# Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China? *

Johan Hombert[†] Adrien Matray[‡]

July 2017

**Abstract**

We study whether R&D-intensive rms are more resilient to trade shocks. We correct for the endogeneity of R&D using tax-induced changes to R&D cost. While rising imports from China lead to slower sales growth and lower pro tability, these e ects are signi cantly smaller for rms with a larger stock of R&D (by about half when moving from the bottom quartile to the top quartile of R&D). We provide evidence that this e ect is explained R&D allowing rms to increase product differentiation. As a result, while rms in import-competing industries cut capital expenditures and employment, R&D-intensive rms downsize considerably less.

*We thank Nick Bloom, Gerard Hoberg, Rich Mathews, Stephen Redding, Amit Seru, Stefan Zeume, Michael Roberts as well as seminar participants at INSEAD, Copenhagen Business School, Stanford University, CSEF{University of Naples, Imperial College, Montreal University, Erasmus University, Ghent University, Harvard Business School and conference participants at the Labex Ecodec Workshop at HEC Paris, the London Business School 2015 Summer Finance Symposium, the 2015 Western Finance Association meeting, the 2015 Workshop on Entrepreneurial Finance and Innovation Around the World, the 2015 Workshop on the Economics of Corporate Ownership, the European Summer Symposium in Financial Markets (Gerzensee) 2015, the 2015 Econometric Society World Meeting, the 2016 NBER Productivity, Innovation and Entrepreneurship. Hombert acknowledges nancial support from the Investissements d'Avenir Labex (ANR-11-IDEX-0003/Labex Ecodec/ANR-11-LABX-0047).

[†]HEC Paris and CEPR

[‡]Princeton University

# 1 Introduction

The rise of China, triggered by its transition to a market-oriented economy and rapid integration to world trade, has been identified as a major source of disruption for high-income economies, re-opening the long-standing debate regarding the effect of trade with low-wage countries on firms and workers in the US and in Europe and regarding which firms are better able to absorb these stocks. In this context, innovation is often viewed as an effective shield against low-cost foreign competition by allowing firms to climb the quality ladder and differentiate their products from low-wage countries' exports. Because wage differences are so large, so the argument goes, competing on costs is bound to fail. Only firms that have invested in R&D and upgraded product quality are able to compete successfully against low-cost imports (e.g., Leamer (2007)). This view has largely influenced public policies and provided further justification for R&D subsidies.[1]

Yet, there is surprisingly little evidence about whether firms that have invested in R&D are indeed shielded from trade shocks. In this paper, we provide direct evidence that the answer is positive and that the magnitude is economically large. We show that firm performance (sales growth and profitability) is less adversely affected by an increase in import competition when the firm has ex ante invested more in R&D. Moreover, we provide evidence that the effect operates through product differentiation.

The innovation literature has analyzed a related, but different question, namely how firms endogenously adjust their R&D investment ex-post, that is, after an increase in import competition. This approach can be interpreted through the lens of a revealed preference argument—firms' choice of innovation after trade shocks "revealing" their expectations on whether R&D is an effective shield against import competition. The recent evidence using this approach is mixed. Bloom, Draca and Van Reenen (2016) find a positive relation between import competition and innovation in Europe, whereas Autor et al. (2016) find a negative relation in the US.

The revealed preference argument has, however, two important limitations. First, the sensitivity of R&D investment to import competition may be informative about the sign

[1] In 2013, 27 of the 34 OECD countries and a number of non-OECD economies provide scal incentives for R&D (OECD (2014)). EU's Lisbon Strategy envisioned to make Europe *"the most competitive and dynamic knowledge-based economy in the world (...) to increase its productivity and competitiveness in the face of ever fiercer global competition"* (European Commission (2010)).

of the relationship between returns to R&D and import competition, but not about its magnitude, because the elasticity also depends on the R&D cost structure. Second, even the estimated sign of this relationship may be wrong even if trade shocks are instrumented, because the decision to innovate in reaction to a shock depends on other factors over and beyond the mere returns to R&D, such as credit constraints, managers' expectations regarding both the effect of the shock and the gain from innovating, and agency issues that may induce manager short-termism.[2] Because import penetration shocks affect cash flows, studying firms' endogenous R&D response to these shocks may yield the wrong answer to the question of whether R&D mitigates the negative effect of trade shocks. For instance, it may be that R&D is an effective shield against import competition but firms sub-optimally cut R&D expenditures after trade shocks, because of financing or agency frictions. This can explain why the evidence on the effect of import competition on ex-post R&D choices is mixed.

In this paper, we adopt a direct approach to estimate the effect of R&D on firms' resilience to import competition. We test whether firm performance measured by sales growth or profitability is less adversely affected by an increase in import competition when the firm has invested more in R&D before the increase in import penetration. We implement this test in the context of the China's export boom and its effect on US manufacturing firms. It allows us to estimate the effect of R&D as an ex ante moderating variable on the disruptive effects of trade with China.

To inform the identification strategy, we first outline a model of the interplay between R&D and product market competition. The first insight of the model is to make rigorous the two limitations of the revealed preference argument discussed above and to show that regressing R&D on import penetration does not identify the effect of R&D on firm resilience to import competition (even if import penetration is correctly instrumented). The second insight of the model is that regressing firm performance on import penetration interacted with R&D yields an unbiased estimate of this effect only if both import penetration and R&D are instrumented.

[2] These frictions are particularly relevant for R&D expenditures because they are typically cut in priority upon negative cash ow shocks. For instance, Aghion et al. (2012) show that credit constraints force rms to cut R&D more than other expenditures in downturns, thereby lowering productivity growth. Bhojraj et al. (2009) show that R&D is a key strategic variable used by managers to manipulate short-term earnings to the detriment of long-term pro tability.

First, China's import penetration in the US may be endogenous to the performance of US firms as lower productivity in the US may lead to higher imports to the US. To isolate the component of China's rising exports that stems from internal supply shocks in China, we borrow a classic identification strategy from international trade economics, which instruments China's import penetration in the US at the industry level using China's import penetration in other high-income countries (e.g., Autor et al. (2013), Hummels et al. (2014)). There is tremendous import growth from China in some industries (e.g., textile, electronic, furniture, industrial equipment) but not in others (e.g., tobacco, printing, food, petroleum). This cross-industry heterogeneity is similar in the US and in the other high-income economies, which suggests that it is driven by supply shocks in China.

Second, the accumulation of firms' stock of R&D capital is potentially endogenous to their productivity, quality of management, and demand for their products. We thus instrument for R&D at the firm level using tax-induced changes to the user cost of R&D capital. After the introduction of the US federal R&D tax credit in 1981, US states started to introduce R&D tax credits as well. In 2006, 32 states were offering tax credits, in some cases considerably more generous than the federal credit (Wilson (2009)). The staggered implementation of these R&D policies generates variations across states and over time of the price of R&D, which in turn generates exogenous variations in firm R&D stock.

With these two instruments in hand, we estimate how firms are affected by (exogenous) import competition depending on their (exogenous) R&D stock before the competition shock. Our preferred specification includes firm fixed effects to absorb time-invariant firm characteristics and industry-by-year fixed effects to account for industry specific productivity shocks and changes in consumer demand.

We first show that China's import penetration has sizable adverse effects on the unconditional (i.e., independently from the R&D level) performance of US manufacturing firms. On average across US manufacturing firms, a one standard deviation increase in import penetration reduces annual sales growth by 1.8 percentage points. This negative shock on sales triggered by increased import competition leads in turn to lower profitability. On average, a one standard deviation in import penetration reduces ROA by

1.1 percentage points. These preliminary results are consistent with the literature showing that US manufacturing industries exposed to low-wage-country imports experience slower growth (Bernard, Jensen and Schott (2006)). These results validate the use of the Chinese export boom as a competition shock negatively impacting US industries.

Second, we study how the effect of import competition on firm performance varies with firms' stock of R&D capital. We show that firms that have accumulated a higher stock of R&D are significantly less affected by import competition. Going from the twenty-fifth percentile to the seventy-fifth percentile of the distribution of R&D stock reduces the drop in annual sales growth by 0.9 percentage points (i.e., half the average effect) and it reduces the drop in ROA by 1 percentage point (i.e., about the same magnitude as the average effect).

Third, we open the black box of the mechanism through which a higher stock of R&D mitigates trade shocks. R&D can lead to higher product market performance for two reasons: vertical differentiation (Sutton (1991)) or higher productivity (Grossman and Helpman (1991) and Aghion and Howitt (1992)). To shed light on the mechanism, we work out a model of competition with vertical differentiation that allows us to contrast the effect of R&D on firm performance through higher vertical differentiation vs. lower cost. The main insight is that the marginal benefit of higher vertical differentiation increases when low-cost competition increases while the marginal benefit of higher productivity decreases when low-cost competition increases. Accordingly, we hypothesize that the mechanism by which the stock of R&D makes firms more resilient to trade shocks works through product differentiation. More precisely, the model suggests two potential channels related to product differentiation.

The first channel is that the *bene ts* of differentiation increases when import competition increases. This channel hinges on two ingredients: (a) firms that have done more R&D in the past have more differentiated products independently of the intensity of import competition; and (b) the marginal benefit of product differentiation increases when import competition increases. Taken together, (a) and (b) imply that the marginal benefit of a higher stock of R&D increases when import competition increases. Using Hoberg and Phillips' (2015) text-based measure of product similarity vis-a-vis peer firms to proxy for differentiation, we provide evidence for (a) and (b).

The second channel is that the *incentives* to differentiate increase when import competition increases. If past R&D makes firms more responsive and improves their ability to differentiate once competition materializes, then firms that have done more R&D in the past should increase differentiation in response to a competition shock, thus mitigating the effect of the shock. We find support for this channel by showing that firms with a larger stock of R&D capital increases product differentiation when import penetration from China increases.

An ancillary prediction of these mechanisms operating through product differentiation is that the effect of R&D on firms' resilience to trade shocks should be stronger in industries in which product differentiation is more prevalent. To test this prediction, we proxy for the extent of differentiation at the industry level using the industry average of firm-level differentiation and find that the effect of R&D is stronger in industries in which differentiation is more important. This result lends further support to the Sutton (1991) view that vertical differentiation is instrumental to absorb and escape competition shocks. Taken together, these results are consistent with the notion that R&D makes firms more resilient to trade shocks because it allows them to climb the quality ladder and differentiate (ex ante and ex post) their products.

Finally, after having shown that R&D has an economically meaningful effect on the resilience of firm performance to trade shocks, we explore the real effects on capital expenditures and employment. We find that, on average across firms, a one standard deviation increase in China's import penetration reduces growth in fixed capital by 1.6 percentage points. However, firms with a larger stock of R&D are significantly less affected. Moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D capital offsets the reduction in capital expenditures by 1.4 percentage points of fixed assets (i.e., almost the same as the average effect). We find a similar pattern regarding employment. Firms at the twenty-fifth percentile of the R&D distribution experience a significant 1.3 percentage points reduction in annual employment growth in response to a one standard deviation increase in import competition. In contrast, firms at the seventy-fifth percentile of the R&D distribution experience only a modest and statistically insignificant reduction in employment growth.

Our paper adds to the literature (surveyed by Bernard et al. (2012)) on the impact of import competition on firms in high-income economies. Most papers in this literature analyze the unconditional effect of trade shocks on various dimensions of firm performance such as output and survival (Bernard, Jensen and Schott (2006)), cost of debt (Valta (2012)), leverage (Xu (2012)), capital expenditure (Fresard and Valta (2016)), employment and outsourcing (Pierce and Schott (2016)). There is, however, little evidence regarding which firms are better able to cope with trade shocks. A notable exception is Bernard, Jensen and Schott (2006) who show that capital-intensive plants are more likely to survive and grow in the wake of import competition.[3] We complement this literature by showing that R&D-intensive firms cope better with trade shocks. Furthermore, our results highlight a complementarity between R&D capital and fixed capital in the face of import competition. In import-exposed industries, firms with an exogenously larger stock of R&D find it optimal to increase their stock of fixed capital as well.

Second, we contribute to the literature on the interaction between innovation and product market competition. In early contributions, Schumpeter (1943) argues that competition erodes the private returns to innovation, whereas Arrow (1962) views innovation as allowing firms to escape competition. The subsequent empirical literature (discussed above) has mostly analyzed how firms' endogenous decision to invest in innovation depends on the intensity of competition. We contribute to this literature by providing direct evidence on how the return to R&D investment depends on import competition, rather than inferring it indirectly from a revealed preference argument that can be biased by financing or agency frictions.

The rest of the paper is organized as follows. Section 2 outlines the theoretical framework. Section 3 describes the empirical strategy and the data. Section 4 presents the results on resilience to trade shocks, Section 5 the results on product differentiation, and Section 6 the results on the real effects on capital expenditures and employment. Section 7 provides robustness checks. Section 8 concludes. Additional materials can be found in the Internet Appendix.

[3] Using aggregate data, Khandelwal (2010) also shows that the negative e ect of low-income country imports is stronger in industries characterized by short-quality ladder (i.e., products are of similar quality).

# 2 Theoretical Framework

This section outlines a stylized model of the interplay between innovation and import competition. We use this framework to guide the empirical identification of the effect of R&D on firms' resilience to import competition.

## 2.1 Setup

There is a large number of risk-neutral firms. Each firm chooses a level of innovation effort $R \geq 0$ (where $R$ stands for $R\&D$) at cost $c(R) = R + \ R + \frac{\rho}{2}R^2$.   varies across firms and reflects the idea that some firms may have a lower opportunity cost of R&D because they are better managed, are less financially constrained, or benefit from innovation subsidies, and $\ > 0$ parameterizes the extent of decreasing returns to R&D investment.

A firm exerting higher innovation effort has a greater probability to innovate. Denoting by $I \in \{0; 1\}$ the dummy variable equal to one if the firm's innovation effort is successful, we assume $P[I \ \mathrm{R}$

Firm performance (1) can be rewritten as:

$$= a_0 + (a_1 - a_0) I + \left[ - b_0 + (b_0 - b_1) I \right] T: \tag{2}$$

The term in brackets in equation (2) measures the sensitivity of performance to import competition, which depends on the outcome of the firm's innovation effort. The sign of $b_0 - b_1$ determines whether this sensitivity is higher for innovators or non-innovators. When $b_0$ is high, import competition weighs heavily on the performance of non-innovators. This effect, identified by Arrow (1962) and called by Aghion et al. (2005) the escape competition effect, implies that innovative firms are better able to escape competition than non-innovative firms and are thus more resilient to competition shocks. Conversely, when $b_1$ is high, import competition erodes strongly the competitive edge of innovative firms as in Schumpeter (1943). In this case, innovative firms are relatively more sensitive to competition shocks.

We denote $= a_0$, $= -b_0$, $= a_1 - a_0$, and $= b_0 - b_1$, and rewrite equation (2) as follows:

$$= \quad + \quad T + \quad I + \quad T \, I: \tag{3}$$

The goal of this paper is to estimate , i.e., how the impact of import competition on a firm's performance depends on its level of innovation. We want to determine whether is positive (the Arrow effect dominates) or negative (the Schumpeterian effect dominates). More importantly, we want to assess the economic magnitude of the net effect, i.e., by how much R&D can (or cannot) mitigate the adverse effect of import competition.

In Internet Appendix A, we work out a simple model of product market competition with vertical differentiation to identify situations in which may be positive or negative. The main insight is that depends on the relation between innovation and product differentiation. When innovation enables firms to increase the quality and differentiation of their products, it allows firms to preserve market shares and the Arrow effect dominates ( $> 0$). On the other hand, when innovation increases productivity but without enhancing product differentiation, its positive effect on performance is eroded by competition and the Schumpeterian effect dominates ( $< 0$). We study empirically the role of product differentiation in Section 5.

## 2.2 Identification

### 2.2.1 Previous literature

Other authors have tackled these issues by studying firms' endogenous choice of innovation in response to an exogenous competition shock (e.g., Scherer and Huh (1992), Aghion et al. (2005), Bloom et al. (2016), Autor et al. (2016) among many others).[7]

This approach has two main limitations to identify  . To see why, we can solve for firms' choice of innovation effort:

$$R = \arg\max_{\tilde{R}} E\left[\ |\tilde{R}\right] - \left((1+\ )\tilde{R} + \frac{\ }{2}\tilde{R}^2\right) = \frac{1}{\ }\left(\ +\ T - (1+\ )\right): \qquad (4)$$

Firms do more R&D when the unconditional return to innovation is large (high  ); when the cost of R&D is low (low  ); and when trade shocks are large and the Arrow effect dominates (high $T$ and $\ > 0$) or when trade shocks are small and the Schumpeterian effect dominates (low $T$ and $\ < 0$). Other authors have regressed innovation choice ($R$) on instrumented competition ($T$). Equation (4) highlights two reasons why doing so provides only indirect, or even biased information about  .

The first limitation of this approach is that, even if there is no endogeneity problem, regressing $R$ on $T$ can identify only $\ = \ $. Since $\ > 0$, the sign of   can be inferred. However, this approach cannot identify the value of   because the cost parameter   is unknown to the econometrician. The economic intuition is that the sensitivity of R&D to competition depends both on the Arrow vs. Schumpeterian effect tradeoff ( ) and on the cost structure of R&D investment ( ). Thus, the economic magnitude of the Arrow vs. Schumpeterian effect tradeoff cannot be quantified from the R&D-competition sensitivity alone.

The second limitation of regressing innovation choice on import competition is that, even if import competition is correctly instrumented, firms' endogenous innovation choice depends not only on returns to innovation ($\ +\ T$) but also on various costs and frictions such as credit constraints and agency issues (captured by parameter   in the model). For

[7] Aghion et al. (2005) instrument for import competition using the introduction of the European Single Market, Bloom et al. (2016) using the removal of product-specific quotas following China's entry into the WTO, and Autor et al. (2016) using imports in other high-income countries.

instance, if an increase in competition reduces firms' cash flows and tightens financing constraints, firms may respond to competition shocks by cutting investment in innovation not because it has negative NPV, but because they are constrained. Formally, the estimate of $=$ is biased in this case because is correlated with $T$. Crucially, the estimate is biased even if $T$ is instrumented, because the correlation between $T$ and comes from $T$ causing . This correlation is therefore not removed by instrumented for $T$.

As such, not only regressing $R$ on $T$ cannot identify , but even the estimated sign of may be incorrect. This may explain why papers that have followed this approach yields conflicting results, e.g., Bloom et al. (2016) find a positive effect, while Autor et al. (2016) find a negative effect. A different approach is thus needed to estimate .

#### 2.2.2 Our approach

Our approach is to study directly how firm performance depends on the interaction between R&D and import competition by estimating:

$$= \quad + \quad T + \quad R + \quad TR + \quad ; \tag{5}$$

where firm performance and R&D $R$ are measured at the firm level and trade flows $T$ are measured at the industry level.

Estimating (5) with OLS may be biased because both R&D and trade flows are endogenous. In Internet Appendix B.1 we study both sources of bias and show how to correct them. We summarize here the main results of this analysis (Propositions B.1 to B.4):

1. The endogeneity of R&D creates two biases in the OLS estimator of . The first one is always a bias away from zero. It arises because firms whose expected returns to R&D are higher, endogenously choose a higher level of R&D. The second bias may go in either direction. It comes from the correlation between R&D opportunities and resilience to trade shocks, which may be driven for instance by unobserved heterogeneity in the quality of firm management.

2. Instrumenting for R&D using an exogenous cost shifter corrects these two biases.

In the empirical analysis, the instrument will be the R&D tax credit.

3. The endogeneity of trade flows creates a negative bias in the OLS estimator of . The bias arises because of random shocks to industry innovation. When firms in a domestic industry successfully innovates, that is, when the realized returns to R&D are above average, it reduces import penetration in this industry because domestic firms have high realized productivity relative to foreign producers. This mechanism creates a spurious negative correlation between realized returns to R&D and import penetration, creating a downward bias in the OLS estimate of .

4. Instrumenting for import penetration in the domestic country using import penetration in comparable countries (other high-income countries in our empirical analysis) corrects this bias.

# 3 Empirical Strategy and Data

We seek to test whether US firms that are more innovative perform better in the wake of import competition from China. We follow the difference-in-difference approach analyzed in Section 2.2.2 and compare the performance of firms with a high stock of R&D relative to firms with a low stock of R&D, operating in industries that are highly exposed to import competition from China relative to industries that are less exposed to import competition from China. The approach is valid if the invested amount of R&D at the firm level is instrumented by an exogenous cost shifter and China's import competition in the US is instrumented using China's import penetration in countries comparable to the US. We present the instrument for import penetration in Section 3.1, the instrument for R&D in Section 3.2, and the econometric specification in Section 3.3.

## 3.1 Instrument for Import Penetration

To isolate the component of Chinese import penetration in the US coming from Chinese productivity and trade cost shocks, we follow the approach of Autor, Dorn and Hanson (2013) analyzed formally in Propositions B.3 and B.4. We instrument imports from China to the US using imports from China to other high-income markets. The strategy is valid if the common within-industry component of rising Chinese imports to the US and other high-income countries stems from China's rising productivity and falling trade costs in these sectors. One possible threat to identification is that productivity shocks may be correlated across high-income economies and this correlation may drive the common component of import growth in the US and other high-income countries. While we cannot categorically reject this possibility, evidence suggests that the surge in China's exports is strongly related to internal changes in China, which has involved massive internal migration to the cities, Chinese industries gaining access to foreign technologies, capital goods, and intermediate inputs, multinational companies being permitted to operate in the country, and the country's accession to the WTO in 2001. This transition to a market economy has led to rapid productivity growth and a massive increase in the country's manufacturing capacity. Between 1991 and 2007, the share of China in manufacturing imports has grown sharply—from 6.7% to 25.0% in the US and from 3.7% to 16.1% in other high-income countries. This is fast even compared to Mexico and Central America, which have signed free trade agreements with the US during that period and whose share has grown from 9.8% to 13.8%.

Data on bilateral trade flows are from UN Comtrade. We use manufacturing imports from China both to the US and to a group of eight high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) aggregated at the four-digit SIC level for the years 1991 to 2007.[8] Figure 1a plots total manufacturing imports from China to the US and to the other high-income countries. From 1991 to 2007, manufacturing imports from China have increased 12-fold in the US, suggesting an economically significant shock for American manufacturing firms. During the same period, Chinese manufacturing imports to other developed economies have followed a similar pattern with a 9-fold increase. The parallel evolution in the US and in other high-income countries is consistent with our assumption that the surge in China's exports is primarily due to forces exogenous to the US economy.

[INSERT FIGURES 1a, 1b, 1c ABOUT HERE]

We define China's import penetration in the US at the industry-year level as imports

[8] The data are available on David Dorn's website.

from China in the industry-year normalized by industry employment. Since employment is endogenous to import shocks, we measure industry employment at the beginning of the period (in 1990) from the County Business Pattern data.[9] Table 1 reports the 1991–2007 change in import penetration for each broad (two-digit SIC) manufacturing industry. Imports from China grew strongly in textile, electronic, furniture, industrial equipment, while tobacco, printing, food, and petroleum did not face increased Chinese competition.

[INSERT TABLE 1 ABOUT HERE]

We define similarly China's import penetration in the other high-income countries. Figure 1b plots the evolution of import penetration in the US and in the other high-income countries between 1991 and 2007 by broad industry. It reveals that the increase in Chinese import penetration in the US is concentrated in the same set of industries as in the other high-income countries.

Figure 1c goes at a more granular level by plotting the 1991–2007 change in import penetration in the US against import penetration in the other high-income countries for each four-digit industry. It confirms that import penetration across industries is highly correlated between high-income economies. These patterns are consistent with the assumption that the surge in China's exports originates from rising productivity in China.

To construct the predicted value for import penetration in the US, we regress China's import penetration in the US at the four-digit industry-year level on China's import penetration in the eight other high-income countries and a full set of industry and year fixed effects. The result of the first stage regression is reported in Table 2. We obtain a positive and statistically significant coefficient of 1.36 (standard error 0.12 clustered by industry and year). The $F$-test is equal to 127, indicating that our instrument is a strong predictor of imports in the US. We then use the predicted value of this regression to construct the predicted China's import penetration in the US that we will use in the second stage. We denote this predicted variable $ImportPenetration$ .

[INSERT TABLE 2 ABOUT HERE]

[9] In Internet Appendix C.1, we show that our results are robust to scaling import penetration with employment ten years before the beginning of the sample period (in 1980).

Importantly, our empirical strategy does not exclude the role of global production chains. During the sample period about half of China's manufacturing exports are produced in export processing plants, which import intermediate inputs from abroad and assemble them into the final goods that are exported (Feenstra and Hanson (2005)). Our empirical strategy does not require that China contributes 100% to the value added of the goods it ships abroad. Instead, we require that China's export growth is driven by internal shocks in China. These shocks may increase the supply of exported goods that are entirely produced in China. They may also improve China's integration into global production chains and increase the supply of exported goods whose last stage of production is done in China. Both situations represent exogenous import competition shocks from the point of view of US producers.

## 3.2 Instrument for R&D Capital Stock

To generate exogenous variations in R&D at the firm level, we exploit tax-induced changes to the user cost of R&D capital. After the introduction of the US federal R&D tax credit in 1981, US states progressively started to provide R&D tax credit to corporations. Figure 2 illustrates the staggered timing of changes in tax credit rates across US states and across time. The process began with Minnesota in 1982 and, as of 2006, 32 states provided tax credit. The average effective credit rate has grown approximately fourfold over this period to equal roughly half the value of the federal effective credit rate, while in some states the tax credit is considerably more generous than the federal credit (Wilson (2009)). These state R&D policies generate variation in the user cost of R&D capital across states and across time. A possible concern is that these tax policy changes may be endogenous to shocks to the economic environment. While this possibility cannot be ruled out, the existing literature suggests a large degree of randomness regarding the introduction and level of R&D tax credits (see the discussion in Bloom, Schankerman and Van Reenen (2013b)). We investigate further this issue in Internet Appendix C.2 where we look for, and find no statistical evidence that changes in economic conditions predict R&D policies.

We use the state-by-year tax-induced changes in user cost of R&D capital ($z_{st}$) for the years 1982 to 2006 from Wilson (2009).[10] R&D expenses are eligible to a tax credit in the state where it is conducted. Thus, firms benefit differentially from these tax credits depending on the cross-state distribution of their R&D activity. We estimate the location of a firm's R&D activity using the location of its inventors.[11] We obtain patent information using the NBER patent file (see Hall, Jaffe and Trajtenberg (2001)) and inventor information using the Harvard Business School patent database (see Lai, D'Amour and Fleming (2009)). These data provide us with the list of all patents filed by each firm with the year of application and the address of the inventors. We measure the geographical distribution of firm $i$'s R&D activity in year $t$ based on the 10-year moving average share, $w_{ist}$, of its inventors located in each state $s$. The weighted-average user cost of R&D for firm $i$ in year $t$ is thus $z_{it} = \sum_s w_{ist} z_{st}$. The advantage of computing the weighted-average user cost of R&D based on the firm's "average location" over the past 10 years is that it alleviates concerns that firms might be moving to states offering more generous tax credits. To further make sure that our results are not polluted by endogenous firm location, we have re-run all our tests using firms' initial locations instead of the 10-year moving average and obtained similar results.

Firm data are from Compustat. We consider US firms operating in the manufacturing sector (SIC codes 2000–3999). We require that firms have non-missing total assets and sales and at least three consecutive years of data. Our instrument for R&D also imposes that we exclude firm-year observations for which the firm has not filed a single patent over the previous 10 years, because in this case we cannot compute the firm-specific user cost of R&D which depends on the firm's inventors location. This leaves us with a sample of 3,334 firms and 41,860 firm-year observations over the 1982-2006 period.

We predict R&D expenditures normalized by total assets using the firm-specific user

[10] The user cost of R&D capital in state $s$ in year $t$ is given by the Hall-Jorgenson formula: $\frac{1-(k_{st}+k_t^f)-(\tau_{st}+\tau_t^f)}{1-(\tau_{st}+\tau_t^f)}[r_t + \delta]$, where $k_{st}$ and $k_t^f$ are the state and federal R&D tax credit rates, $\tau_{st}$ and $\tau_t^f$ are the state and federal corporation income tax rates, $r_t$ is the real interest rate, and $\delta$ is the depreciation rate of R&D capital.

[11] R&D expenses can be o set against state-level corporation tax liabilities. State-level corporation tax liabilities are calculated on total rm pro ts allocated across states according to a weighted combination of the location of rm sales, employment, and property. Hence, any rm with an R&D lab within the state is likely to be both liable for state corporation tax (due to its employees and property in the state) and eligible for an o setting R&D tax credit. Hence, inventor location provides a good proxy for eligibility for state-level R&D tax credits. In Internet Appendix C.3, we show that our results are robust to measuring rms' exposure to state tax credits based on the location of their headquarters.

cost of R&D ($z_{it}$) and controlling for firm and year fixed effects. The result of the first stage regression is reported in Table 3. The coefficient on $_{it}$ is equal to $-0.11$ with an $F$-test of $12.4$ (standard errors clustered at the industry level). Hence, a one percentage point drop in the user cost of R&D capital raises R&D expenditures by $0.11$ percent of total assets. Given that R&D expenditures over total assets is on average $8.4\%$, our estimate implies a price-elasticity of R&D of $1.3$. This elasticity is in line with the estimates of Wilson (2009) and Bloom, Schankerman and Van Reenen (2013).

[INSERT TABLE 3 ABOUT HERE]

The innovation of a firm depends on its current and past R&D expenditures. To account for this, we use the predicted value of R&D expenditures to create a predicted value of R&D capital stock ($R\&DStock$) using the perpetual inventory method. We use a depreciation rate of R&D capital of 15% as suggested by Hall, Jaffe and Trajtenberg (2005).[12] We initialize the R&D capital stock at zero in the first year the firm appears in Compustat or in 1982, whichever comes last.[13] One possible concern is that, even if the predicted value of R&D flow is exogenous, the predicted value of R&D stock is related to firm age. It may threaten our identification strategy if firms of different age react differently to import competition. For instance, older firms may have better access to credit, which allows them to better absorb negative shocks, whereas young firms tend to be more pro-cyclical (Fort, Haltiwanger, Jarmin, and Miranda (2013)). On the other hand, young firms may have higher productivity levels (Foster, Haltiwanger and Syverson (2008)) or hold more cash, which provides them with an advantage when facing import competition shocks (Fresard (2010)). To account for such potential confounding effects, we will control for firm age interacted with import penetration in the second stage regression.

### 3.3 Econometric Specification

The sample period for the second stage is 1991–2007, which corresponds to the rise of China illustrated in Figure 1a. Table 4 reports summary statistics. Variables that can

[12] In unreported tables, we use a depreciation rate of 10% as in Peri (2005) and obtain similar results.

[13] Since states started to o er R&D tax credit from 1982 on, we can construct the instrumented R&D ow only starting in 1982 even for rms that were already in Compustat prior to 1982.

be positive or negative are winsorized at 1% in each tail and variables that can only be positive are winsorized at 1% in the upper tail.

[INSERT TABLE 4 ABOUT HERE]

With instruments for import penetration and R&D capital stock in hand, we can estimate the following regression:

$$\begin{aligned} Y_{i,j,t} = \quad + \quad ImportPenetration \quad {}_{j,t-1} + \quad R\&DStock\ {}_{i,j,t-1} \\ + \quad ImportPenetration \quad {}_{j,t-1} \times R\&DStock\ {}_{i,j,t-1} \\ + Controls \quad {}_{i,j,t-1} + \quad {}_{i} + \omega_{j,t} + \varepsilon_{i,j,t}; \end{aligned} \quad (6)$$

where $Y_{ijt}$ is an outcome variable for firm $i$ operating in sector $j$ in year $t$, *Import Penetration*$_{j,t-1}$ is predicted import penetration from China at the industry-year level where we use the historical four-digit SIC code to identify the industry of a firm,[14] and $R\&DStock\ {}_{i,j,t-1}$ is predicted stock of R&D capital at the firm-year level. Controls include log of total assets, log of firm age, and log of firm age interacted with predicted import penetration. The variable of interest is . $> 0$ implies that a greater stock of R&D capital leads to a higher outcome of the dependent variable in sectors with large import penetration relative to sectors with low import penetration.

${}_{i}$ are firm fixed effects and absorb all time-invariant determinants of the outcome variable at the firm level. These firm fixed effects are important to remove a potential source of endogeneity coming from the unbalanced nature of the panel. For instance, if firms that are more resilient to import competition enter during the sample period in states that offer generous R&D tax credit, then the estimate of would be biased by this change in the composition of the firm population. Firm fixed effects allow us to control for such selection effects. Alternatively, if states populated by more productive firms in import-competing industries offer more generous R&D tax credit, then firms in

[14] When the historical SIC code is missing for a firm in a given year, we back fill the variable using the SIC code in the earliest subsequent year in which the variable is not missing. Results are robust when we do not back fill and when we use the current main SIC code. Results are also robust if we use Compustat Business Segments data to construct a firm-level measure of import penetration as the average of predicted import penetration across all segments weighted by the share of each segment (see Internet Appendix C.4)

import-competing industries with high predicted stocks of R&D will appear to have higher performance. In this case, there would be a positive correlation between firm performance and import competition interacted with predicted R&D in the cross section of firms, but this correlation would be spurious. Firm fixed effects absorb any such cross-firm spurious correlation.

$!_{j,t}$ are industry-by-year fixed effects. They ensure that is identified from comparing firms with different stocks of R&D capital within the same industry-year. If, for instance, there is cross-industry heterogeneity in the resilience to trade shocks and if states with lots of resilient industries offer more generous R&D tax credits, then there will be a spurious positive correlation between firm performance and import competition interacted with predicted R&D. Such spurious correlation is absorbed by industry-year fixed effects. Note that including industry-year fixed effects implies that the identification is coming from variations in firms' R&D tax credit rate within industry-years. Since a firm's R&D credit rate depends on its location, the specification with industry-year fixed effects requires that there is at least some geographic dispersion of firms within industry-years. This condition might not be satisfied if industries are highly clustered geographically. To investigate whether this is the case, for each industry, we rank states based on the share of R&D activity conducted in each state.[15] We then compute the average, across all industries, of the share of R&D conducted in the top state (which is not the same state for all industries), in the second state, and so on. These summary statistics are reported in Table 5. The average industry has 33% of its R&D activity in the top state, 17% in the second state, 11% in the third state, 8% in the fourth state, 6% in the fifth state, and thus 25% in the remaining states. These statistics suggest that while there is some clustering by industry, this clustering is far from perfect and there is still significant geographic dispersion that allows us to implement the specification with industry-year fixed effects.[16]

[INSERT TABLE 5 ABOUT HERE]

[15] This share is computed using the weights we constructed in Section 3.2 to locate firms' inventors. Specifically, for a given industry, we compute the share of R&D activity in each state as the average share of firm's inventors located in the state across all firm-years in this industry.

[16] A related issue is that California is the top state for 28% of industries. To check that the results are not driven by Californian firms, in Internet Appendix C.5 we re-run the regressions after excluding firms that have more than 50% of their R&D activity in California and obtain similar results.

Finally, because we use predicted imports and predicted R&D capital as explanatory variables, we need to adjust the standard errors to account for these predicted regressors. In all our regressions, we thus report bootstrapped standard errors clustered by industry and year.[17]

# 4 Resilience to Import Competition

[INSERT TABLE 6 ABOUT HERE]

We first estimate equation (6) using sales growth as the dependent variable and report results in Table 6. To begin with, we only include predicted import penetration from China (not interacted with R&D capital stock). The coefficient on imports is negative and significant at the 1% level (column (1)). The point estimate implies that a one standard deviation increase in import penetration from China (22 k$/worker) leads on average to a 1.8 percentage point decline in annual sales growth.[18] This result is consistent with previous literature showing that US manufacturing industries exposed to low-wage-country imports grow more slowly (Bernard, Jensen and Schott (2006)).

In order to assess whether a larger stock of R&D capital mitigates the negative effect of import competition on sales growth, we interact import penetration with the predicted stock of R&D. The interaction term is positive and significant at the 5% level (column (2)), which implies that more innovative firms are less hurt by import competition shocks. The point estimate implies that going from the twenty-fifth percentile to the seventy-fifth percentile of the sample distribution of R&D stock (i.e., from 4% to 43% of total assets) reduces the negative effect of a one standard deviation increase in import competition

[17] The bootstrap has been done as follows. We rst draw a random sample with replacement within the sample of industry-years used to predict imports; we run the rst-stage regression for imports; and we generate the predicted imports in the US. We then draw a random sample with replacement within the sample of rm-years used to predict R&D; we run the rst-stage regression for 99(one)-318(distribution)-313ec(p)-27(e

on sales growth by 0.7 percentage points. When we include industry-year fixed effects, the effect becomes slightly larger and significant at the 1% level (column (3)). In this case, moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock reduces the effect of import competition by 0.9 percentage point, that is, by half the average effect.

One possible concern is that, even if the predicted value of R&D flow is exogenous, the predicted value of R&D stock is related to firm age. This is a problem if firms of different age react differently to import competition. To account for this potential effect, we control for firm age interacted with import penetration. The coefficient on this interaction term is not significantly different from zero (column (4)), suggesting that there is no systematic pattern between exposure to trade shocks and firm age. Accordingly, the coefficient on the interaction term between import penetration and R&D does not change when we control for the interaction between import penetration and firm age.

Aghion et al. (2005) suggest that the effect of import competition can be non-monotonic. In Internet Appendix C.6, we test for non-monotonicity by allowing for a quadratic effect of import penetration on the returns to R&D. We find that the relation is increasing at all levels of import penetration in the sample distribution.

[INSERT TABLE 7 ABOUT HERE]

We turn to the effect on profitability in Table 7. We expect that the negative shock on sales triggered by increased import competition will also reduce profitability. When we only include import penetration from China (not interacted with R&D stock), we find that the unconditional effect of import competition on profitability is negative and statistically significant at the 5% level (column (1)). The point estimate implies that a one standard deviation increase in import penetration from China leads on average to a 1.1 percentage point drop in ROA. This average decline in profitability following trade shocks is consistent with Xu (2012). More important for our analysis is how this decline depends on the R&D stock.

When we interact import penetration with the stock of R&D, the interaction term is positive and significant at 5% (column (2)). Moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock reduces the negative effect on ROA by 1 percentage points, i.e., by the same magnitude as the average effect. The effect is slightly larger and significant at 1% when we include industry-year fixed effects (column (3)) and unchanged when we control for firm age interacted with import penetration (column (4)). Overall, the results in this section suggest that R&D allows firms to cushion the negative effects of trade shocks on firm performance, both in terms of growth and profitability.

# 5 Product Differentiation

What is the mechanism that makes R&D an ex ante moderating variable of the effect of trade shocks on firm performance? Generally speaking, R&D can improve firm performance in two ways: by increasing product differentiation as in Sutton (1991); or by increasing productivity as in Grossman and Helpman (1991) and Aghion and Howitt (1992). However, it is a priori unclear which channel becomes more important as import competition increases.

To shed light on this question, we develop in Internet Appendix A a model of competition with vertical differentiation that allows us to contrast the effect of R&D on firm performance through higher vertical differentiation vs. higher productivity. The main insight is that, while both types of innovation lead to an *unconditional* increase in firm profit, they have opposite effects *conditional* on the intensity of competition. The marginal benefit of higher vertical differentiation increases when low-cost competition increases, while the marginal benefit of higher productivity decreases when low-cost competition increases. Therefore, the model predicts that the mechanism by which R&D capital makes firms more resilient to trade shocks works through product differentiation. More specifically, the model generates two potential channels.

The first channel is that the *bene ts* of differentiation increase when import competition increases. The prediction of the model is that firms that have ex ante more differentiated products are better shielded from import competition. Combined with the (testable) hypothesis that firms with a higher stock of R&D capital have more differentiated products independently of the intensity of import competition, this channel can explain why the benefits of R&D increases when import competition increases.

The second channel is that the *incentives* to differentiate increase when import competition increases. If past R&D makes firms more responsive and improves their ex-post ability to differentiate once competition materializes, then the model predicts that firms with a higher stock of R&D capital increase product differentiation as import competition increases, thus mitigating the effect of the shock.

An ancillary prediction of the model is that the effect of R&D on firms' resilience to trade shocks is stronger in industries in which product differentiation is more important.

In this section, we leverage our design, which allows us to use proxies for product differentiation as a right-hand side variable or a left-hand side variable, to test these three predictions. We provide evidence for the first channel in Section 5.1, for the second channel in Section 5.2, and for the cross-industry prediction in Section 5.3.

## 5.1 Channel 1: Differentiation Becomes More Important

To study if R&D makes firms more different and differentiation becomes more important as import competition increases, we exploit the Text-based Network Industry Classification developed by Hoberg and Phillips (2015). Using the product description in firms' 10-K, Hoberg and Phillips (2015) compute pairwise word similarity scores for each pair of US public firms. The similarity score ranges from zero to one and indicates the relative number of words that two firms share in their product description. Two firms are deemed to be closer in the product market space when their product similarity score is closer to one and more differentiated if the score is closer to zero. To ease the reading, we use one minus the similarity score and refer to this variable as product differentiation. For each firm in each year, we compute average product differentiation from US peers. Average differentiation measures whether the firm sells more unique products that will be less exposed to the competitive pressure. Because Hoberg and Phillips' product similarity data start in 1996, the sample period is now 1996–2007.

The first channel relies on a combination of two ingredients: (a) higher R&D leads to greater product differentiation independently of the intensity of import competition and (b) the impact of differentiation on firm performance increases as import competition increases.

[INSERT TABLE 8 ABOUT HERE]

To test for (a), we regress product differentiation on instrumented R&D stock and the same set of controls and fixed effects as before. The result is reported in Table 8. In column (1), the positive and statistically significant coefficient on R&D stock indicates that a higher level of R&D leads to more differentiated products. In column (2), the effect is robust to controlling for industry-year fixed effect. These results are consistent with the finding of Hoberg and Phillips (2015) that firms with higher (endogenous) R&D have more differentiated products.

To test for (b), we regress firm performance on instrumented import penetration interacted with product differentiation as well as the non-interacted variables and the same controls and fixed effects as before. Note that we do not have an instrument for product differentiation.[19] The results should thus be interpreted while keeping in mind that variation in differentiation on the right-hand side might be endogenous, for instance if firms more exposed to trade shocks try harder to increase differentiation. To alleviate such reverse causality concerns, we lag differentiation by one year while acknowledging this is of course imperfect.

We focus on sales growth in columns (3) and (4). The coefficient on import penetration interacted with product differentiation is positive and statistically significant. Thus, differentiation becomes more and more important as import competition increases. Columns (5) and (6) depict a similar pattern when we use ROA as a measure of firm performance. These results are in line with the model in Internet Appendix A, which predicts that returns to differentiation increase with competition.

Taken together, evidence for (a) and (b) indicates that R&D helps firms escape import competition because it allows them to differentiate their products, which becomes more essential as the competitive pressure from China increases.

[19] Instrumenting di erentiation using our instrument for R&D would boil down to running our baseline regression of rm performance on instrumented imports interacted with instrumented R&D. This approach does not allow one to identify whether the e ect of R&D on resilience to trade shocks operates through higher sensitivity of performance to di erentiation after trade shocks (channel 1) or through higher di erentiation after trade shocks (channel 2).

## 5.2 Channel 2: Differentiation Increases

We now test if firms that have invested more in R&D in the past, differentiate more following an increase in import competition. We estimate equation (6) using product differentiation as the dependent variable.

[INSERT TABLE 9 ABOUT HERE]

Results are reported in Table 9. In column (1) we only include import penetration not interacted with R&D and obtain a positive and statistically significant coefficient. Thus, an increase in import competition leads firms to become more differentiated. The point estimate implies that a one standard deviation increase in import competition leads to an increase in product differentiation of 0.05 standard deviations. In line with the prediction of the model in Internet Appendix A, firms have more incentives to increase differentiation when competition increases.

When we interact import penetration with the stock of R&D, we obtain a positive coefficient on the interaction term. Depending on the specification, the $p$-value is between 0:03 (when industry-year fixed effects are included, columns (3) and (4)) and 0:12 (when industry-year fixed effects are not included, column (2)). Moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock increases the effect of import penetration on differentiation by 25% of the unconditional effect. Thus, firms that have invested more in R&D for reasons unrelated to competition are better able to increase differentiation when the competitive pressure tightens and the benefits from differentiation increase.

Note that ideally, we would like to measure differentiation from Chinese products. We cannot do so directly because the product similarity score is defined only for pairs of US firms. Our approach of looking instead at differentiation from US competitors should be understood as using this variable as a proxy for differentiation from Chinese competitors, capturing firms' ability to bring to market more unique products that will be less subject to competition from both US and Chinese rivals. In Internet Appendix C.7, we follow a complementary approach and test whether a firm's products become more similar to the products of other US firms less exposed to Chinese competition when the firm has a higher stock of R&D. The results are in line with those reported here. Overall, the evidence lends support to the notion that R&D helps firms withstand import competition by improving their ability to differentiate when competition materializes.

### 5.3 Product Differentiation Across Industries

Another implication of the hypothesis that R&D helps firms overcome import competition through differentiation is that the effect of R&D on resilience to trade shocks should be stronger in industries in which product differentiation is more prevalent. To test this prediction, we proxy for the extent of differentiation between firms at the industry level using the industry average of the measure of firm-level differentiation used above and we create a dummy *IndustryDi erentiation* equal to one if the average score of the industry is above the sample median. To test whether the effect of R&D on resilience to trade shocks is stronger in industries in which differentiation is more important, we regress firm performance on the triple interaction between R&D stock, import penetration, and industry-level importance of differentiation, as well as on the simple interaction and non-interacted terms and the same controls and fixed effects as before.

[INSERT TABLE 10 ABOUT HERE]

Columns (1) and (2) of Table 10 focus on the effect on sales growth. The coefficient on the triple interaction term is positive and significant whether industry-year fixed effects are included or not. Therefore, the effect of R&D on firms' ability to escape foreign competition is stronger in industries in which product differentiation is more important. We obtain a similar result in columns (3) and (4) where we use ROA as a measure of firm performance.

## 6 Capital Expenditures and Employment

After having shown in Section 4 that R&D mitigates the disruptive effects of trade with China on firm performance, we explore the real effects on capital expenditures and employment. Given that more innovative firms maintain their market shares and profitability, are they also able to keep on investing and hiring or do they downsize?

It should be noted that while the model developed in Section 2 has fixed production factors, it is straightforward to extend it to the case of endogenous productions factors. For instance, if we reinterpret as total factor productivity and assume a Cobb-Douglas production function with two factors, capital $K$ and labor $L$, and decreasing returns to scale, $Y = K^{\alpha} L^{\beta}$, with $> 0$, $> 0$, and $+ < 1$, then the optimal quantity of factors $K^*$ and $L^*$ are increasing functions of .[20] Therefore, the model predicts that capital and labor decrease *unconditionally* when import competition increases, but less so for firms with a higher stock of R&D.

[INSERT TABLE 11 ABOUT HERE]

In Table 11, we estimate equation (6) with capital expenditures normalized by lagged fixed assets as the dependent variable. First, we only include import penetration from China and obtain a negative coefficient statistically significant at 1% (column (1)). The point estimate implies that following a one standard deviation increase in import competition, firms reduce their capital expenditures on average by 1.6% of fixed assets. Given that the average ratio capital expenditures over fixed assets is 38%, this effect amounts to a 4.2% decline in capital expenditures. This unconditional negative effect of import competition on capital expenditures is consistent with the results of Fresard and Valta (2016). We now investigate whether this effect is mitigated for more innovative firms.

Since innovative firms do not experience as much of a negative shock on sales and profits (see Tables 6 and 7), we expect that their investment opportunities will also shrink less. To test whether this is true, we add the interaction term between import competition and R&D stock. The interaction term is positive and significant at 1% (column (2)), which means that more innovative firms cut less their capital expenditures when import competition increases. The point estimate implies that moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock reduces the negative effect of a one standard deviation increase in import competition on capital expenditures by 1.4% of fixed assets, i.e., by almost as much as the unconditional effect. The effect is slightly larger when we include industry-year fixed effects (column (3)) and unchanged when we

[20] Denoting by $r$ the interest rate and by $w$ the wage, it follows from the rst order conditions with respect to $K$ and $L$ that $K^* = \left(\frac{\alpha}{r}\right)^{\frac{1-\beta}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\alpha-\beta}} \pi^{\frac{1}{1-\alpha-\beta}}$ and $L^* = \left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha-\beta}} \left(\frac{\beta}{w}\right)^{\frac{1-\alpha}{1-\alpha-\beta}} \pi^{\frac{1}{1-\alpha-\beta}}$.

control for firm age interacted with import penetration (column (4)). Overall, while the average firm in industries exposed to Chinese competition cut capital expenditures, more innovative firms are able to keep on investing in fixed capital. This result implies that the complementarity between R&D capital and fixed capital is amplified when competition tightens.

[INSERT TABLE 12 ABOUT HERE]

In Table 12, we estimate equation (6) with employment growth as the dependent variable. When we only include import penetration from China (not interacted with R&D), we find that the unconditional effect of import penetration on employment is negative and not statistically significant (column (1)). The result that the average effect on employment is weaker (both economically and statistically) than the effect on sales has two, non-exclusive explanations. First, since sales are measured in dollar amount, the decline in sales can come from a reduction in quantities or a reduction in prices or both. Employment should decline only because of the drop in sales coming from the drop in quantities. Second, labor adjustment costs can make employment more sticky than sales.

When we add the interaction term between import competition and R&D, we find that the effect on employment depends significantly on the stock of R&D (column (2)). Employment in firms at the twenty-fifth percentile of the R&D stock distribution reduces employment growth by 0.7 percentage points (statistically significant at 5%) more than firms at the seventy-fifth percentile of the R&D stock distribution when hit by a one standard deviation increase in import penetration. The coefficient estimates imply that firms at the bottom quartile of R&D reduce employment growth by 1.3 percentage points (statistically significant at 5%). In contrast, firms at the top quartile reduce employment growth by a statistically insignificant 0.6 percentage points. The difference between firms with a high level and a low level of R&D becomes slightly larger when we include industry-year fixed effects (column (3)) and unchanged when we control for firm age interacted with import penetration (column (4)). Innovative firms are therefore less likely to shrink the labor force in import-competing industries.

# 7 Robustness

## 7.1 Alternative Instrument for Trade Shock

In this section, we show that our results are robust to using an alternative source of variation in China's import penetration in the US, which comes from changes in barriers to trade specifically between China and the US. We follow Pierce and Schott (2016) and exploit the fact that the US changed its tariff agreement with China in 2000. Since the Smoot-Hawley Tariff of 1930, imports to the US from nonmarket economies such as China are subject to relatively high tariff rates, known as non-Normal Trade Relations tariff (non-NTR). Since 1980, the President of the US granted a waiver to China on a annual basis, that needed to be approved every year by Congress. Following the agreement between China and the US in 1999 governing China's eventual entry into WTO, the US granted China Permanent Normal Trade Relations (PNTR) status.[21]

This agreement has a positive effect for Chinese imports in the US by eliminating potential tariff increases on Chinese imports, as it reduces expected tariff rates and removes uncertainty about the US trade policy vis-a-vis China. One key element of this agreement is that all industries are not affected in the same way, as NTR tariff rate varies across industries. As such, the adoption of PNTR leads to a larger drop in expected tariff in industries that have high NTR tariff. We define the NTR gap as the difference between the non-NTR rate to which tariffs would have risen if annual renewal had failed and the NTR tariff rate that is locked in by PNTR for industry $j$: $NTRGap_j = NonNTRRate_j - NTRRate_j$. Pierce and Schott (2016) show that industries facing a larger drop in expected tariffs experience a larger increase in Chinese imports.[22]

[INSERT TABLE 13 ABOUT HERE]

We first study the unconditional effect of the PNTR agreement on firm performance and investment decisions. We regress each firm outcome variable on $NTRGap$ interacted with a dummy variable $Post$ equal to one after the year 2000 and the same controls

[21] See Pierce and Schott (2016) for more detail about this policy.

[22] We have replicated this result in our sample. The result is the same as the one in Pierce and Schott (2016) and is omitted for the sake of space.

and fixed effects as in the baseline regressions. Results are reported in odd-numbered columns of Table 13. Firms in industries with a higher NTR gap experience lower sale growth, lower profitability, lower capital expenditures, and lower employment growth. Moving from the twenty-fifth percentile (0.19) to the seventy-fifth percentile (0.38) of the NTR gap leads on average to a 2.2 percentage points decline in annual sales growth ($-0.12 \times (0.38 - 0.19)$, significant at 5%, column (1)) and a 1.9 percentage point decline in ROA (significant at 1%, column (3)).[23]

Then, we analyze how the effect depends on firms' R&D capital stock. We interact $NTR\,Gap \times Post$ with instrumented R&D stock and use our preferred specification with industry-year fixed effects.[24] Results are reported in odd-numbered columns of Table 13. For all four dependent variables, the interaction term is positive and statistically significant. The point estimates imply that going from the twenty-fifth to the seventy-fifth percentile of the sample distribution of R&D stock reduces the negative effect of the interquartile NTR gap by 1.3 percentage point (significant at 1%, column (2)), that is, by half the unconditional effect, which is the same order of magnitude that we obtained using the other instrument in Section 4.[25]

## 7.2 Intermediate Inputs

Export growth from China leads not only to greater competition for US producers but also to greater supply of intermediate inputs, which may offset the adverse effect of import competition in final good markets. To account for this effect, we define a measure of input-adjusted import penetration by netting import penetration in input markets from our baseline measure of import penetration in the final good market. We calculate import penetration in input markets as the average of import penetration across all input markets weighted by the share of each input from the 1992 US input-output table. For inputs coming from the manufacturing sector, import penetration is measured as previously

[23] The e ect on the production factors is to decrease capital expenditures by 2.7% of xed assets (signi cant at 5%, column (5)) and employment growth by 1 percentage point (column (7), p-value of 0.15).

[24] Results are similar using the speci cation without industry-year xed e ects.

[25] The reduction in the negative e ect on ROA is 0.7 percentage point (signi cant at 5%, column (4), about one-third the unconditional e ect), on capital expenditure it is 2.3% of xed assets (signi cant at 1%, column (6), about the same as the unconditional e ect), and for employment growth it is 1.1 percentage point (signi cant at 1%, column (8), about the same as the unconditional e ect).

as imports per worker. For non-manufacturing inputs, import penetration is taken to be zero. As before, input import penetration in the US is instrumented input import penetration in other high-income economies.

[INSERT TABLE 14 ABOUT HERE]

In columns (1) and (4) of Table 14, we use input-adjusted import penetration as the measure of trade exposure and study the impact on firm performance. We report the results using our preferred specification with the full set of fixed effects and controls. The coefficient on input-adjusted import competition interacted with R&D stock is positive and significant for both sales growth and ROA. The economic magnitudes are similar to the ones obtained in Tables 6 and 7 where we do not adjust for imports of intermediate inputs. Therefore, accounting for import competition in input markets does not modify our conclusion that a higher level of R&D allows US producers to cushion trade shocks.

Next, we try to isolate the effect of input import competition by estimating separately the effects of import penetration in the final good market and import penetration in intermediate input markets. Instead of netting the latter from the former, we now include the two variables separately in the regression. In column (2) we start by estimating the unconditional effect on sales growth of import competition in the final good market and of import competition in input markets without interacting these variables with the R&D stock. We find as before that trade shocks in the final good market have a negative effect on sales growth. The coefficient on trade shocks in input markets is positive, pointing to a positive effect of positive supply shocks in input markets, but statistically insignificant. This result is consistent with Acemoglu et al. (2016) who estimate the effect of trade shocks in input markets measured in a similar way to ours on employment growth measured from the County Business Patterns data and find that the effect is imprecisely estimated and unstable in sign. In column (5) we study the unconditional effect on profitability. The effect of import competition is still negative and strongly significant. The effect of import competition in input markets is now positive and significant at the 10% level. These results are consistent with the notion that positive supply shocks in input markets lead to cheaper inputs and higher profits but we cannot detect significant effects that firms respond to cheaper inputs by expanding production, at least on average.

Finally, we study whether firms respond differently to these supply shocks in input markets depending on their level of R&D capital. Theory makes no clear prediction on whether innovation and intermediate inputs are complements or substitutes. The model in Internet Appendix A predicts that cost is a more important factor for less innovative firms that compete head-to-head with Chinese producers. On the other hand, innovative firms might be better able to integrate into global production chains. In columns (3) and (6) we interact import competition in the final good market and in input markets with R&D stock. As in the baseline specification, we find that the interaction term between import competition in the final good market and R&D stock is positive and significant. In contrast, the interaction term between import competition in intermediate input markets is insignificant and close to zero. Therefore, it does not appear that more innovative firms benefit either more or less from import competition shocks in their input markets.

# 8 Concluding Remarks

We exploit the staggered changes of R&D tax credits across US states and across time as a quasi-natural experiment to examine whether more innovative firms are better shielded from import competition from China. We further instrument for China's import penetration in the US using Chinese imports by other high-income countries. We show that, while rising imports lead to slower sales growth and lower profitability for firms in import-competing industries, this effect is significantly smaller for firms that have invested large amounts in R&D thanks to generous R&D tax credit policies. We also show that the effect of R&D on firm performance happens mostly through higher product differentiation, as in Sutton (1991)'s theory or R&D, rather than through lower costs, as in Grossman and Helpman (1991) and Aghion and Howitt (1992)'s models of innovation. As a result of higher performance, R&D-intensive firms can avoid to downsize and continue to invest in capital and labor despite being exposed to trade shocks.

Our results have policy implications when put in perspective of previous work that studies how firms endogenously adjust R&D investment after trade shocks. The mixed evidence on this question (see Bloom et al. (2016) versus Autor et al. (2016)) suggests that firms may cut R&D investment not because its NPV becomes negative, but because trade shocks tighten frictions such as credit constraints. In this case, public policies aiming at relaxing credit constraints may be better than distorting firm investment choices via R&D tax credit as all firms may not have positive NPV R&D investment to undertake.

While we are cautious about extrapolating the results, our findings may be relevant in other contexts. First, the Chinese export boom starting in the late 1990s has represented a considerable shock to competition for most developed economies, not just the US. More broadly, it is neither the first nor the last time that profitability and employment in the manufacturing sector in high-income countries is hit by foreign competition from low- and middle-income countries (Bernard et al. (2006)). Second, the interaction between impact of import competition and R&D tax credit is also relevant outside the US as most high-income countries have engaged in such tax credit policies to promote innovation.

An open issue left for future research pertains to general equilibrium effects. What would happen if all US firms had invested large amounts in R&D? Would they all preserve their market shares or would they start crowding each other out? Our research design cannot, by construction, answer this question because it relies on a difference-in-difference approach. While we show that innovative firms preserve their market shares following increased competition from China, we cannot assert whether this is because these firms are able not to lose market shares to Chinese competitors or because they gain market shares at the expense of other, less innovative US firms. In the first case, innovation would imply a positive effect for the US economy as a whole. In contrast, the second scenario would imply a reallocation of market shares among US firms but the overall impact on the US economy might not be positive. Understanding how our micro estimates add-up to the macro level should provide fruitful avenues for future works.

# References


Acemoglu, D., Autor, D.H., Dorn, D., Hanson, G.H., and Price, B., 2016. "Import Competition and the Great U.S. Employment Sag of the 2000s". *Journal of Labor Economics* 34, 141-198.

Aghion, P., P. Askenazy, N. Berman, G. Cette, and L. Eymard, 2012. "Credit Constraints and the Cyclicality of R&D Investment: Evidence from France". *Journal of the European Economic Association* 10(5), 1001–1024.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., and P. Howitt, 2005. "Competition and Innovation: an Inverted-U Relationship". *Quarterly Journal of Economics* 120, 701-728.

Aghion, P., and P. Howitt, 1992. "A Model of Growth Through Creative Destruction." *Econometrica* 60(2), 323-354.

Arrow, K., 1962. "Economic Welfare and the Allocation of Resources for Invention". In R. Nelson, ed., *The Rate and Direction of Inventive Activity*, Princeton University Press, 609-625.

Autor, D.H., 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, 2121-68.

Autor, D., Dorn, D., Hanson, G. H., Shu, P., and Pisano, G., 2016. "Foreign Competition and Domestic Innovation: Evidence from U.S. Patents." *NBER Working Paper*, (22879)

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 U.S. manufacturing plants". *Journal of International Economics* 68, 219-237.

Bernard, A., Jensen, J., Redding, S., and Schott, P., 2012. "The Empirics of Firm Heterogeneity and International Trade". *Annual Review of Economics* 4, 283-313.

Bloom, N., Draca, M., and Van Reenen, J., 2016. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *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, 1347-1393.

Bloom, N., Schankerman, M., and Van Reenen, J., 2013b. Supplement to "Identifying Technology Spillovers and Product Market Rivalry". *Econometrica*, 81, Econometrica Supplementary Material.

Bhojraj, S., Hribar, P., Picconi, M., and McInnis, J., 2009. “Making Sense of Cents:

Leamer, E., 2007. "A Flat World, a Level Playing Field, a Small World After All, or None of the Above?" *Journal of Economic Literature*, 45(1), 83-126.

OECD, 2014. "OECD Science, Technology and Industry Scoreboard". *OECD Publishing*, Paris.

Peri, G., 2005. "Determinants of Knowledge Flows and their Effect on Innovation". *Review of Economics and Statistics* 87, 308-322.

Pierce, J., and P. Schott, 2016. "The Surprisingly Swift Decline of U.S. Manufacturing Employment." *American Economic Review* 106(7), 1632-1662.

Schumpeter, J., 1943. *Capitalism, Socialism and Democracy* (London: Allen Unwin).

Scherer F.M. and Huh K., 1992. "R&D Reactions to High-Technology Import Competition", *Review of Economics and Statistics*, 74 (2), 202–212

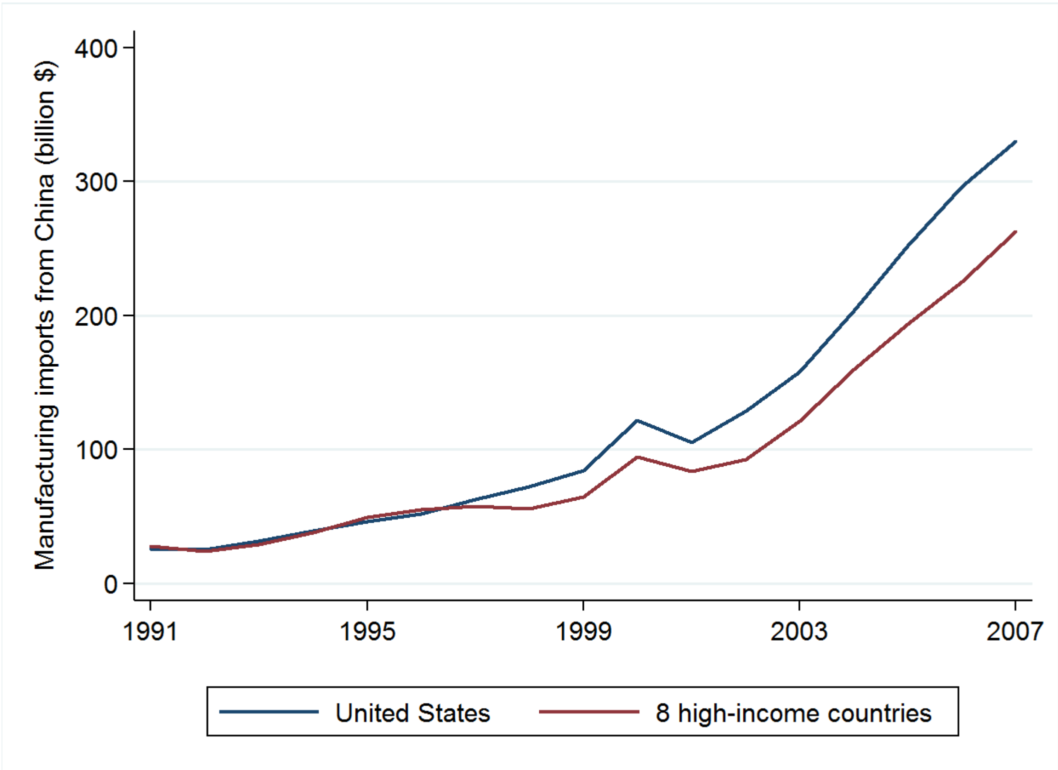
Sutton, John. 1991. "Sunk Costs and Market Structure" *(MIT Press: Cambridge, Mass)*.

Valta, P., 2012. "Competition and the cost of debt". *Journal of Financial Economics* 105, 661-682.

Wilson, D., 2009. "Beggar thy Neighbor? The In-State, Out-of-State and Aggregate Effects of R&D Tax Credits". *Review of Economics and Statistics* 91, 431-436.

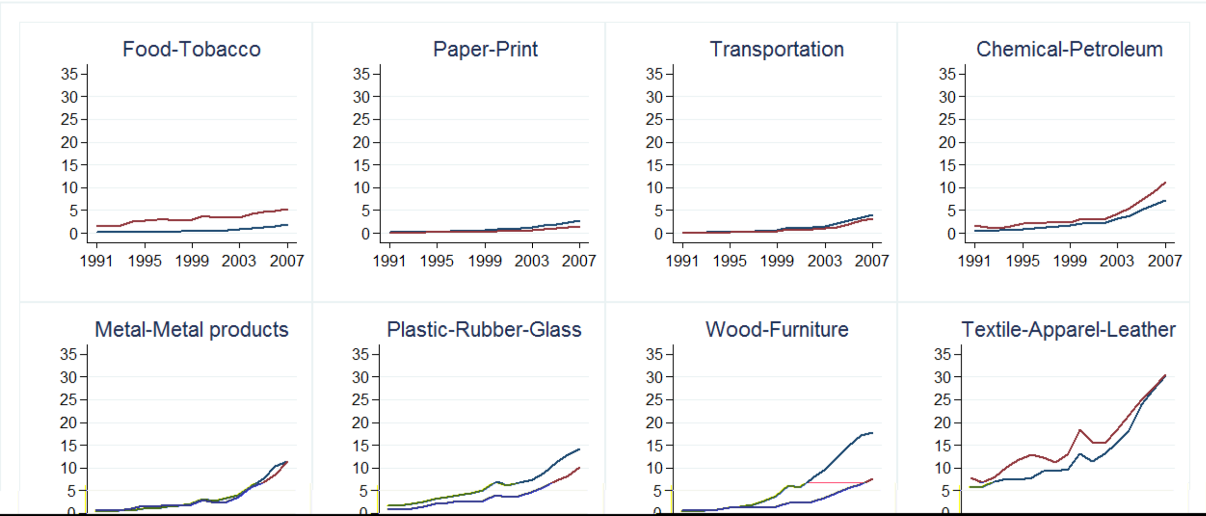
Xu, J., 2012. "Profitability and capital structure: Evidence from import penetration". *Journal of Financial Economics* 106, 427-446.

Figure 1a: Manufacturing Imports from China to the US and to Other High-Income Countries




The figure plots total manufacturing imports (in 2007 billion USD) from China to the US (blue line) and to a group of eight other high-income countries (red line; Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland).

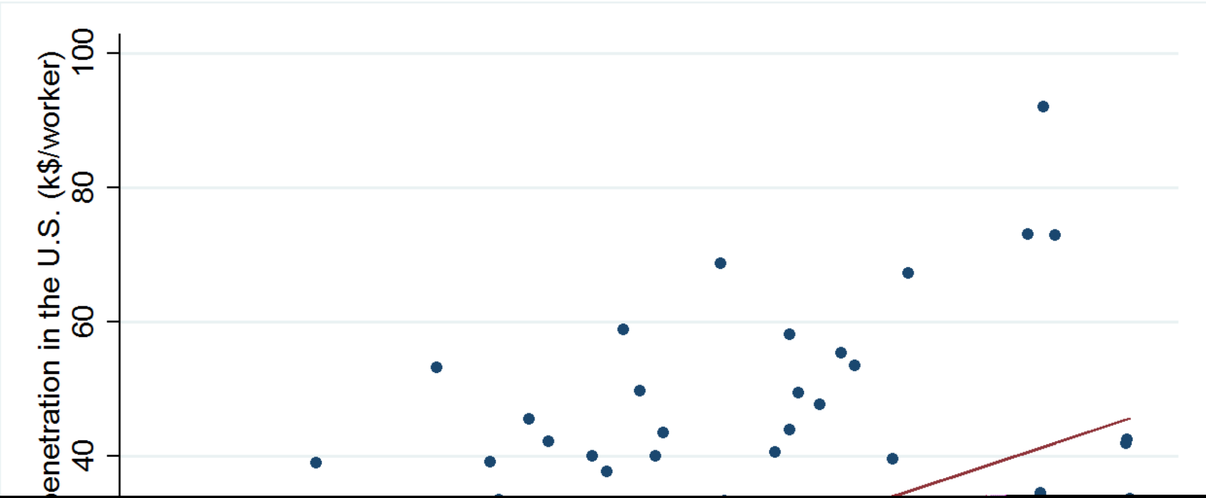
Figure 1b: Manufacturing Imports from China to the US and to Other High-Income Countries




[redacted]

The figure plots China's import penetration in the US (blue line) and in a group of eight other high-income countries (red line; Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) by broad manufacturing industry. For each broad industry, import penetration is measured as imports (in 2007 k$) from China in the industry divided by industry employment in 1990.

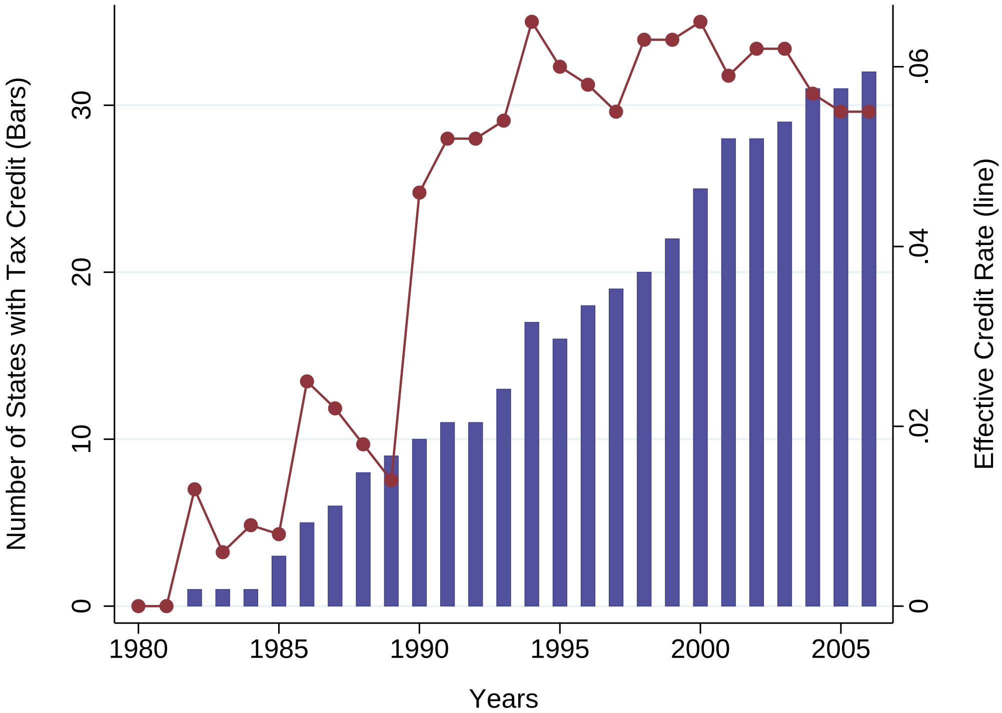
Figure 1c: Change in China's import Penetration by Industry in the US vs. Other High-Income Countries




[redacted]

The figure plots the 1991–2007 change in China's import penetration in the US on the *y*-axis against China's import penetration in a group of eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) on the *x*-axis. Each dot represents a manufacturing industry. For each inddHiustry, change in import penetration is measured as the chandHige in imports (in 2007 k$) from China in the industry from 1991 to 2007 divided by industry employment in 1990.

Figure 2: Number and Average Value of State R&D Tax Credits in the United States




Blue bars represent the number of US states with R&D tax credits (left scale). Red dots plot average effective R&D tax credit rate across the 50 states (right scale).

Table 1: Change in Import China Penetration by Broad Industry

| Two-digit SIC industries | | 1991-2007 change in China import penetration (k$/worker) |
|---|---|---|
| 31 | Leather and leather products | 103.5 |
| 39 | Miscellaneous manufacturing industries | 82.2 |
| 36 | Electronic and other electronic equipment | 50.4 |
| 25 | Furniture and xtures | 34.0 |
| 35 | Industrial machinery and equipment | 33.0 |
| 23 | Apparel and other textile products | 28.0 |
| 33 | Primary metal industries | 13.8 |
| 30 | Rubber and miscellaneous plastics products | 13.4 |
| 32 | Stone, clay, and glass products | 10.9 |
| 34 | Fabricated metal products | 9.6 |
| 38 | Instruments and related products | 7.8 |
| 28 | Chemicals and allied products | 7.1 |
| 24 | Lumber and wood products | 5.6 |
| 26 | Paper and allied products | 5.3 |
| 37 | Transportation equipment | 3.9 |
| 22 | Textile mill products | 2.9 |
| 29 | Petroleum and coal products | 2.6 |
| 20 | Food and kindred products | 1.8 |
| 27 | Printing and publishing | 1.5 |
| 21 | Tobacco products | 0.2 |

The table ranks two-digit manufacturing industries in descending order of change in China's import penetration in the US. For each industry, change in import penetration is measured as the change in imports (in 2007 k$) from China in the industry from 1991 to 2007 divided by industry employment in 1990.

Table 2: Instrument for Import Penetration: First Stage Regression

| | Import penetration in the US |
|---|---|
| Import penetration in other high-income countries | 1.36*** |
| | (0.12) |
| Industry FE | Yes |
| Year FE | Yes |
| Observations | 2,885 |
| Adjusted-R2 | .94 |

The sample is four-digit industries over 1991–2007. We estimate a linear regression model where the dependent variable is China's import penetration in the US at the industry-year level. The dependent variable is China's import penetration a group of eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Import penetration is measured as imports (in 2007 k$) from China divided by industry employment in 1990. The regression include industry fixed effects and year fixed effects. Standard errors are clustered by industry and year. *** means statistically different from zero at the 1% level of significance.

Table 3: Instrument for R&D: First Stage Regression

| | R&D |
|---|---|
| User cost of R&D | -0.11*** |
| | (0.03) |
| Firm FE | Yes |
| Year FE | Yes |
| Observations | 55,541 |
| Adjusted-R2 | .75 |

The sample is US manufacturing firms over 1973–2006 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is R&D expenses over total assets. User cost of R&D at the firm-year level is calculated as the weighted-average of state-year-specific user of cost of R&D to which the firm is eligible, where the weights are based on the 10-year moving average of the share of firm's inventors located in each state and the user cost of R&D at the state-year level is from Wilson (2009) and calculated using Hall-Jorgenson formula as explained in Footnote 10. The regression include firm fixed effects and year fixed effects. Standard errors are clustered by industry. *** means statistically different from zero at the 1% level of significance.

Table 4: Summary Statistics

| | Mean | Std.Dev. | 25th | 50th | 75th | N |
|---|---|---|---|---|---|---|
| Sales growth | .12 | .34 | -.032 | .079 | .23 | 24,753 |
| ROA | .023 | .37 | -.0095 | .12 | .2 | 25,424 |
| Capex/PPE | .38 | .53 | .12 | .22 | .41 | 25,210 |
| Employment growth | .063 | .26 | -.055 | .026 | .14 | 24,015 |
| Import penetration (M$/worker) | .0080 | .022 | .0000 | .0012 | .0056 | 24,598 |
| R&D stock/Total assets | .38 | .62 | .042 | .17 | .43 | 25,494 |
| Product di erentiation | .973 | .016 | .968 | .977 | .984 | 16,387 |

The table reports summary statistics for the sample of US manufacturing firms over 1991-2007 that we use in our second stage regressions.

Table 5: Geographic Distribution of R&D by Industry

| Industry-by-industry ranking of states | Share of industry R&D in the state |
|---|---|
| Top state | 32.9% |
| 2nd state | 17.2% |
| 3rd state | 11.3% |
| 4th state | 8.2% |
| 5th state | 6.1% |
| 6th state | 4.7% |
| 7th state | 3.6% |
| 8th state | 2.9% |
| 9th state | 2.4% |
| 10th state | 2.0% |

For each industry, we rank states based on the share of R&D conducted in the state. The table reports the average share for each rank across all industries. Reading: The average industry has 32.9% of its R&D activity in the top state, 17.2% in the second state, and so on.

Table 6: R&D Capital in Import-Competing Industries: Effect on Sales Growth

| | Sales growth | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Import penetration | -0.84*** | -1.30*** | | |
| | (0.21) | (0.24) | | |
| Import penetration × R&D stock | | 0.83** | 1.07*** | 1.11*** |
| | | (0.33) | (0.40) | (0.39) |
| Assets | 0.01 | 0.03*** | 0.03*** | 0.03*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | -0.20*** | -0.23*** | -0.23*** | -0.23*** |
| | (0.01) | (0.01) | (0.02) | (0.02) |
| R&D stock | | 0.07*** | 0.07*** | 0.07*** |
| | | (0.02) | (0.03) | (0.03) |
| Import penetration × Age | | | | -0.67 |
| | | | | (0.46) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | { | { |
| Industry-Year FE | No | No | Yes | Yes |
| Observations | 23,907 | 23,907 | 23,907 | 23,907 |
| R2 | .24 | .24 | .34 | .34 |

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is sales growth. All specifications include firm fixed effects, year fixed effects in columns (1) and (2), industry-by-year fixed effects in columns (3) and (4), and log of total assets and log of firm age as controls. *ImporPenetraton* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are bootstrapped within industry-year clusters and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 7: R&D Capital in Import-Competing Industries: Effect on Profitability

| | ROA | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Import penetration | -0.49** | -1.06*** | | |
| | (0.20) | (0.22) | | |
| Import penetration × R&D stock | | 1.13** | 1.41*** | 1.42*** |
| | | (0.47) | (0.54) | (0.54) |
| Assets | 0.06*** | 0.01 | 0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | 0.06*** | 0.13*** | 0.15*** | 0.15*** |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| R&D stock | | -0.19*** | -0.21*** | -0.21*** |
| | | (0.02) | (0.03) | (0.03) |
| Import penetration × Age | | | | -0.20 |
| | | | | (0.34) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | { | { |
| Industry-Year FE | No | No | Yes | Yes |
| Observations | 24,533 | 24,533 | 24,533 | 24,533 |
| R2 | .68 | .68 | .72 | .72 |

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is ROA. All specifications include firm fixed effects, year fixed effects in columns (1) and (2), industry-by-year fixed effects in columns (3) and (4), and log of total assets and log of firm age as controls. *ImportPenetration* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are bootstrapped within industry-year clusters and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 8: Product Differentiation Becomes More Important (Channel 1)

| | Di erentiation | | Sales growth | | ROA | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| R&D stock | .0015** | .0011* | | | | |
| | (.00067) | (.00062) | | | | |
| Import penetration | | | -16** | | -9.7*** | |
| | | | (7.2) | | (3.7) | |
| Import penetration × Di erentiation(t-1) | | | 16** | 15* | 9.4** | 12*** |
| | | | (7.4) | (9.2) | (3.9) | (4.5) |
| Assets | -.00043** | -.00044** | .016 | .015 | .065*** | .07*** |
| | (.00022) | (.00021) | (.012) | (.012) | (.0088) | (.0096) |
| Age | .00031 | .00072 | -.21*** | -.2*** | .027* | .027 |
| | (.00047) | (.00046) | (.031) | (.031) | (.015) | (.016) |
| Di erentiation(t-1) | | | -.51 | -.73 | .02 | -.069 |
| | | | (.37) | (.46) | (.17) | (.21) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | { | Yes | { | Yes | { |
| Industry-Year FE | No | Yes | No | Yes | No | Yes |
| Observations | 15,637 | 15,637 | 12,767 | 12,767 | 12,767 | 12,767 |
| R2 | 0.83 | 0.84 | 0.25 | 0.35 | 0.74 | 0.77 |

The sample is US manufacturing firms over 1996–2011 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is average product differentiation (one minus the Hoberg and Phillips (2015) product similarity index) from US peers in columns (1) and (2), sales growth in columns (3) and (4) and ROA in columns (5) and (6). All specifications include firm fixed effects, year fixed effects, and log of total assets and log of firm age as controls. Specifications in columns (2), (4) and (6) also include industry-by-year fixed effects. *ImporPenetraton* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 9: Product Differentiation Increases (Channel 2)

| | Product di erentiation | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Import penetration | .035* | .024 | | |
| | (.02) | (.018) | | |
| Import penetration × R&D stock | | .026 | .023** | .023** |
| | | (.017) | (.011) | (.011) |
| Assets | -.00082*** | -.00021 | -.00029 | -.00029 |
| | (.00026) | (.00034) | (.00034) | (.00034) |
| Age | .001** | .00034 | .00058 | .0004 |
| | (.00052) | (.00058) | (.00059) | (.00059) |
| R&D stock | | .0018** | .00087 | .00086 |
| | | (.00088) | (.00073) | (.00073) |
| Import penetration × Age | | | | -.019 |
| | | | | (.022) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | { | { |
| Industry-Year FE | No | No | Yes | Yes |
| Observations | 15,896 | 15,896 | 15,896 | 15,896 |
| R2 | 0.78 | 0.78 | 0.83 | 0.83 |

The sample is US manufacturing firms over 1996–2011 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is average product differentiation (one minus the Hoberg and Phillips (2015) product similarity index) from US peers. All specifications include firm fixed effects, year fixed effects in columns (1) and (2), industry-by-year fixed effects in columns (3) and (4), and log of total assets and log of firm age as controls. *ImporPenetraton* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 10: R&D Matters More in Industries with High Differentiation

| | Sales growth | | ROA | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Import penetration × R&D stock | 0.25 | 0.48 | 0.01 | 0.21 |
| | (0.35) | (0.40) | (0.62) | (0.64) |
| Import penetration × R&D stock × Industry differentiation | 1.55* | 1.88** | 2.43*** | 3.13*** |
| | (0.90) | (0.97) | (0.92) | (1.00) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | { | Yes | { |
| Industry-Year FE | No | Yes | No | Yes |
| Observations | 23,074 | 23,074 | 23,710 | 23,710 |
| R2 | 0.25 | 0.33 | 0.69 | 0.73 |

The sample is US manufacturing firms over 1996–2011 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is sales growth in columns (1) and (2) and ROA in columns (3) and (4). All specifications include firm fixed effects, year fixed effects, and log of total assets and log of firm age as controls. Specifications in columns (2) and (4) also include industry-by-year fixed effects. *ImportPenetration* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. *IndustryDifferentiation* is a dummy variable equal to one if the average product differentiation (one minus the Hoberg and Phillips (2015) product similarity index) of the industry is above the median of the sample distribution. All specifications include all the double and triple interactions between these three variables; non-interacted terms are also included but not reported. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 11: R&D Capital in Import-Competing Industries: Effect on Capital Expenditures

| | Capital expenditures | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Import penetration | -0.74* | -1.65*** | | |
| | (0.39) | (0.45) | | |
| Import penetration × R&D stock | | 1.67*** | 1.77*** | 1.79*** |
| | | (0.60) | (0.68) | (0.67) |
| Assets | 0.03*** | 0.04*** | 0.05*** | 0.05*** |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| Age | -0.41*** | -0.42*** | -0.44*** | -0.44*** |
| | (0.02) | (0.03) | (0.03) | (0.03) |
| R&D stock | | 0.01 | 0.02 | 0.02 |
| | | (0.04) | (0.04) | (0.04) |
| Import penetration × Age | | | | -0.33 |
| | | | | (0.82) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | { | { |
| Industry-Year FE | No | No | Yes | Yes |
| Observations | 24,321 | 24,321 | 24,321 | 24,321 |
| R2 | .34 | .34 | .41 | .41 |

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is capital expenditures divided by lagged property, plant, and equipment. All specifications include firm fixed effects, year fixed effects in columns (1) and (2), industry-by-year fixed effects in columns (3) and (4), and log of total assets and log of firm age as controls. *ImporPenetraton* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 12: R&D Capital in Import-Competing Industries: Effect on Employment

| | Employment growth | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Import penetration | -0.18 | -0.63** | | |
| | (0.21) | (0.28) | | |
| Import penetration × R&D stock | | 0.77** | 0.88** | 0.92** |
| | | (0.32) | (0.39) | (0.37) |
| Assets | 0.02*** | 0.06*** | 0.07*** | 0.07*** |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | -0.20*** | -0.25*** | -0.24*** | -0.25*** |
| | (0.01) | (0.01) | (0.02) | (0.02) |
| R&D stock | | 0.13*** | 0.13*** | 0.13*** |
| | | (0.02) | (0.02) | (0.02) |
| Import penetration × Age | | | | -0.81* |
| | | | | (0.47) |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | { | { |
| Industry-Year FE | No | No | Yes | Yes |
| Observations | 23,197 | 23,197 | 23,197 | 23,197 |
| R2 | .24 | .25 | .36 | .36 |

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is employment growth. All specifications include firm fixed effects, year fixed effects in columns (1) and (2), industry-by-year fixed effects in columns (3) and (4), and log of total assets and log of firm age as controls. *ImporPenetraton* is industry-year-level import penetration from China in the US instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 13: Alternative Instrument for Import Competition

| | Sales growth | | ROA | | Capital expenditures | | Employment growth | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| NTR Gap × Post | -0.12** | | -0.10*** | | -0.14** | | -0.05 | |
| | (0.06) | | (0.03) | | (0.06) | | (0.04) | |
| NTR Gap × Post × R&D stock | | 0.17*** | | 0.09** | | 0.31*** | | 0.15*** |
| | | (0.05) | | (0.04) | | (0.06) | | (0.04) |
| Assets | 0.03*** | 0.03*** | 0.01 | 0.00 | 0.04*** | 0.04*** | 0.06*** | 0.07*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | -0.24*** | -0.23*** | 0.06*** | 0.08*** | -0.33*** | -0.32*** | -0.24*** | -0.22*** |
| | (0.01) | (0.02) | (0.01) | (0.01) | (0.02) | (0.02) | (0.01) | (0.01) |
| R&D stock | 0.08*** | 0.05* | -0.14*** | -0.18*** | 0.03 | -0.03 | 0.15*** | 0.12*** |
| | (0.02) | (0.03) | (0.02) | (0.02) | (0.03) | (0.03) | (0.02) | (0.02) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | { | Yes | { | Yes | { | Yes | { |
| Industry-Year FE | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 23,471 | 23,471 | 23,471 | 23,471 | 23,471 | 23,471 | 22,234 | 22,234 |
| R2 | 0.24 | 0.33 | 0.71 | 0.75 | 0.35 | 0.42 | 0.24 | 0.34 |

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate a linear regression model on a firm-year panel. All specifications include firm fixed effects, year fixed effects, and log of total assets and log of firm age as controls. Specifications in even-numbered columns also include industry-by-year fixed effects. *NTRGap* is the difference between NTR tariff and non-NTR tariff at the industry level. *Pot* is a dummy equal to one from year 2000 onwards. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 14: Controlling for Import Competition in Input Markets

| | Sales growth | | | ROA | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Net import penetration × R&D stock | 1.31*** | | | 1.74*** | | |
| | (0.47) | | | (0.62) | | |
| Final market import penetration | | -0.84*** | | | -0.71*** | |
| | | (0.24) | | | (0.27) | |
| Input market import penetration | | 0.24 | | | 1.65* | |
| | | (0.93) | | | (1.02) | |
| Final good import penetration | | | 1.20** | | | 1.67** |
| × R&D stock | | | (0.53) | | | (0.69) |
| Input market import penetration | | | -0.24 | | | -1.23 |
| × R&D stock | | | (2.14) | | | (2.69) |
| Assets | 0.03*** | 0.01 | 0.03*** | 0.01 | 0.06*** | 0.01 |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Age | -0.23*** | -0.20*** | -0.23*** | 0.15*** | 0.06*** | 0.15*** |
| | (0.02) | (0.01) | (0.02) | (0.02) | (0.01) | (0.02) |
| R&D Stock | 0.08*** | | 0.07*** | -0.21*** | | -0.21*** |
| | (0.03) | | (0.03) | (0.03) | | (0.03) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | { | Yes | { | { | Yes | { |
| Industry-Year FE | Yes | No | Yes | Yes | No | Yes |
| Observations | 23,843 | 23,843 | 23,843 | 24,461 | 24,461 | 24,461 |
| R2 | .33 | .24 | .33 | .72 | .68 | .72 |

The sample is US manufacturing firms over 1991–2007 from Compustat. In columns (1) and (4), we estimate the same regression as in columns (4) of Tables 6 and 7 except that we now use input-adjusted import competition defined as import competition in the final market minus import competition in intermediate input markets. In columns (2) and (5), we estimate the same regression as in columns (1) of Tables 6 and 7 except that we now use both import competition in the final market and import competition in intermediate input markets. In columns (3) and (6), we estimate the same regression as in columns (4) of Tables 6 and 7 except that we now use both import competition in the final market and import competition in intermediate input markets. Standard errors are bootstrapped within industry-year clusters and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.