. The effect is also much stronger: a one-standard-deviation (8.87) increase in Chinese import penetration propelled a large public manufacturing firm to have nine additional new inventors on net or an increase of 180% (three-years' lag specification, see Table 11).

How much did those new inventors contribute to the innovation of large public manufacturing firms? The answer is, almost all. Table 12 examines how large firms' annual

[20] This is an innocuous assumption. Assuming the first-time patenter came to her current employer one or two years before she filed her first patent delivers similar and even slightly stronger results. It is also possible that the first-time patenter was an old employee who had been working at the firm for a long time, but just produced the very first patent. In that case, I still consider her to be a new inventor.

[21] For the purposes of my study and to err on the conservative side, I include all relevant inventors, regardless of the number of patents they filed.

Table 10: Import Penetration and Firm's Net Number of New Inventors

	IV1	IV2	IV3	IV4	IV5
L.IPW	0.3516***				
	(0.1089)				
L2.IPW		0.3689***			
		(0.1230)			
L3.IPW			0.4195**		
			(0.1638)		
L4.IPW				0.3807**	
				(0.1903)	
L5.IPW					0.2403
					(0.1666)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	12.58	30.45	40.71	32.21	24.78
R-squared	0.6894	0.7023	0.7023	0.6976	0.6951
Observations	25545	23605	21571	19495	17285

Notes: This table examines firms' net number of new inventors when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual net number of new inventors. Note that this variable can take negative values, which then indicates a net decrease of new inventors. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Import Penetration and Firm's Net Number of New Inventors (1991 Subsample: Large vs. Small)

	IV1		IV2		IV3		IV4		IV5	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
L.IPW	0.0012	0.6269***								
	(0.0301)	(0.2016)								
L2.IPW			-0.0155	0.7995***						
			(0.0432)	(0.2828)						
L3.IPW					0.0073	1.0420**				
					(0.0521)	(0.4054)				
L4.IPW							0.0148	0.9865**		
							(0.0456)	(0.4812)		
L5.IPW									-0.0623	0.6284
									(0.0526)	(0.3891)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	7.66	13.56	15.30	29.72	25.19	38.46	19.24	30.24	17.08	19.84
R-squared	0.7247	0.7121	0.6935	0.7253	0.6914	0.7214	0.6864	0.7138	0.5220	0.7100
Observations	4216	8078	3763	7227	3313	6416	2888	5635	2487	4887

Notes: This table examines the heterogeneous response in having new inventors between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. A firm is large if its employment was above the industry median in 1991 and small otherwise. Large and small firms are analyzed in separate regressions. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is each firm's annual net number of new inventors. Note that this variable can take negative values, which then indicates a net decrease of new inventors. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Import Penetration and Large Firms' Innovation by New Inventors

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0304				
	(0.0186)				
L2.IPW		0.0360*			
		(0.0194)			
L3.IPW			0.0470**		
			(0.0197)		
L4.IPW				0.0544***	
				(0.0180)	
L5.IPW					0.0599***
					(0.0220)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	13.56	29.72	38.46	30.24	19.84
Observations	8078	7227	6416	5635	4887

Notes: This table examines large firms' changes in innovation by new inventors when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. Large firms are those that had been public for at least three years in 1991, and had employment above industry median. The dependent variable is each firm's annual number of patents produced by new inventors. To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

number of patents produced by new inventors responded to rising Chinese import penetration. Based on three-years' lag specification, a one-standard-deviation (8.87) increase in Chinese import penetration induced a 51.7% increase of patents by new inventors. This roughly corresponds to eight additional patents, which account for all of the rise in large firms' innovation.

6.2 At Inventor-Level

I now go one level down and examine the individual inventor's decision to move. In particular, I investigate whether the inventors at a firm that was hit harder by Chinese import competition were more likely to leave. Here, I focus on inventors who were already working at public manufacturing firms in 1991 and test how their moving decisions were affected by the subsequent trade shock from China. The unit of observation is inventor-employer-year, and the dependent variable is a dummy that takes value one when an inventor left her employer in a given year, and zero otherwise. From 1991 to 2004, about 4.1% observations are associated with a move, or roughly 35,103 moves.[22] We can see that only inventors initially working at small firms (same definition as before) tended to leave when Chinese import penetration surged (see Table 13). For instance, based on three-years' lag specification, a one-standard-deviation (8.87) increase in Chinese import penetration induced an inventor working at a small firm to be 6 percentage points (146%) more likely to leave.

So where did those inventors go? About 58% (18,311 moves) of the inventors went to other public firms, while the rest went to private entities. Among those who went to other public firms, approximately 65% (11,895 moves) joined other public manufacturing firms.

To examine whether moving inventors were more likely to work for large public firms, I limit my sample to inventor-employer-year observations corresponding to a move between two public manufacturing firms. The dependent variable is the relative size of the inventor's present employer to former employer in the year she moved (in logarithm). Thus, positive and significant coefficients imply that rising Chinese import penetration made an inventor more likely to leave for large public manufacturing firms,[23] which is exactly what Table 14 shows.

Relatedly, at the intensive margin, were new inventors at large firms also patenting at higher frequency? To investigate this issue, I look at how the annual number of patents of each new inventor at a large firm changed against rising Chinese import penetration. The results in Table A.4 indicate that those new inventors indeed patented more. In particular, a one-standard-deviation (8.87) increase in import penetration encouraged a new inventor to produce 30.8% more patents, i.e., 0.13 additional patent. The magnitude seems modest, and may suggest that the increase in innovation at large firms mainly came from the extensive margin–rising number of new inventors, rather than from the intensive margin–of the annual number of patents produced by each new inventor.

[22] Note that I also include inventors who only patented once during the entire sample period; some of them were very likely to have retired and exited the patenting population permanently, so the percentage of move is a lower bound of true value.

[23] Because I limit my sample to inventors moving between two public manufacturing firms that were already public in 1991, the results are only indicative and should be taken with a grain of salt.

Table 13: Import Penetration and Inventor's Leaving Decisions

	IV1	IV2	IV3	IV4	IV5
L.IPW	-0.0005				
	(0.0006)				
L.IPW*Small	0.0043***				
	(0.0009)				
L2.IPW		-0.0002			
		(0.0007)			
L2.IPW*Small		0.0047***			
		(0.0011)			
L3.IPW			-0.0000		
			(0.0006)		
L3.IPW*Small			0.0069***		
			(0.0016)		
L4.IPW				0.0003	
				(0.0005)	
L4.IPW*Small				0.0085***	
				(0.0020)	
L5.IPW					0.0012
					(0.0009)
L5.IPW*Small					0.0132***
					(0.0027)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	7.40	16.77	22.62	21.48	18.89
R-squared	0.0355	0.0355	0.0355	0.0367	0.0396
Observations	781625	742499	697187	646013	589228

Notes: This table examines whether an inventor is more likely to leave when her employer is hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. I focus on inventors who were already working at public manufacturing firms in 1991 and test how their moving decisions were affected by the subsequent trade shock from China. In each specification, I've added an interaction term where "small" is a dummy variable that takes value one if an inventor's employer had below industry median employment in 1991 and zero otherwise. The dependent variable is a dummy that takes value one when an inventor left her employer in a given year and zero otherwise. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Import Penetration and Inventor's Propensity to Leave for Large Firms (Firms' Relative Size)

	IV1	IV2	IV3	IV4	IV5
L.IPW	0.0361**				
	(0.0180)				
L2.IPW		0.0699***			
		(0.0217)			
L3.IPW			0.0538**		
			(0.0233)		
L4.IPW				0.0760***	
				(0.0257)	
L5.IPW					0.0244
					(0.0561)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	8.06	24.71	35.96	23.02	28.39
R-squared	0.5810	0.5845	0.5906	0.5943	0.5985
Observations	7789	7584	7126	6616	5874

Notes: This table investigates whether moving inventors (i.e., conditional on moving) are more likely to work for large public firms when their initial employers are hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. The unit of observation is inventor-employer-year corresponding to a move between two public manufacturing firms. The dependent variable is the relative size of the inventor's present employer to former employer in the year she moved (in logarithm). To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To conclude, the reallocation of inventors from small firms to large firms constitutes one important source of increased firm innovation, and is consistent with the heterogenous treatment effects between them. In the face of an increasingly competitive environment, large firms were more resilient: they had more new inventors(partly hired from their smaller counterparts), generated more patents, explored new technical fields, and entered new product markets. Such strategies differentiated large firms horizontally from Chinese competitors and thus allowed them to escape Chinese competition.

7 Discussion

In this section, I discuss four main topics. First, I explain how my findings on horizontal differentiation relate to the theoretical literature. Second, I discuss possible explanations on the heterogenous responses between large and small firms. Third, I address the concern that my sample is limited to Compustat firms, and that the aggregate impact may turn negative once private firms are included. Finally, I conduct detailed analyses to reconcile my findings with those of Autor et al. (2016).

Escape Competition via Horizontal Differentiation Large firms' innovation response to increased market competition informs the theory debate on the relationship between innovation and competition. In general, their response is consistent with the "Escape Competition Effect" proposed by Aghion et al. (2001, 2005). These papers predict that when initial market competition is low, and firms are in neck-and-neck state, pre-innovation rent is reduced more than post-innovation rent. Firms thus have greater incentive to escape competition via innovation. However, previous studies of the "Escape Competition Effect" primarily focus on vertical differentiation, where firms climb up the quality ladder, provide better products to replace existing ones, and then enjoy temporary monopoly rents until the next generation of products appears. My findings, in contrast, emphasize horizontal differentiation as an additional strategy that firms adopt to escape competition. Firms experiencing intense rivalry from Chinese imports, on top of upgrading the quality of their existing products, can also expand their product portfolio by exploring new technical fields, creating more varieties, and entering new markets as monopolies. In endogenous growth literature (Romer, 1990; Grossman and Helpman, 1991), both types of innovation–quality-enhancing and variety-enriching–promote long-term economic growth. Yet, their welfare implications differ. Successful quality-based innovation results in both positive and negative externalities. It generates positive consumer surplus by providing higher-quality products at the same price as before innovation; it also produces positive knowledge spillover that makes follow-up innovation easier. However, it also imposes negative externality on other firms via business-stealing effect. The net impact thus depends on the relative magnitude of positive and negative externalities. For a successful variety-based innovation, the consumer-surplus effect and the business-stealing effect cancel each other out, and a net positive externality of knowledge spillover remains. Recent works (Klette and Kortum, 2004; Akcigit and Kerr, 2016) have also explicitly incorporated firm innovation choices into their framework to confront firm-level evidence. In particular, Akcigit and Kerr (2016) predict that in steady state, large incumbents are more likely to make innovations that improve their existing product lines while small firms contribute disproportionately to creating new products and capturing markets from others. The horizontal differentiation strategy uncovered in this paper depicts how firms adapt to non-steady state environment, when competitive market disruptions occur.

On a micro level, horizontal differentiation is also related to papers on direction of firm innovation. This strand of literature is emerging and most attention is paid to the inefficiencies in firm research lines under current research regimes (Acemoglu, 2011; Bryan and Lemus, 2016; Squintani and Hopenhayn, 2016). Bryan and Lemus (2016), in one of their theoretical applications, examine the impact of trade liberalization on firm research direction, and predict that a decrease in trade barriers can force firms to switch to research projects that are either more immediately lucrative or quicker to complete. Those newly pursued research lines, however, may not be socially optimal. My empirical evidence on horizontal differentiation is consistent with their theoretical prediction, but does not explore the welfare implications of such directional changes. It is then interesting to investigate in future work, when market competition intensifies, how firms choose between different "escape competition" strategies, and the welfare implications of adopting them.

Alternatively, horizontal differentiation can be interpreted through the lens of the "Resource View" in corporate diversification literature. This literature proposed the "Resource View" to explain the direction of firm diversification. It contends that a firm's level of profit and breath of diversification are a function of its resource stock, and the direction of firm expansion is often guided by firms' existing organizational capabilities, particularly in R&D and marketing.[24] The empirical evidence that firms had more new inventors and more inventions in new technical fields when entering new product markets seems to suggest that, firms' direction of market expansion revolves around their core human capital–inventors.

[24] Lemelin (1982); MacDonald (1985); Montgomery and Hariharan (1991); Collis (1988); Collis and Stuart (1991); Collis and Noda (1993); Itami and Roehl (1991); Silverman (1999); Neffke and Henning (2013).

Heterogeneity Between Large and Small Firms Why did large firms respond differently than small firms? One possible explanation is the "Deep Pockets Effect" (Schumpeter, 1942; Galbraith, 1952; Hall and Lerner, 2010): due to capital market imperfections, firms mostly rely on their internal resources to undertake costly and risky innovative activities.[25] Large firms are more likely to have such "deep pockets." This could be especially important when market competition is intense and firms suffer from declining sales. Small firms in tough times tend to be liquidity constrained. A selective reading of firms' 10-K files also suggests that capital is at play. Witnessing surging Chinese imports, large firms changed their direction of innovation primarily via 1) acquisition of firms in targeted new fields (M&A), and 2) strategic alliances and partnerships with other firms in targeted new industry. Both strategies require deep pockets to close the deal. Leveraging other firms' expertise in related fields, large firms quickly reoriented their businesses, produced new patents and new products, and therefore successfully differentiated themselves from Chinese competitors. Small firms, unfortunately, didn't seem to have pockets deep enough to follow suit. Moreover, firms in other fields may also prefer forming partnerships with large firms.

Another possible explanation hinges on firms' "Absorptive Capacity" (Cohen and Levinthal, 1990; Griffith et al., 2003): a firm's investment in R&D nurtures its ability to recognize the value of new, external information and to assimilate it towards commercial ends. Large firms, on average, have higher R&D expenditures (in absolute terms) that contribute to their absorptive capacity. As a result, they are better equipped to assimilate new knowledge and identify new, valuable fields of innovation. When Chinese imports came in strongly, a higher absorptive capacity helped large firms quickly produce patents in new technology fields and introduce novel products in new markets. One could certainly come up with other mechanisms consistent with the heterogenous treatment effects between large and small firms. Due to data limitations, pinning down the exact mechanism is beyond the scope of this paper and left for future work.

Aggregate Impact on Innovation Because my analysis is limited to Compustat firms only, and large firms responded differently than small firms, one would naturally wonder whether the aggregate impact of Chinese import competition remains positive once the pri-

[25] Brown et al. (2009) present direct evidence that U.S. firms relied heavily on cash reserves to smooth R&D spending during the 1982-2002 boom and bust in stock market returns. For more empirical evidence, please see Hall and Lerner (2010).

vate firms are included. Although I can not answer this question definitively due to a lack of data on private firms, I can approximate the aggregate impact by constructing the China trade shock at the technology class level.

Specifically, I calculate the share of all patents of each 4-digit SIC code within each technology class filed by Compustat firms between 1975 and 1991.[26] Using these shares as initial weights, I then construct the annual China trade shock in each technology class by taking a weighted average of industry-level import penetration.

In Appendix C, I examine how the number of U.S. corporate patents within each technology class responded to Chinese import competition. Again, I use both Poisson and Negative Binomial specifications. In Poisson estimates, for example, the net impact ranges from 19.7% to 13%, if import penetration increased by one-standard-deviation, consistent with the increase in innovation among Compustat firms (see Table C.2).[27]

Reconciliation with Autor et al. (2016) My baseline results on firm innovation response to Chinese import penetration differ from those found in Autor et al. (2016). In particular, I find firms on average increased their number of patents, while Autor et al. (2016) find the opposite. In this section, I provide possible reconciliation for our different findings. In Appendix D, I replicate results of the first three columns from rows a) through e) in Table 2 in Autor et al. (2016), using the dataset from Kogan et al. (2017). Based on the replication results, I believe the differences of our findings mainly come from two sources:

1) Different Time Frame: I'm using a firm-level annual panel data from 1991 to 2004, whereas Autor et al. (2016) use three years only: 1991, 1999 and 2007. Because the majority of firms didn't patent every single year, firms patented in years other than 1991, 1999, and 2007 are not included in their analysis. Because I have an annual panel, I can identify a broader set of patenting firms and examine their innovative response to Chinese import competition.

2) Different Firm Coverage: In my analysis, I limit my attention to all U.S. publicly listed manufacturing firms in Compustat. Autor et al. (2016) study the same group of firms, but include them when they were still private. Their sample is thus a mixture of public and

[26]Results are very similar if I construct the initial shares using only U.S. headquartered publicly listed firms. To save space, I just report one set of results. Additional results can be requested from the author.

[27]Negative Binomial estimates imply a smaller but more stable increase, from 8% to 7% (see Table C.3).

private firms, with the number of private observations far exceeding that of public ones. Their negative results may therefore better represent private firms' response. Private firms, on average, are smaller than their publicly listed counterparts, and their response is more likely to resemble the small firm reaction in my analysis. In fact, Autor et al. (2016) also find that the negative impact is mainly driven by small firms in their sample.

8 Conclusion

This paper provides insight into the impact of rising Chinese imports on innovation by U.S. public manufacturing firms. Exploiting cross-industry and over-time trade variations between 1991 and 2004, I find that when Chinese import penetration intensified, average U.S. public manufacturing firms increased their number of patents. They also differentiated themselves horizontally from Chinese competitors by patenting in new technology classes and entering new product markets. Meanwhile, there was great heterogeneity between large and small firms. The increase in innovation came entirely from large firms; they appeared to be quite resilient to the competitive environment and managed to escape Chinese competition via horizontal differentiation. Small firms, however, were hit hard by Chinese imports. They significantly reduced their R&D expenditures and were more likely to exit. Capitalizing on inventor data, I also find consistent evidence: 1) at the firm level, new inventors at large firms contributed to almost all new innovation, and 2) at the inventor level, inventors initially working at small firms had a higher propensity to leave for large firms.

These findings not only paint a nuanced picture of firms' responses to Chinese import competition, but also uncover firm-level strategies for dealing with increased market competition. In addition to climbing up the quality ladder and becoming vertically differentiated from lower-cost competitors (Schott, 2008; Freeman and Kleiner, 2005; Bartel et al., 2007), firms also explore new technical fields and enter new product markets to be horizontally differentiated. Innovation, therefore, seems to offer an effective escape from competition. However, a highly competitive environment also generates tougher firm selection, and not every firm can innovate its way out. It seems that large firms were more resilient and could adapt quickly, while small firms lost their innovative talents to large firms.

There are a number of open issues for future work. To begin with, what is driving the heterogeneity between large and small firms remains unclear. Capital constraints and absorptive capacity, among others, are two possible explanations. It would be helpful to pin down the exact mechanism to better understand firm strategies in sailing through competitive environment. Second, this paper focuses only on U.S. public manufacturing firms and hence draws no conclusions on general equilibrium outcomes. It is also important to include the private sector and estimate the overall impact of China's trade on firm innovation. Finally, although this paper finds that large firms switched their direction of innovation, it does not explore whether those new research lines are socially desirable. Firms could be chasing after projects that are immediately lucrative or quicker to complete. It is therefore worthwhile to learn how firms choose between different "escape competition" strategies and the welfare implications of such changes.

References

Acemoglu, D. (2002). Directed Technical Change. *The Review of Economic Studies*, 69(4):781–809.

Acemoglu, D. (2011). Diversity and Technological Progress. In *The Rate and Direction of Inventive Activity Revisited*, pages 319–356. University of Chicago Press.

Acemoglu, D., Autor, D., Dorn, D., Gordon H., H., and Price, B. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Acemoglu, D., Gancia, G., and Zilibotti, F. (2015). Offshoring and Directed Technical Change. *American Economic Journal: Macroeconomics*, 7(3):84–122.

Aghion, P., Bergeaud, A., Lequien, M., and Melitz, M. (2017). The Impact of Exports on Innovation: Theory and Evidence. Technical report, Working Paper.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics*, 120(2):701–728.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., and Prantl, S. (2004). Firm Entry, Innovation and Growth: Theory and Micro Evidence. *Unpublished Manuscript. Institute for Fiscal Studies & Harvard University.*

Aghion, P., Harris, C., Howitt, P., and Vickers, J. (2001). Competition, Imitation and Growth with Step-by-Step Innovation. *The Review of Economic Studies*, 68(3):467–492.

Aghion, P. and Tirole, J. (1994). The Management of Innovation. *The Quarterly Journal of Economics*, 109(4):1185–1209.

Akcigit, U. and Kerr, W. R. (2016). Growth Through Heterogeneous Innovations. *Working Paper.*

Amihud, Y. and Lev, B. (1981). Risk Reduction as a Managerial Motive for Conglomerate Mergers. *The Bell Journal of Economics*, pages 605–617.

Amiti, M., Dai, M., Feenstra, R. C., and Romalis, J. (2017). How Did China's WTO Entry Benefit U.S. Consumers? *NBER Working Paper No. 23487.*

Arrow, K. (1962). Economic Welfare and the Allocation of Resources for Invention. In *The Rate and Direction of Inventive Activity: Economic and Social Factors*, pages 609–626. Princeton University Press.

Autor, D., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103:2121–2168.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., and Shu, P. (2016). Foreign Competition and Domestic Innovation: Evidence from US Patents. *NBER Working Paper No. 22879.*

Autor, D., Dorn, D., Hanson, G. H., and Song, J. (2014). Trade Adjustment: Worker Level Evidence. *Quarterly Journal of Economics*, 118(4):1799–1860.

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *The Quarterly Journal of Economics*, 122(4):1721–1758.

Bernard, A. B., Jensen, J. B., and Schott, P. K. (2006). Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of US Manufacturing Plants. *Journal of International Economics*, 68(1):219–237.

Bernheim, B. D. and Whinston, M. D. (1990). Multimarket Contact and Collusive Behavior. *The RAND Journal of Economics*, pages 1–26.

Bloom, N., Draca, M., and Reenen, J. V. (2016). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *The Review of Economic Studies*, 83(1):87–117.

Bloom, N., Schankerman, M., and Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, 81(4):1347–1393.

Branstetter, L., Chen, J.-R., Glennon, B., Yang, C.-H., and Zolas, N. (2017). Does Offshoring Manufacturing Harm Innovation in the Home Country? Evidence From Taiwan and China. Technical report, Working Paper.

Brown, J. R., Fazzari, S. M., and Petersen, B. C. (2009). Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom. *The Journal of Finance*, 64(1):151–185.

Bryan, K. A. and Lemus, J. (2016). The Direction of Innovation. *Working Paper*.

Bustos, P. (2011). Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. *The American Economic Review*, 101(1):304–340.

Carlin, W., Schaffer, M., and Seabright, P. (2004). A Minimum of Rivalry: Evidence From Transition Economies on the Importance of Competition for Innovation and Growth. *Contributions in Economic Analysis & Policy*, 3(1).

Christensen, H. K. and Montgomery, C. A. (1981). Corporate Economic Performance: Diversification Strategy Versus Market Structure. *Strategic Management Journal*, 2(4):327–343.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, pages 128–152.

Collis, D. J. (1988). The Walt Disney Company: Corporate Strategy. *Boston: Harvard Business School Publishing.*

Collis, D. J. and Noda, T. (1993). Sharp Corporation: Corporate Strategy. *Boston: Harvard Business School Publishing.*

Collis, D. J. and Stuart, T. (1991). Cooper Industries: Corporate Strategy. *Boston: Harvard Business School Publishing.*

De Bondt, R. and Vandekerckhove, J. (2012). Reflections on the Relation Between Competition and Innovation. *Journal of Industry, Competition and Trade*, 12(1):7–19.

Dunne, T., Klimek, S., and Schmitz, J. (2008). Does Foreign Competition Spur Productivity? Evidence from Post WWII US Cement Manufacturing. *Working Paper, Fed. Reserve Bank Minneapolis.*

Edwards, C. D. (1955). Conglomerate Bigness as a Source of Power. In *Business Concentration and Price Policy*, pages 331–359. Princeton University Press.

Freeman, R. B. and Kleiner, M. M. (2005). The Last American Shoe Manufacturers: Decreasing Productivity and Increasing Profits in the Shift from Piece Rates to Continuous Flow Production. *Industrial Relations: A Journal of Economy and Society*, 44(2):307–330.

Galbraith, J. K. (1952). *American Capitalism: The Concept of Countervailing Power.* Houghton Mifflin Boston.

Gilbert, R. (2006). Looking for Mr. Schumpeter: Where Are We in the Competition–Innovation Debate? *Innovation Policy and the Economy*, 6:159–215.

Gilbert, R. J. and Newbery, D. M. (1982). Preemptive Patenting and the Persistence of Monopoly. *The American Economic Review*, pages 514–526.

Gomellini, M. (2013). Innovation and Competition: A Survey. *Working Paper*.

Gribbin, J. D. (1976). The Conglomerate Merger. *Applied Economics*, 8(1):19–35.

Griffith, R., Redding, S., and Van Reenen, J. (2003). R&D and Absorptive Capacity: Theory and Empirical Evidence. *The Scandinavian Journal of Economics*, 105(1):99–118.

Grossman, G. M. and Helpman, E. (1991). Quality Ladders in the Theory of Growth. *The Review of Economic Studies*, 58(1):43–61.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. *NBER Working Paper No. 8498*.

Hall, B. H. and Lerner, J. (2010). The Financing of R&D and Innovation. *Handbook of the Economics of Innovation*, 1:609–639.

Helper, S., Krueger, T., and Wial, H. (2012). Why Does Manufacturing Matter? Which Manufacturing Matters? *Metropolitan Policy Program Paper*, pages 1–53.

Hill, C. W. L. (1985). Diversified Growth and Competition: The Experience of Twelve Large UK Firms. *Applied Economics*, 17(5):827–847.

Hombert, J. and Matray, A. (2016). Can Innovation Help US Manufacturing Firms Escape Import Competition from China? *Working Paper*.

Iacovone, L., Keller, W., and Rauch, F. (2011). Innovation Responses to Import Competition. Technical report, mimeo, Princeton University, March.

Itami, H. and Roehl, T. W. (1991). *Mobilizing Invisible Assets*. Harvard University Press.

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, 76(2):323–329.

Kamien, M. I. and Schwartz, N. L. (1975). Market Structure and Innovation: A Survey. *Journal of Economic Literature*, 13(1):1–37.

Klette, T. J. and Kortum, S. (2004). Innovating Firms and Aggregate Innovation. *Journal of Political Economy*, 112(5):986–1018.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics*, 132(2):665–712.

Lai, R., D'Amour, A., Yu, A., Sun, Y., and Fleming, L. (2015). Disambiguation and Co-authorship Networks of the U.S. Patent Inventor Database (1975 - 2010).

Lecraw, D. J. (1984). Diversification Strategy and Performance. *The Journal of Industrial Economics*, pages 179–198.

Lemelin, A. (1982). Relatedness in the Patterns of Interindustry Diversification. *The Review of Economics and Statistics*, 64(4):646–657.

MacDonald, J. M. (1985). R & D and the Directions of Diversification. *The Review of Economics and Statistics*, pages 583–590.

MacDonald, J. M. (1994). Does Import Competition Force Efficient Production? *The Review of Economics and Statistics*, pages 721–727.

Melitz, M. J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6):1695–1725.

Melitz, M. J. and Redding, S. J. (2013). Firm Heterogeneity and Aggregate Welfare. *Working Paper*.

Montgomery, C. A. (1985). Product-Market Diversification and Market Power. *Academy of Management Journal*, 28(4):789–798.

Montgomery, C. A. (1994). Corporate Diversification. *The Journal of Economic Perspectives*, 8(3):163–178.

Montgomery, C. A. and Hariharan, S. (1991). Diversified Expansion by Large Established Firms. *Journal of Economic Behavior & Organization*, 15(1):71–89.

Montgomery, C. A. and Wernerfelt, B. (1992). Risk Reduction and Umbrella Branding. *Journal of Business*, pages 31–50.

Mueller, D. C. (1969). A Theory of Conglomerate Mergers. *The Quarterly Journal of Economics*, 83(4):643–659.

Neffke, F. and Henning, M. (2013). Skill Relatedness and Firm Diversification. *Strategic Management Journal*, 34(3):297–316.

Palepu, K. (1985). Diversification Strategy, Profit Performance and the Entropy Measure. *Strategic Management Journal*, 6(3):239–255.

Pavcnik, N. (2002). Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants. *The Review of Economic Studies*, 69(1):245–276.

Penrose, E. T. (2009). *The Theory of the Growth of the Firm*. Oxford University Press.

Pierce, J. R. and Schott, P. K. (2016). The Surprisingly Swift Decline of US Manufacturing Employment. *The American Economic Review*, 106(7):1632–1662.

Rhoades, S. A. (1974). A Further Evaluation of the Effect of Diversification on Industry Profit Performance. *The Review of Economics and Statistics*, pages 557–559.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5, Part 2):S71–S102.

Rumelt, R. P. (1982). Diversification Strategy and Profitability. *Strategic Management Journal*, 3(4):359–369.

Schott, P. K. (2008). The Relative Sophistication of Chinese Exports. *Economic Policy*, 23(53):6–49.

Schumpeter, J. A. (1942). *Socialism, Capitalism and Democracy.* Harper and Brothers.

Shleifer, A. and Vishny, R. W. (1989). Management Entrenchment: The Case of Manager-Specific Investments. *Journal of Financial Economics*, 25(1):123–139.

Silverman, B. S. (1999). Technological Resources and the Direction of Corporate Diversification: Toward an Integration of the Resource-Based View and Transaction Cost Economics. *Management Science*, 45(8):1109–1124.

Squintani, F. and Hopenhayn, H. A. (2016). On the Direction of R&D. In *2016 Meeting Papers*, number 1357. Society for Economic Dynamics.

Teece, D. J. (1980). Economies of Scope and the Scope of the Enterprise. *Journal of Economic Behavior & Organization*, 1(3):223–247.

Trefler, D. (2004). The Long and Short of the Canada-US Free Trade Agreement. *The American Economic Review*, 94(4):870–895.

Utton, M. A. (1977). Large Firm Diversification in British Manufacturing Industry. *The Economic Journal*, 87(345):96–113.

Varadarajan, R. and Ramanujam, V. (1987). Diversification and Performance: A Reexamination Using a New Two-Dimensional Conceptualization of Diversity in Firms. *Academy of Management Journal*, 30(2):380–393.

A Additional Tables from the Main Analysis

Table A.1: Top 10 Affected 2-Digit SIC Industries

Rank	2-Digit SIC Industry
1	31: Leather and Leather Products
2	39: Misc. Manufacturing Industries
3	23: Apparel and Other Textile Products
4	36: Electronic and Other Electronic Equipment
5	25: Furniture and Fixtures
6	35: Industrial Machinery and Equipment
7	32: Stone, Clay, and Glass Products
8	30: Rubber and Misc. Plastic Products
9	38: Measuring, Analyzing, and Controlling Instruments;
	38: Photographic, Medical
10	34: Fabricated Metal Products

Notes: Top 10 2-digit SIC industries that are most affected by Chinese imports.

Table A.2: Import Penetration and Firm Innovation: Balanced Panel (IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0325				
	(0.0228)				
L2.IPW		0.0335			
		(0.0237)			
L3.IPW			0.0402*		
			(0.0235)		
L4.IPW				0.0458**	
				(0.0196)	
L5.IPW					0.0387*
					(0.0201)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	11.14	27.63	39.47	29.21	21.60
Observations	10679	9853	9028	8203	7382

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Only firms that existed throughout the entire period are included, hence the panel is balanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Import Penetration and Firm R&D Expenditure (1991 Subsample: Large vs. Small)

	IV1		IV2		IV3		IV4		IV5	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
L.IPW	-0.0516**	-0.0051								
	(0.0203)	(0.0207)								
L2.IPW			-0.0561**	-0.0086						
			(0.0237)	(0.0215)						
L3.IPW					-0.0559**	-0.0095				
					(0.0240)	(0.0215)				
L4.IPW							-0.0560*	-0.0105		
							(0.0299)	(0.0200)		
L5.IPW									-0.0684*	-0.0173
									(0.0362)	(0.0219)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	6.61	12.13	11.96	27.44	19.69	37.35	15.87	29.51	14.50	19.04
R-squared	0.8797	0.9525	0.8872	0.9554	0.8924	0.9583	0.9051	0.9615	0.9162	0.9653
Observations	3228	6444	2893	5751	2552	5107	2229	4488	1919	3894

Notes: This table investigates heterogeneous R&D expenditures (in logarithm) between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. A firm is large if its employment is above the industry median and small otherwise. Large and small firms are analyzed in separate regressions. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is each firm's annual R&D expenditures (in logarithm). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Import Penetration and New Inventors' Patenting Intensity

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0156				
	(0.0155)				
L2.IPW		0.0200			
		(0.0150)			
L3.IPW			0.0303**		
			(0.0131)		
L4.IPW				0.0356***	
				(0.0135)	
L5.IPW					0.0342**
					(0.0154)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	14.12	32.82	44.60	39.94	35.18
Observations	582309	550675	515017	476142	433861

Notes: This table examines whether a new inventor working at a large firm would increase her patenting intensity when her employer is hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. All new inventors that came to large public manufacturing firms between 1991 and 2004 are included, starting from the time they joined the firms. The dependent variable is the annual number of patents produced by each new inventor at large firms. To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Tables from Robustness Checks

B.1 Alternative Dataset with Longer Time Span: 1991-2007

B.1.1 Industry-Level Results: 1991-2007

Table B.1.1: Import Penetration and Industry-Level Innovation (IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0322***				
	(0.0111)				
L2.IPW		0.0318***			
		(0.0100)			
L3.IPW			0.0353***		
			(0.0108)		
L4.IPW				0.0397***	
				(0.0131)	
L5.IPW					0.0404***
					(0.0152)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
IndFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	21.65	21.81	22.51	20.31	13.04
Observations	5158	4825	4482	4138	3795

Notes: This table shows industry-level response to rising Chinese imports from 1991 to 2007. L*.IPW represents *-years lag of import penetration. Industry is defined at 4-digit SIC level. The dependent variable is each industry's annual number of patents (dated by application year). Both year fixed effects and industry fixed effects are included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For example, the coefficients in the three-years' lag specification imply that a one-standard-deviation (11.68) increase of import competition would increase industry innovation by 51%; alternatively, it represents about 50 additional patents. The following firm-level results are also similar to my NBER baseline results, and to save space I only show regression tables without magnitude interpretation.

B.1.2 Firm-Level Results: Unbalanced Panel 1991-2007

Table B.1.2: Import Penetration and Firm Innovation: IV Poisson (1991-2007)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0098**				
	(0.0039)				
L2.IPW		0.0117***			
		(0.0042)			
L3.IPW			0.0149***		
			(0.0050)		
L4.IPW				0.0212***	
				(0.0062)	
L5.IPW					0.0254***
					(0.0080)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-Stats	56.53	46.9	42.42	33.82	22.83
Observations	30988	29286	27389	25388	23288

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2007. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). Both year fixed effects and firm fixed effects are included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.1.3: Import Penetration and Firm Innovation: IV Poisson (1991-2007)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0154**				
	(0.0063)				
L2.IPW		0.0184***			
		(0.0070)			
L3.IPW			0.0214***		
			(0.0079)		
L4.IPW				0.0209**	
				(0.0103)	
L5.IPW					0.0146
					(0.0115)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-Stats	30.19	21.98	21.75	48.81	64.01
Observations	30770	29086	27206	20519	17637

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2007. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.1.3 Firm-Level Results: Balanced Panel 1991-2007

Table B.1.4: Import Penetration and Firm Innovation: IV Poisson (1991-2007)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0095**				
	(0.0042)				
L2.IPW		0.0111***			
		(0.0043)			
L3.IPW			0.0141***		
			(0.0049)		
L4.IPW				0.0186***	
				(0.0060)	
L5.IPW					0.0206***
					(0.0070)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-Stats	61.4	53.24	53.29	54.86	58.6
Observations	11808	11070	10332	9594	8856

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2007. L*.IPW represents *-years lag of import penetration. Only firms that existed throughout the entire period are included, hence the panel is balanced. The dependent variable is each firm's annual number of patents (dated by application year). Both year fixed effects and firm fixed effects are included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.1.5: Import Penetration and Firm Innovation: IV Poisson (1991-2007)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0238***				
	(0.0071)				
L2.IPW		0.0262***			
		(0.0076)			
L3.IPW			0.0288***		
			(0.0085)		
L4.IPW				0.0298***	
				(0.0089)	
L5.IPW					0.0219**
					(0.0086)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-Stats	46.03	41.09	39.25	47.2	70.54
Observations	11360	10650	9940	9230	8520

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2007. L*.IPW represents *-years lag of import penetration. Only firms that existed throughout the entire period are included, hence the panel is balanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2 Alternative Instrument for Trade Shock

Table B.2.1: PNTR and U.S. Firm Innovation: Poisson

	(1)	(2)	(3)	(4)
	1991-2004	1991-2004	1991-2007	1991-2007
Post*NTR Gap	1.3168**	0.6936*	1.3250***	0.9810***
	(0.5212)	(0.3953)	(0.4144)	(0.3174)
FirmFixedEffects	Yes	Yes	Yes	Yes
YearFixedEffects	Yes	No	Yes	No
YearbyIndFixedEffects	No	Yes	No	Yes
Observations	27651	27119	32542	31870

Notes: This table uses the United States' granting of Permanent Normal Trade Relations (PNTR) status to China in 2000 as an alternative instrument for trade shock. The "NTR gap" is defined as the difference between the non-NTR rates and the NTR tariff rates, and "Post" is a dummy variable equal to one after the year 2000. All regressions exploit cross-sectional variation in the NTR gap to test whether firms in industries with higher NTR gaps (first difference) innovated more after the change in policy relative to innovation pre-PNTR era (second difference). Hence, the outcome variable is each firm's annual number of patent counts. The first two columns employ the NBER dataset that covers all Compustat patenting firms from 1991 to 2004. Columns (3) and (4) use data from Kogan et al. (2017), which includes firms in the CRSP database from 1991 to 2007. All columns include firm fixed effects. The odd number columns include year fixed effects and even number columns include year by 3-digit SIC industry fixed effects. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.3 Placebo Tests

Table B.3.1: Import Penetration and Firm Innovation (Placebo Tests)

	IVPois	IVNB
IPW	0.0025	-0.0044
	(0.0109)	(0.0036)
YearbyIndFixedEffects	Yes	Yes
FirmFixedEffects	Yes	Yes
First Stage F-stats	26.92	26.92
Observations	26538	26538

Notes: This table shows placebo tests that examine any pre-trends that might generate a spurious positive relationship between import penetration and firm innovation. In particular, IPW represents import penetration from 1991 to 2007. The dependent variable is each firm's annual number of patents (dated by application year) from 1975 to 1991. Hence, both specifications regress firms' patents from 1975 to 1991 on future import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson and IV Negative Binomial regressions are both estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.4 Sales-Weighted Import Penetration

Table B.4.1: Import Penetration (Sales-Weighted) and Firm Innovation (IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0478***				
	(0.0127)				
L2.IPW		0.0478***			
		(0.0172)			
L3.IPW			0.0504**		
			(0.0201)		
L4.IPW				0.0428*	
				(0.0258)	
L5.IPW					0.0282
					(0.0328)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	15.52	36.02	49.79	38.70	33.47
Observations	16873	15095	13355	11681	10083

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Here, each firm faces unique import penetration, which is the sales-weighted average of industry-level import penetration across all 4-digit SIC markets it operates in. To rule out subsequent trade-related confounders, the weights are based on firm sales in 1991, the start of the rising Chinese imports era. As a result, only firms that were already public in 1991 are included. Firm exit is allowed and hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.5 Anticipation Effects

Table B.5.1: Future Import Penetration and Firm Innovation (Anticipation Effects, IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
F.IPW	0.0206				
	(0.0137)				
F2.IPW		0.0161			
		(0.0129)			
F3.IPW			0.0109		
			(0.0100)		
F4.IPW				0.0084	
				(0.0089)	
F5.IPW					0.0057
					(0.0079)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	9.58	12.74	18.81	23.17	28.00
Observations	27418	27418	27418	27418	27418

Notes: This table examines whether firms would increase their innovation in anticipation of rising Chinese imports. F*.IPW represents *-years lead of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year) from 1991 to 2004. To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.6 Offshoring

Table B.6.1: Import Penetration and Firm Sales (in Logarithm) across 4-digit SIC Codes

	IV1	IV2	IV3	IV4	IV5
L.IPW	-0.0105				
	(0.0073)				
L2.IPW		-0.0132			
		(0.0084)			
L3.IPW			-0.0175*		
			(0.0098)		
L4.IPW				-0.0232**	
				(0.0113)	
L5.IPW					-0.0312**
					(0.0142)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	39.60	69.93	62.84	50.02	36.05
R-squared	0.8789	0.8793	0.8798	0.8810	0.8824
Observations	33587	31112	28542	25913	23117

Notes: This table investigates how sales across different 4-digit SIC markets **within the same firm** react to Chinese import penetration from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual sales (in logarithm) in a 4-digit SIC market it operates in. To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Aggregate Impact on Both Public and Private Firms

Table C.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75	P95
NPAT	5852	152.154	258.555	0	3108	21	66	164	619
IPW	5852	3.213	5.036	0	76.342	.635	1.564	3.743	11.586
IPWOTH	5852	1.728	2.433	0	38.548	.428	.985	2.047	5.916

Notes: First row reports summary statistics of each technology class' annual patent counts; second and third rows show summary statistics of pooled Chinese import penetration (constructed at the technology class level) to the United States and other eight high-income economies respectively.

Table C.2: Import Penetration and U.S. Corporate Innovation by Technology Class (IV Poisson)

	IVPois1	IVPois2	IVPois3	IVPois4	IVPois5
L.IPW	0.0360***				
	(0.0065)				
L2.IPW		0.0358***			
		(0.0067)			
L3.IPW			0.0323***		
			(0.0069)		
L4.IPW				0.0279***	
				(0.0062)	
L5.IPW					0.0244***
					(0.0059)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
TechClassFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	231.01	179.20	181.82	174.09	158.82
Observations	5838	5838	5838	5838	5838

Notes: This table shows changes in the number of annual patent counts at technology class level in response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. The dependent variable is each technology class' annual number of patents (dated by application year). Both year fixed effects and technology class fixed effects are included. IV Poisson regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at technology class level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: Import Penetration and U.S. Corporate Innovation by Technology Class (IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
L.IPW	0.0143***				
	(0.0039)				
L2.IPW		0.0156***			
		(0.0038)			
L3.IPW			0.0144***		
			(0.0038)		
L4.IPW				0.0142***	
				(0.0037)	
L5.IPW					0.0135***
					(0.0036)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
TechClassFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	231.01	179.20	181.82	174.09	158.82
Observations	5838	5838	5838	5838	5838

Notes: This table shows changes in the number of annual patent counts at technology class level in response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. The dependent variable is each technology class' annual number of patents (dated by application year). Both year fixed effects and technology class fixed effects are included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at technology class level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D Replication of Autor et al. (2016)

In this section, I use the dataset from Kogan et al. (2017) to replicate Autor et al. (2016). I choose this alternative dataset because it contains firm innovation in 2007. In Table D.1, I present replication results of the first three columns from row a) to row e) in Table 2 in Autor et al. (2016). I didn't pursue a complete replication because other columns and rows require additional data collection and cleaning (i.e., a significant amount of time and effort). For the purpose of my argument, I believe the following table is sufficient.

Table D.1: Effect of Chinese Import Competition on Firm-Level Patenting, 1991-2007. Dependent Variable: Change in Patents by U.S.-Based Inventors (% pts), Relative to Mid-Period Number of Patents

	1991-1999	1999-2007	1991-2007
	A. Models without Controls		
a. OLS, no controls	4.3852**	-0.1943	0.1680
	(1.9939)	(0.3011)	(0.2802)
b. 2SLS, no controls	3.4954*	0.1132	0.3661
	(1.9327)	(0.4381)	(0.4657)
	B. Models with Controls		
c. OLS, 2 mfg sector dummies	-0.5851	-0.1128	-0.8914*
(computers, chemicals)	(1.6535)	(0.4253)	(0.4875)
d. 2SLS, 2 mfg sector dummies	-0.2281	0.3437	-0.7275
(computers, chemicals)	(1.8148)	(0.7130)	(0.6619)
e. 2SLS, 11 mfg sector dummies	-0.3166	-0.1818	-0.9263
	(1.8462)	(0.6052)	(0.6704)
Observations	923	908	1831

Notes: This table replicates the first three columns from row a) to row e) in Table 2 in Autor et al. (2016). 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. Note that firm entry and exit into patenting is allowed. For example, if a firm only has patents in 1991 and 1999, but not in 2007, it is missing in the subsequent 2007-1999 period. 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. All models are weighted by the number of patents in a firm, averaged over patents at the start and end of a period. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Due to sample differences, the majority of my estimates are insignificant. Yet, the general pattern is consistent with that of Autor et al. (2016).

E Negative Binomial Regression Results

Table E.1: Import Penetration and Industry Innovation (IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
L.IPW	0.0335***				
	(0.0085)				
L2.IPW		0.0331***			
		(0.0091)			
L3.IPW			0.0454***		
			(0.0116)		
L4.IPW				0.0461***	
				(0.0123)	
L5.IPW					0.0519***
					(0.0137)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
IndustryFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	15.82	13.60	12.77	11.45	10.04
Observations	2467	2273	2078	1885	1691

Notes: This table shows industry-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Industry is defined at 4-digit SIC level. The dependent variable is each industry's annual number of patents (dated by application year). Both year fixed effects and industry fixed effects are included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.2: Import Penetration and Firm Innovation: Unbalanced Panel (IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
L.IPW	0.0261***				
	(0.0073)				
L2.IPW		0.0262***			
		(0.0101)			
L3.IPW			0.0362***		
			(0.0105)		
L4.IPW				0.0298***	
				(0.0096)	
L5.IPW					0.0186*
					(0.0095)
YearFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	16.67	14.99	12.76	10.73	8.25
Observations	25726	23771	21725	19637	17416

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). Both year fixed effects and firm fixed effects are included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.3: Import Penetration and Firm Innovation: Unbalanced Panel (IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
L.IPW	0.0142				
	(0.0177)				
L2.IPW		0.0197			
		(0.0166)			
L3.IPW			0.0291*		
			(0.0168)		
L4.IPW				0.0230	
				(0.0170)	
L5.IPW					0.0170
					(0.0176)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	12.58	30.45	40.71	32.21	23.23
Observations	25545	23605	21571	19495	16389

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.4: Import Penetration and Firm Innovation: Balanced Panel (IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
L.IPW	0.0385				
	(0.0293)				
L2.IPW		0.0531*			
		(0.0284)			
L3.IPW			0.0689**		
			(0.0279)		
L4.IPW				0.0693**	
				(0.0289)	
L5.IPW					0.0565*
					(0.0292)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	11.14	27.63	39.47	29.21	21.60
Observations	10679	9853	9028	8203	7382

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Only firms that existed throughout the entire period are included, hence the panel is balanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.5: Import Penetration (Sales-Weighted) and Firm Innovation (IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
L.IPW	0.0389***				
	(0.0120)				
L2.IPW		0.0400***			
		(0.0151)			
L3.IPW			0.0537***		
			(0.0187)		
L4.IPW				0.0523**	
				(0.0210)	
L5.IPW					0.0364
					(0.0282)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	15.52	36.02	49.79	38.70	33.47
Observations	16873	15095	13355	11681	10083

Notes: This table shows firm-level response to rising Chinese imports from 1991 to 2004. L*.IPW represents *-years lag of import penetration. Here, each firm faces unique import penetration, which is the sales-weighted average of industry-level import penetration across all 4-digit SIC markets it operates in. To rule out subsequent trade-related confounders, the weights are based on firm sales in 1991, the start of the rising Chinese imports era. As a result, only firms that were already public in 1991 are included. Firm exit is allowed and hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.6: Future Import Penetration and Firm Innovation (Anticipation Effect, IV Negative Binomial)

	IVNB1	IVNB2	IVNB3	IVNB4	IVNB5
F.IPW	0.0150				
	(0.0108)				
F2.IPW		0.0117			
		(0.0077)			
F3.IPW			0.0067		
			(0.0066)		
F4.IPW				0.0019	
				(0.0058)	
F5.IPW					0.0009
					(0.0053)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	9.58	12.74	18.81	23.17	28.00
Observations	27418	27418	27418	27418	27418

Notes: This table examines whether firms would increase their innovation in anticipation of rising Chinese imports. F*.IPW represents *-years lead of import penetration. Firm entry and exit are allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year) from 1991 to 2004. To control for differential industrial trends over time, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. IV Negative Binomial regressions are estimated using control function approach and first stage F statistics are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.7: Import Penetration and Firm Innovation (1991 Subsample: Large vs. Small)

	IVNB1		IVNB2		IVNB3		IVNB4		IVNB5	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
L.IPW	-0.0252	0.0440								
	(0.0235)	(0.0278)								
L2.IPW			-0.0156	0.0554**						
			(0.0267)	(0.0258)						
L3.IPW					-0.0071	0.0757**				
					(0.0217)	(0.0305)				
L4.IPW							-0.0257	0.0824**		
							(0.0315)	(0.0325)		
L5.IPW									-0.0669	0.0864**
									(0.0643)	(0.0342)
YearbyIndFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixedEffects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-stats	7.66	13.56	15.30	29.72	25.19	38.46	19.24	30.24	17.08	19.84
Observations	4216	8078	3763	7227	3313	6416	2888	5635	2487	4887

Notes: This table investigates the heterogeneous innovation response between large and small firms when hit hard by Chinese imports. L*.IPW represents *-years lag of import penetration. To effectively distinguish small from young firms (which have very different growth dynamics), and to rule out subsequent trade-related confounders, I focus on firms that had been public for at least three years in 1991. A firm is large if its employment was above the industry median in 1991 and small otherwise. Large and small firms are analyzed in separate regressions. Firm exit is allowed, hence the panel is unbalanced. The dependent variable is each firm's annual number of patents (dated by application year). To control for differential industrial trends overtime, year by 3-digit SIC industry fixed effects are included. Firm fixed effects are also included. First stage F statistics from 2SLS are displayed. Standard errors (in parentheses) are clustered at 4-digit SIC level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$