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

Johan Hombert† Adrien Matray‡

Abstract

We study whether R&D-intensive firms 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 profitability, these effects are significantly smaller for firms with a larger stock of R&D (by about half when moving from the bottom quartile to the top quartile of R&D). As a result, while firms in import-competing industries cut capital expenditures and employment, R&D-intensive firms downsize considerably less. Finally, we provide evidence that these effects are explained by R&D allowing firms to increase product differentiation.

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†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 the manufacturing sector in high-income economies. Autor, Dorn and Hanson (2013) estimate that the surge in China's exports over the last two decades is responsible for as much as 25% of the aggregate decline of US manufacturing employment.

In this context, innovation is often viewed as a panacea against import competition from low-wage countries. Because wage differences will take time to adjust, so the argument goes, competing on costs is bound to fail. The best hope for firms in high-income countries is to upgrade the quality of their products to differentiate them from low-wage countries' exports (e.g., Leamer (2007)). Innovation plays a crucial role as it allows firms to climb the quality ladder, increase product differentiation, and therefore escape competition (Sutton (1991), Hoberg and Phillips (2015)). This view has largely influenced corporate and public policies: import competition has induced firms to invest in technological change (Bloom, Draca and Van Reenen (2015)) and in product quality upgrading (Amiti and Khandelwal (2013)), while governments allocate large amounts of taxpayers money to subsidize R&D.[1] There is, however, little evidence that R&D does allow firms to better escape import competition from low-wage countries.

On the theory side, predictions regarding whether competition hurts relatively more innovative or non-innovative firms are actually ambiguous. Schumpeter (1943) argues that competition reduces innovation rents and shrinks the profit differential between innovative and non-innovative firms. Accordingly, the Schumpeterian logic predicts that the benefits from innovating are reduced when competition increases. On the other hand, Arrow (1962) argues that market power allows even non-innovative firms to sell their products and earn large profits, therefore bringing to market new products will only crowd out their existing products and have little impact on their profits.

[1] In 2013, 27 of the 34 OECD countries and a number of non-OECD economies provide fiscal incentives for R&D (OECD (2014)).

Conversely, when product market competition is fierce, only innovative firms are able to escape the competitive pressure and generate profits. Therefore, the Arrow effect, which Aghion et al. (2005) also call the escape-competition effect, predicts that the benefits from innovating become larger when competition increases.

In this paper, we test whether innovation allows US manufacturing firms to escape import competition from China. Identifying the causal effect of firms' R&D capital stock on their resilience to trade shocks is challenging, because both import competition and R&D investment are endogenous variables. We thus need to instrument both for import competition and for R&D.

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 instrument for China's import penetration in the US at the industry level using China's import penetration in other high-income countries (see for instance Autor, Dorn and Hanson (2013) for a similar approach). 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, firms' R&D decisions are potentially endogenous to their productivity and to the 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 variation across states and over time of the price of R&D, which in turn generates exogenous variation in firm R&D stock (see Bloom, Schankerman and Van Reenen (2013) for a similar approach). With these two instruments in hand, we estimate

how firms are affected by (exogenous) import competition depending on their (exogenous) R&D stock. 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 or changes in consumer demand.

We first show that China' import penetration has sizable adverse effects on the unconditional (i.e., independently from their 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 across firms, 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 (e.g., Bernard, Jensen and Schott (2006)).

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 invested more in R&D are significantly less affected by trade shocks. Going from the 25th percentile to the 75th 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). These results suggest that firms that have climbed the quality ladder and are able to bring to market more innovative products are better armed to face import competition from low-wage countries.

Third, we investigate whether firms adjust their factors of production in response to trade shocks. In the face of declining sales and profitability, we expect firms to downsize. The factors of production we consider are fixed capital and labor. We find that, on average across firms, a one standard deviation 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

25th percentile to the 75th 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 25th 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 75th percentile of the R&D distribution experience only a modest (and statistically insignificant) reduction in employment growth.

As discussed at the beginning of the introduction, the Schumpeterian effect and the Arrow's escape-competition effect imply that the relationship between innovation and resilience to trade shocks can go either way. The model of Aghion et al. (2005) encompasses both effects and predicts that the return to innovation should be an inverse U-shaped function of product market competition. Intuitively, when there is no competition innovation is worthless because profits are large regardless of the innovation level (the escape-competition effect dominates). On the contrary, when competitive is very strong innovation makes no difference because profits are close to zero regardless of the innovation effort (the Schumpeterian effect dominates). Our results that the performance differential between innovative and less-innovative firms increases with import competition suggest that, on average, the escape-competition effect dominates. To further investigate whether this positive linear relationship conceals a non-monotonic effect, we estimate a model where return to R&D is a quadratic function of import competition. We find that the squared term is negative and statistically significant, which implies that return to R&D is an inverse U-shaped function of import competition, as in the model of Aghion et al. (2005). However, returns to R&D become decreasing in import competition only when import competition reaches the 99th percentile of the sample distribution. Therefore, the Arrow's escape-competition effect (almost) always dominates and R&D is more valuable when import competition is stronger.

Finally, we test the channel through which more innovative firms better escape import compe-

tition. The hypothesis is that R&D allows firms to differentiate their products and thus reduce the competitive pressure (Sutton (1991)). We test this idea using Hoberg and Phillips' (2015) text-based measure of product similarity vis-a-vis peer firms. We use two firm-level proxies of product differentiation from Chinese competitors. The first proxy is differentiation from US competitors. The idea is to capture a firm's effort to develop unique products and to bring to market products that will be less subject to Chinese competition. Our second proxy is the average exposure to Chinese imports of a firm's closest neighbors in the product market space. This second proxy measures whether a firm's products are more similar to the products of other US firms that are exposed to China's import competition or similar to products of other US firms that less exposed to China's import competition. Based on these measures, we find that firms with a higher level of R&D react to import competition by increasing the differentiation of their products in a way that make their products more unique and less similar to the products most exposed by Chinese competition.

Our paper makes several contributions to the literature. First, it 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)), employment (Autor, Dorn and Hanson (2013)), wages (Autor et al. (2014)), cost of debt (Valta (2012)), leverage (Xu (2012)), and capital expenditure (Fresard and Valta (2014)). There is, however, little evidence on 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.[2] 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

[2]Using aggregate data, Khandelwal (2010) also shows that the negative effect of low-income country imports is stronger in industries characterized by short-quality ladder (i.e., products are of similar quality). Amore and Zaldokas (2014) show that firms with better corporate governance fared better when import competition from Canada increased.

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 product market competition and innovation. Aghion et al. (2005) study how the equilibrium level of innovation depends on competition. In the context of international trade, Bloom, Draca and Van Reenen (2015) show that firms innovate more in response to increased import competition.[3] By a revealed preference argument, this line of research provides indirect evidence on how the benefits from innovating depend on competition. Our approach is different: we take firm innovation as exogenously given by our instrument and estimate directly how the effect of R&D on firm performance depends on competition. This strand of literature also stresses the need for instrumenting for R&D since it is endogenously chosen by firms in response to import competition shocks.[4] Our paper follows this road and uses tax policy changes to instrument for R&D.

The rest of the paper is organized as follows. Section 2 describes the empirical strategy and the data. Section 3 presents the results. Section 4 provides robustness checks. Section 5 concludes.

2 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. Towards this aim, we follow a difference-in-difference approach and compare the performance of firms with a high stock of R&D capital relative to firms with a low stock of R&D capital, 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 empirical challenge is to find exogenous variations in the amount invested in R&D at the firm level and in China's import penetration at the industry level. In Section 2.1, we describe how we instrument

[3] Amiti and Khandelwal (2013) study how quality upgrading is affected by import competition.

[4] Bloom, Draca and Van Reenen (2015) study how firm performance depends on (endogenous) firm-level R&D but have no instrument at their disposal.

for China's import penetration in the US using China's import penetration in other high-income countries. In Section 2.2, we explain how we instrument for firm-level R&D capital stock using tax-induced changes to the user cost of R&D capital. We present the econometric specification in Section 2.3.

2.1 Instrument for Import Penetration

A possible concern when using imports from China to the US as a trade shock for the US industry is that US—rather than Chinese—productivity shocks may be driving import growth to the US. If, for instance, the US experiences poor productivity growth in textile, imports of Chinese textile to the US will increase, thus creating a negative relation between the performance of US firms and US imports from China.

To isolate the component of import growth to the US coming from Chinese productivity and trade cost shocks, we follow Autor, Dorn et Hanson (2013) and instrument imports from China to the US using imports from China to other high-income markets. This IV 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 the UN Comtrade Database. 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 4-digit SIC level for the years 1991 to 2007.[5] Figure 1 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 developed countries is consistent with our assumption that the surge in China's exports is primarily due to forces exogenous to the US economy.

[INSERT FIGURE 1 ABOUT HERE]

We define China import penetration in the US at the industry-year level as imports 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. Table 1 reports the 1991–2007 change in import penetration for each broad (2-digit SIC) manufacturing industry. Imports from China have grown strongly in textile, electronic, furniture, industrial equipment, while tobacco, printing, food, and petroleum have not faced increased Chinese competition.

[INSERT TABLE 1 ABOUT HERE]

We define similarly China import penetration in the other high-income countries. Figure 2 plots the 1991–2007 change in import penetration in the US against import penetration in the

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

other high-income countries for each 4-digit industry. Consistent with the assumption that the surge in China's exports originates mainly from rising Chinese productivity, Figure 2 reveals that import penetration across industries is highly correlated between high-income economies.

[INSERT FIGURE 2 ABOUT HERE]

To construct the predicted value for import penetration in the US, we regress at the industry-year level China's import penetration in the US on China's import penetration in the 8 other high-income countries and a full set of industry and year fixed effects. 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 values 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 $ImportPenetration$.

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.

2.2 Instrument for R&D Capital Stock

To generate exogenous variations in R&D at the firm level, we follow Bloom, Schankerman and Van Reenen (2013) and 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 3 illustrates the staggered timing of changes in tax credit rates across US states and over 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 over 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 Section 4.1 where we look for, and find no statistical evidence that changes in economic conditions (such as lagged changes in R&D or GDP) predict R&D policies.

We use the state-by-year tax-induced user cost of R&D capital (ρ_{st}) for the years 1982 to 2006 from Wilson (2009).[6] 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.[7] We obtain patent information using the NBER patent file (Hall, Jaffe and

[6] 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, τ_{st} and τ_t^f are the state and federal corporation income tax rates, r_t is the real interest rate, and δ is the depreciation rate of R&D capital.

[7] R&D expenses can be offset against state-level corporation tax liabilities. State-level corporation tax liabilities are calculated on total firm profits allocated across states according to a weighted combination of the location of firm sales, employment, and property. Hence, any firm 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 offsetting R&D tax credit. Hence, inventor location provides a good proxy for eligibility for state-level R&D tax credits.

Trajtenberg (2001)) and inventor information using the Harvard Business School patent database (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 $\rho_{it} = \sum_s w_{ist}\rho_{st}$. 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 alleviate 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 cost of R&D (ρ_{it}) and firm and year fixed effects. The coefficient on ρ_{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).

We then 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).[8] We initialize the R&D capital stock at zero in the first year the firm appears in Compustat or in 1982, whichever comes last.[9] 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 may threaten our identification strategy if firms of different age react differently to import competition. To account for this potential confounding effect, we will control for firm age interacted with import penetration in the second stage regression.

2.3 Econometric Specification

The sample period for the second stage is 1991–2007, which corresponds to the rise of China illustrated in Figure 1. Table 2 reports summary statistics on the main variables used in the regressions for our sample of manufacturing firms. All variables that can 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 2 ABOUT HERE]

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

$$Y_{ijt} = \alpha + \beta \cdot ImportPenetration_{jt} + \gamma \cdot R\&DStock_{ijt} + \delta \cdot ImportPenetration_{jt} \times R\&DStock_{ijt} + Controls_{ijt} + \text{Firm FE} + \text{Industry-Year FE} + \varepsilon_{ijt}, \quad (1)$$

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

[9] Since states started to offer R&D tax credit from 1982 on, we can construct the instrumented R&D flow only starting in 1982 even for firms that were already in Compustat prior to 1982.

where Y_{ijt} is an outcome variable for firm i operating in sector j in year t, $ImportPenetration_{jt}$ is predicted import penetration from China at the industry-year level where we use the historical 4-digit SIC code to identify the industry of a firm,[10] and $R\&DStock_{ijt}$ 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 δ. $\delta > 0$ 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. Since both R&D capital stock and import penetration are instrumented, δ can be interpreted in a causal way as long as the exclusion restriction is satisfied. Nevertheless, we include firm fixed effects and industry-by-year fixed effects.

Firm fixed effects absorb all time-invariant determinants of the outcome variable at the firm level. If, for instance, the R&D policy is endogenous and states populated by more productive firms in import-competing industries offer more generous R&D tax credit, then firms in 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.

Industry-by-year fixed effects ensure that δ 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-

[10]When the historical SIC code is missing for a firm in a given year, we backfill 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 backfill and when we use the current main SIC code.

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.[11] 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 3. 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 our specification with industry-year fixed effects.[12]

[INSERT TABLE 3 ABOUT HERE]

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.[13]

[11] This share is computed using the weights we constructed in Section 2.2 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.

[12] A related issue is that California is the top state for 28% of industries. To check that our results are not driven by Californian firms, we re-run our regressions after excluding firms that have more than 50% of their R&D activity in California and obtain similar results (see Section 4.2).

[13] The bootstrap has been done as follows. We first draw a random sample with replacement within the sample of industry-years used to predict imports; we run the first-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 firm-years used to predict R&D; we run the first-stage regression for R&D; and we generate predicted R&D expenditures that we use to construct predicted R&D capital stock. We then draw a random sample with replacement within the sample of firm-years used to estimate the second-stage regression (1); to correct for the correlation structure of this sample at the industry-year level, this random draw is made at the industry-year level, and not at the firm-year level (i.e., we randomly draw with replacement an industry-year and then select all the firms within this industry-year); we finally run our second-stage regression (1) on this sample. We repeat this procedure 500 times, and the standard errors we report correspond to the empirical distribution of the coefficients estimated.

3 Results

3.1 Firm Performance

[INSERT TABLE 4 ABOUT HERE]

We first estimate equation (1) using sales growth as the dependent variable and report results in Table 4. To begin with, we only include our predicted variable of 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.[14] 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)).

Then, to assess whether a larger stock of R&D capital mitigates this negative effect of import competition on sales growth, we interact import penetration with the 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 25th percentile to the 75th 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 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 25th percentile to the 75th 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

[14] Imports are in million USD per worker in Table 4. The effect of a one standard deviation increase in import penetration is thus $0.022 \times (-0.84) = -0.018$ change in sales growth.

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.

[INSERT TABLE 5 ABOUT HERE]

We turn to the effect on profitability in Table 5. 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 25th percentile to the 75th 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. The next section investigates the real effects on capital expenditures and employment.

3.2 Capital Expenditures and Employment

We ask whether firms adjust their factors of production in response to trade shocks and how this adjustment depends on firms' stock of R&D. We hypothesize that the average firm will respond to slower growth and lower profitability by downsizing but that more innovative firms will downsize less because they are less exposed to import competition. The two factors of production we consider are fixed capital and labor.

[INSERT TABLE 6 ABOUT HERE]

In Table 6, we estimate equation (1) 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 (2014). 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 4 and 5), 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 25th percentile to the 75th 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 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 7 ABOUT HERE]

In Table 7, we estimate equation (1) 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 25th percentile of the R&D stock distribution reduces employment growth by 0.7 percentage points (statistically significant at 5%) more than firms at the 75th 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 percentages 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.

3.3 Arrow vs. Schumpeter

Theory makes ambiguous predictions regarding the effect of innovation on the resilience to trade shocks. On the one hand, the Schumpeterian (1943) argument is that product market competition decreases post-innovation rents, which reduces the profit differential between innovative and less innovative firms. Conversely, market power protects post-innovation rents. Therefore, the increase in performance brought about by innovation decreases when competition increases. On the other hand, Arrow (1962) argues that in poorly competitive markets even non-innovative firms are able to sell their products and earn comfortable profits. For these firms, bringing to market new products will crowd out the sales of their existing products with little effect on their overall profits.[15] Conversely, when competition is fierce, only innovative firms are able to escape the competitive pressure and make profits. Aghion et al. (2005) refer to the Arrow effect effect as the escape-competition effect. It predicts that the increase in performance brought about by innovation increases when competition increases. The model of Aghion et al. (2005) encompasses these two effects and delivers the prediction that the return to innovation is an inverse U-shaped function of competition. The intuition is that in the extreme cases of very weak competition or very strong competition innovation makes little difference, in the former case because profits are large no matter what, in the latter case because profits are close to zero no matter what.

Our results in Section 3.1 show that the performance differential between innovative firms and less innovative firms increases with the degree of import competition. To test whether this average positive relation conceals a non-monotonic relation, we estimate a specification where the return from innovating is a quadratic function of import competition. To do so, we interact the predicted R&D stock with both predicted import penetration and its square.[16] We adopt our preferred

[15] Arrow (1962) called this effect the "displacement effect."

[16] We have also done this analysis using the linear prediction of squared import penetration (instead of taking the square of the linear prediction of import penetration), where in the first stage we predict both import penetration in the US and squared import penetration in the US using import penetration in the other 8 high-income countries and squared import penetration in the other 8 high-income countries. Results are very similar with this alternative specification.

specification with firm and industry-year fixed effects as well as firm age interacted with import penetration and squared import penetration to control for the correlation between firm age and instrumented R&D stock, as in columns (4) of Tables 4 to 7.

[INSERT TABLE 8 ABOUT HERE]

In Table 8, we estimate this quadratic specification on the dependent variables we have considered in Sections 3.1 and 3.2: sales growth, ROA, capital expenditures, and employment growth. The interaction between R&D and imports is positive and significant while the interaction between R&D and squared imports is negative (and significant for three out of four variables and the fourth one has a p-value of 0.14). The returns to R&D thus seem to be an inverse U-shaped function of import competition, like in Aghion et al. (2005). However, this function becomes decreasing only for values of import competition that lie on the fringe of the sample distribution. Using sales growth or ROA as the performance measure, the returns to R&D become negative when import penetration goes above 100 k$/worker, which corresponds to the 99th percentile of the sample distribution. When we look at the effect on capital expenditures or employment growth, the returns to R&D turn decreasing in import penetration above 80 k$/worker, which is at the 98th percentile of the sample distribution. Hence, the Arrow's escape-competition effect (almost) always dominates and R&D is all the more valuable when import competition is stronger.

3.4 Channel: Product Differentiation

To study if R&D allows firms to differentiate more when facing greater import competition, 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 0 to 1 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 1 and more differentiated if the score is closer to 0. To ease the reading, we use one minus the similarity score and refer to this variable as product differentiation between each pair of firms.

Ideally, we would like to measure differentiation of US manufacturing firms relative to Chinese competitors. We cannot do so because the product similarity score is defined only for pairs of US firms. To overcome this limitation of the data, we follow two complementary approaches to proxy for differentiation from Chinese products. First, we use differentiation from US competitors as a proxy for differentiation from Chinese competitors. For each firm in each year, we compute average product differentiation (one minus the product similarity score) from its US competitors. Average differentiation captures the firm's ability to bring to market more unique products that will be less subject to competition from (US and Chinese) rivals. We estimate the same equation (1) as before using average product differentiation as the dependent variable. Because Hoberg and Phillips' product similarity data start in 1996, the sample period is now 1996–2007.

[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. This is consistent with the concept of within-industry product differentiation developed by Chamberlain (1933), who shows that differentiation allows firms to escape competition in their industry. This is also consistent with Hoberg and Phillips (2015) who show that firms surrounded by more firms with similar products are more likely to mention being exposed to "high competition" in the 10-K.[17] In line with this framework, we find that firms react to increased competition by increasing product differentiation.

[17]Hoberg and Phillips (2015) use the methodology in Hoberg and Maksimovic (2014) and examine the "Management's Discussion and Analysis" section of each firm's 10-K, in which managers discuss their firm performance and perspective for the future.

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, column (3) and (4)) and 0.12 (when industry-year fixed effects are not included, column (2)). Moving from the 25th percentile to the 75th percentile of R&D stock increases the effect of import penetration on differentiation by 25% of the unconditional effect. Thus, consistent with Shaked and Sutton (1987) and Sutton (1991) theories on endogenous barriers to entry, firms that have invested more in R&D for exogenous reasons are able to create product differentiation. This is consistent with Hoberg and Phillips (2015) who show that R&D is associated with subsequent differentiation from competitors and increased profitability. We add to this literature by showing that R&D leads to greater differentiation when the competitive pressure increases, i.e., when the incentives to differentiate are stronger.

Our second proxy is designed to measure more precisely differentiation from Chinese competitors. The idea is to 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. For each firm i in each year t, we compute the weighted average import penetration faced by the firms to which firm i is close in the product market space:

$$ChineseProductsSimilarity_{it} = \sum_{k \neq i} w_{ikt} \times ImportPenetration_{kt}, \tag{2}$$

where the weight w_{ikt} on firm k is proportional to the Hoberg and Phillips (2015) product similarity index between firm i and firm k:

$$w_{ikt} = \frac{ProductSimilary_{ikt}}{\sum_{k' \neq i} ProductSimilary_{ik't}}, \tag{3}$$

and $ImportPenetration_{kt}$ is the instrumented measure of import penetration of firm k. The value of $ChineseProductsSimilarity_{it}$ is large when firm i's products are similar to the products of US

firms exposed to competition from Chinese firms; it is low when firm i's products are more similar to the products of US firms not exposed to Chinese competition. Thus, a lower value of this variable reflects more differentiation from Chinese firms. We estimate the same specification as before using $ChineseProductsSimilarity$ as the dependent variable.

[INSERT TABLE 10 ABOUT HERE]

Results are reported in Table 10. In column (1) the positive coefficient on import penetration is purely mechanical: when a firm is more exposed to China's import penetration (higher value of the RHS variable), it is closer in the product market space to other US firms that are also exposed to China's import penetration (higher value of the LHS variable). The more interesting question is whether this relation is weaker for firms with a higher stock of R&D. In column (2) we interact import penetration with R&D and obtain a negative and statistically significant coefficient on the interaction term. Thus, when competition from China increases, firms with a higher level of R&D are able to differentiate their products in a way that makes their products less similar to the products of US firms in import-competing industries and more similar to the products of US firms less exposed to Chinese competition. When we include industry-year fixed effects, the point estimate barely changes but the statistical significance is weaker (p-value is 0.20, columns (3) and (4)).

Overall, the results using the two proxies for differentiation from Chinese products point to the same conclusion that R&D allows firms to escape competition via a modification of their product portfolio and lend support to the notion that innovation allows firms to "climb the quality ladder."

4 Robustness

4.1 Exogeneity of R&D Policy

A concern is that changes to the R&D tax credit policy may be endogenous. Do states offer more generous tax credits when they anticipate an increase in R&D expenditures, for example? This issue is standard and have been been discussed in previous literature. For instance, Bloom, Schankerman and Van Reenen (2013) review the literature on US state R&D and corporate tax rates and conclude that "the existing literature suggests a large degree of randomness regarding the introduction and level of R&D tax credits" (page 1366). Papers that have tried to explain the evolution of state-level corporate tax credits have found that aggregate variables (such as the federal credit rate) have some explanatory power, but local economic or political variables do not seem important (e.g., Chirinko and Wilson (2008, 2011)). To investigate further that issue, we ask whether changes in R&D or economic activity predicts changes in the tax-induced user cost of R&D capital that we use as our instrument.

[INSERT TABLE 11 ABOUT HERE]

We use three explanatory variables to predict changes in the R&D tax cedit. The first one is the change in state GDP measured over various horizons: from year $t-1$ to year t, from year $t-3$ to year t, and from year $t-5$ to year t. The second variable is the change in state-level R&D. To construct this variable, we compute, for each state-year, the weighted average ratio of R&D expenditures to total assets across all firms with inventors in the state, where firms are weighted by the share of their inventors located in the state (using the same weights w_{ist} used in Section 2.2 to compute the weighted average user cost of R&D). Again, we consider changes in state R&D activity over the past 1, 3, and 5 years. The third variable is the change in the number of doctorates awarded in the state over the past 1, 3, or 5 years, which we obtain from the NSF WebCaspar database. We ask whether these variables predict the one-year ahead change in R&D tax credit ($\rho_{s,t+1} - \rho_{s,t}$).

Results in Table 11 show that, at all horizons, past changes in GDP, R&D, or number of doctorates do not predict changes in the R&D tax credit policy.

4.2 Excluding California

[INSERT TABLE 12 ABOUT HERE]

27% of firms in our sample have more than half of their R&D activity in California. To check that our results are not driven by California, we re-run our regressions on sales growth, ROA, capital expenditures and employment growth after excluding these firms. We use our preferred specification with the full set of controls and fixed effects, as in columns (4) of Tables 4 to 7. Results are reported in Table 12. They are similar to the results on the entire sample both in terms of statistical significance and economic magnitude. The point estimates are similar for the effect on sales and profitability and somewhat larger for the effect on capital expenditures and employment. Standard errors are a bit higher than when using the entire sample, which is due to the fact that the number of observations drops by 27%.[18] Overall, California does not drive our results.

4.3 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 as imports per worker. For non-manufacturing inputs, import penetration

[18] Reducing the sample size by 27% mechanically increases the standard error by $1/\sqrt{1-27\%}-1=17\%$.

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 13 ABOUT HERE]

In Table 13 we use input-adjusted import penetration as our measure of trade exposure and study the impact on the same four dependent variables as in the baseline analysis. 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 all dependent variables. The economic magnitudes are similar to the ones in Tables 4–7 columns (4) 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.

[INSERT TABLE 13 ABOUT HERE]

In Table 14 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 as in Table 13, we include the two variables separately in the regression. In column (1) 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. (2014) 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 who find that the effect is imprecisely estimated and unstable in sign. In column (3) 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. This set of results are consistent with the interpretation 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.

We next 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. It might be that more innovative firms are better able to take advantage of cheaper or of a greater variety of inputs. On the other hand, costs might be a more important factor for less innovative firms that compete head-to-head with Chinese producers. In columns (2) and (4) 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 appear that more innovative firms benefit either more or less from import competition shocks in their input markets.

4.4 Multi-Segment Firms

We have used so far the historical main 4-digit SIC industry to measure firms' exposure to import competition from China. This measure is noisy in the case of multi-segment firms since these firms can have operations in industries that are differently exposed to trade shocks. To refine our measure of exposure to China's import penetration, we use Compustat Business Segments data. These data provide disaggregated financial information for business segments that represent at least 10% of the firm's sales, assets, or profits.[19] 55% of firms in our sample report more than one business

[19]These data are not without flaws. Villalonga (2004) documents that firms sometimes change the segments they report when there is no real change in their operations. This should not, however, affect the sign of the estimated effects to the extent that it only adds noise in the import penetration variable.

segment. We compute for each firm i in each year t the fraction of sales in each segment j defined at the 4-digit SIC code level: f_{itj}. We then construct import penetration at the firm-year level as the average of predicted China's import penetration in the US across all segments weighted by the share of each segment: $\sum_j f_{itj} ImportPenetration_{jt}$. Some multi-segment firms whose main SIC is in the manufacturing sector have operations in segments outside the manufacturing sector. Since the data for China's import penetration only cover manufacturing industries, part of these multi-segment firms' sales cannot be matched with the import penetration measure. We assume that segments outside the manufacturing sector are not exposed to import competition from China and assign a value of zero to import penetration for non-manufacturing industries. However, when a firm has more than 25% of its sales that cannot be matched with industry import penetration, we drop the observation, which excludes 10% of observations.

[INSERT TABLE 15 ABOUT HERE]

We re-run our second stage regression (1) using predicted import penetration based on segment sales. We adopt again our preferred specification with the full set of fixed effects and controls and use the same dependent variables as in the main analysis. Results are reported in Table 15 and can be compared to columns (4) in Tables 4 to 7. The estimated effects are qualitatively similar when using the main industry and when using segment-based weighted industries to construct the predicted value of import penetration. Depending on the depending variable, coefficient estimates using the main SIC code range from one-fifth to one-third smaller than when using business segments. This difference can reflect the fact that segment-based weighted industries are a more accurate proxy of a firm's true industry composition than the firm's main industry. The bias towards zero induced by noisy explanatory variables may thus be reduced in this case. In conclusion, our results are robust to, and even slightly strengthened by the use of business segment data to identify the industries of multi-segment firms.

5 Conclusion

We use the staggered changes of R&D tax credits across US states and over time as a quasi-natural experiment to examine whether more innovative firms are better able to escape 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 considerably smaller for firms which have invested large amounts in R&D thanks to generous R&D tax credit policies. As a result, R&D-intensive firms can avoid to downsize in the wake of import competition. While the average firm cuts capital expenditures and employment when import competition increases, firms that have accumulated large stocks of R&D can continue to invest in capital and labor. Finally, we provide evidence on the channel through which more innovative firms are better able to escape import competition. We show that firms with a higher level of R&D react to import competition by increasing the differentiation of their products in a way that make their products more unique and less similar to the products most exposed by Chinese competition.

An open issue left for future research pertains to general equilibrium effects. What would happen if all US firms 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., 2014. "Import Competition and the Great U.S. Employment Sag of the 2000s". *NBER Working Paper.*

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

Amiti, M., and Khandelwal, A. K., 2013. "Import Competition and Quality Upgrading". *Review of Economics and Statistics* 95, 476-490.

Amore, M.D., and Zaldokas, A., 2014. "Corporate Governance and International Trade Shocks". *Working Paper.*

Arrow, K., 1962. "Economic Welfare and the Allocation of Resources for Invention". In R. Nelson, ed., *The Rate and Direction of Inventive Activity* (Princeton, NJ: 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.H., Dorn, D., Hanson, G.H., and Song J., 2014. "Trade Adjustment: Worker Level Evidence". *Quarterly Journal of Economics* 118(4), 1799-1860.

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., 2015. "Trade Induced Technical Change: The Impact of Chinese Imports on Innovation, Diffusion and Productivity,". *forthcoming Review of Economic Studies.*

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.

Chamberlin, E. 1933. "The Theory of Monopolistic Competition". *(Harvard University Press: Cambridge).*

Chirinko, R.S., and Wilson, D.J., 2008. "State Investment Tax Incentives: A Zero-Sum Game?" *Journal of Public Economic* 92, 2362-2384.

Chirinko, R.S., and Wilson, D.J., 2011. "Tax Competition Among U.S. States: Racing to the Bottom or Riding on a Seesaw". *Working Paper*.

Ellickson, Paul. 2007. "Does Sutton Apply to Supermarkets?" *Rand Journal of Economics*. 38,43-59.

Foucault, T., and Fresard, L., 2015. "Corporate Strategy , Conformism , and the Stock Market". *Working Paper*.

Fresard, L., and Valta, P., 2014. "How Does Corporate Investment Respond to Increased Entry Threat?". *Working Paper*

Hall, B., Jaffe, A., and Trajtenberg, M., 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools.". *NBER Working Paper*.

Hall, B., Jaffe, A., and Trajtenberg, M., 2001. "Market Value and Patent Citations." *RAND Journal of Economics* 36, 16-38.

Hoberg, G., and V. Maksimovic. 2014. "Redefining Financial Constraints: A Text-Based Analysis." *Review Financial Studies, Forthcoming.*

Hoberg, G., and G. Phillips 2015. "Text-Based Network Industries and Endogenous Product Differentiation." *Journal of Political Economy, Forthcoming.*

Khandelwal, A. 201). "The Long and Short (of) Quality Ladders". *Review of Economic Studies*, 77(4), 1450-1476.

Lai, R., D'Amour, A., and Fleming, L., 2009. "The Careers and Co-Authorship Networks of U.S. Patent-Holders, Since 1975". *Harvard Institute for Quantitative Social Science*.

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.

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

Shaked, A., and J. Sutton. 1987. "Product Differentiation and Industrial Structure." *Journal of Industrial Economics* 26, 131-146.

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

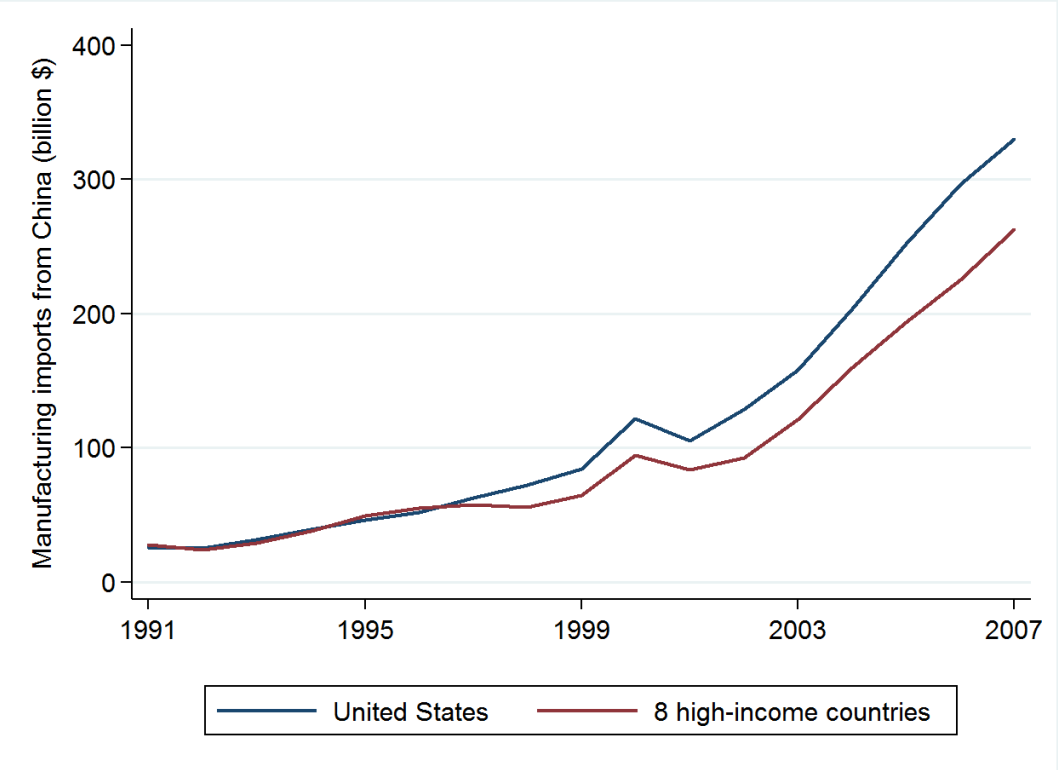
Valta, P., 2012. "Competition and the cost of debt". *Journal of Financial Economics* 105, 661-682.

Villalonga, B., 2004. "Diversification Discount or Premium? New Evidence from the Business Information Tracking Series". *Journal of Finance* 59, 479-506.

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.

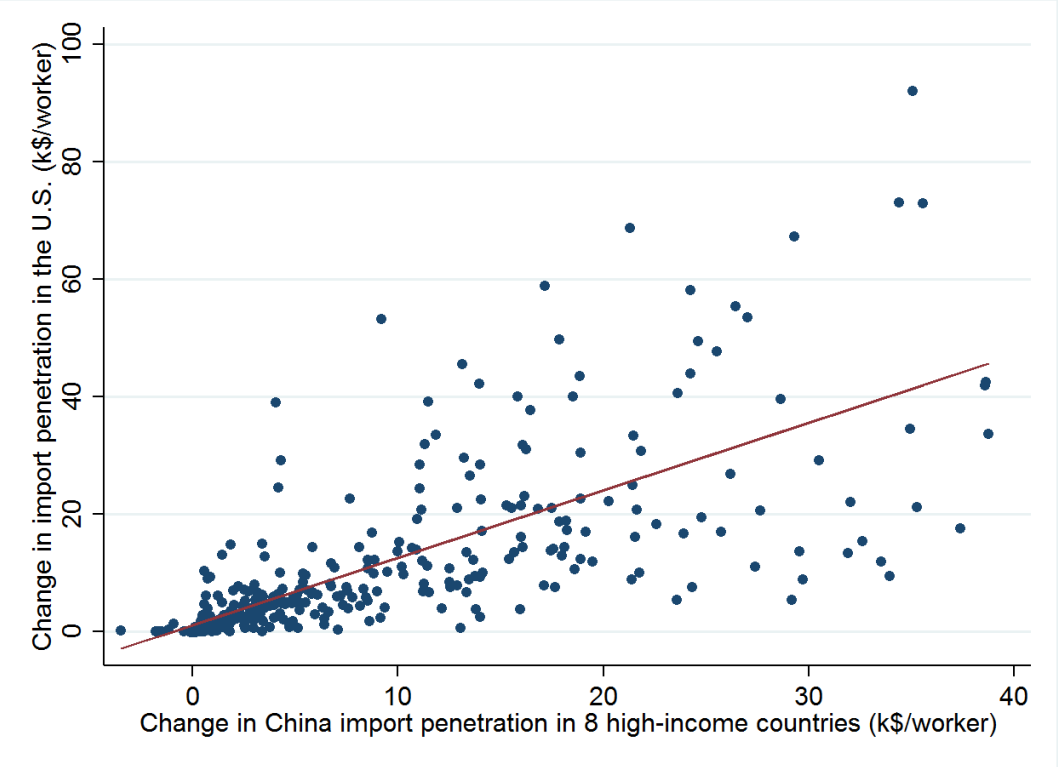
Xu, J., 2012. "Profitability and capital structure: Evidence from import penetration". *Journal of Financial Economics* 106, 427-446.

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



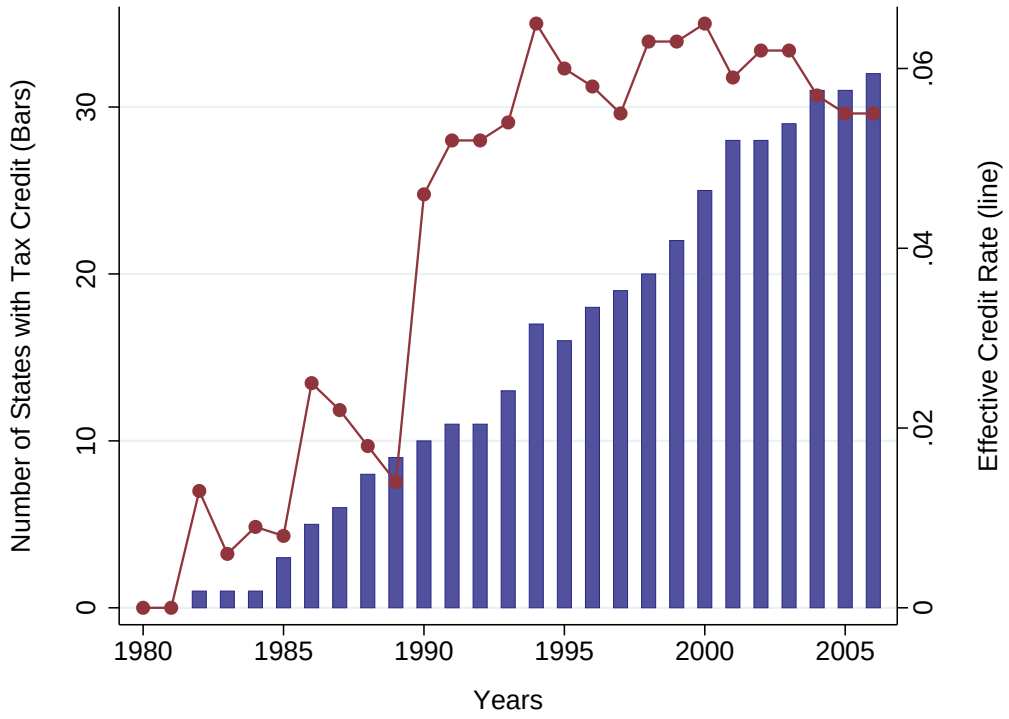
The figure plots total manufacturing imports (in 2007 billion USD) from China to the US (blue line) and to a group of 8 high-income countries (red line; Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland).

Figure 2: Change in China Import Penetration by Industry in the US vs. Other High-Income Countries



The figure plots the 1991–2007 change in China import penetration in the US on the y-axis against China import penetration in a group of 8 high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) on the x-axis. Each dot represents a 4-digit manufacturing industry. 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.

Figure 3: 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

2-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 fixtures	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 2-digit manufacturing industries in descending order of change in China 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: 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
Average product differentiation	.973	.016	.968	.977	.984	16,387
Chinese products similarity	.0083	.016	.0009	.0026	.0074	16,562

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

Table 3: 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 4: 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. *ImportPenetration* is industry-year-level import penetration from China in the US instrumented using China 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 5: 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 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 6: 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. $ImportPenetration$ is industry-year-level import penetration from China in the US instrumented using China 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 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. $ImportPenetration$ is industry-year-level import penetration from China in the US instrumented using China 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: R&D Capital in Import-Competing Industries: Arrow vs. Schumpeter

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Import penetration × R&D Stock	2.63**	2.72**	6.82***	3.09***
	(1.07)	(1.17)	(1.75)	(0.90)
Import penetration^2 × R&D Stock	-13.13*	-11.61	-43.76***	-18.76***
	(7.75)	(7.87)	(12.78)	(6.71)
Assets	0.03***	0.01	0.05***	0.07***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.23***	0.15***	-0.44***	-0.24***
	(0.02)	(0.02)	(0.03)	(0.02)
R&D Stock	0.07**	-0.22***	0.00	0.12***
	(0.03)	(0.03)	(0.04)	(0.02)
Import penetration × Age	-0.76**	-0.63***	-1.13**	-0.55**
	(0.30)	(0.24)	(0.51)	(0.27)
Import penetration^2 × Age	1.53	1.14	5.77**	1.80
	(1.45)	(1.20)	(2.42)	(1.26)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	23,907	24,533	24,321	23,197
R2	.34	.72	.41	.36

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate the same regression as in column (4) of Tables 4 to 7 with as additional regressors squared predicted China import penetration interacted with predicted stock of R&D capital, and predicted China import penetration interacted with log of firm age. 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 9: R&D Capital in Import-Competing Industries: Differentiation From US Peers

	Average Product Differentiation			
	(1)	(2)	(3)	(4)
Import penetration	.035**	.024		
	(.016)	(.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)
Observations	15,896	15,896	15,896	15,896
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	–	–
Industry-Year FE	No	No	Yes	Yes

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. *ImportPenetration* is industry-year-level import penetration from China in the US instrumented using China 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 10: R&D Capital in Import-Competing Industries: Differentiation From Chinese Products

	Chinese Products Similarity			
	(1)	(2)	(3)	(4)
Import penetration	.3***	.33***		
	(.028)	(.031)		
Import penetration × R&D Stock		-.064**	-.039	-.041
		(.029)	(.031)	(.031)
Assets	-.00019	-.00034	-.0002	-.0002
	(.00019)	(.00025)	(.00021)	(.00021)
Age	-.000079	.000043	.00018	.00065
	(.00054)	(.00057)	(.00052)	(.00055)
R&D Stock		.00042	.00033	.00036
		(.0006)	(.00053)	(.00053)
Import penetration × Age				.05
				(.035)
Observations	16,061	16,061	16,061	16,061
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	–	–
Industry-Year FE	No	No	Yes	Yes

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 defined in equations (2)–(3) and is equal to the weighted average China's import penetration of the firm's peers where the weights are proportional to the Hoberg and Phillips (2015) product similarity index with respect to the 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. $ImportPenetration$ is industry-year-level import penetration from China in the US instrumented using China 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 11: Exogeneity of R&D Tax Credit Policy

	Change in State R&D Tax Credit $(t \to t+1)$		
	(1)	(2)	(3)
	$h=1$	$h=3$	$h=5$
Change in GDP $(t-h \to t)$	-.0022	.0013	.0053
	(.0068)	(.0052)	(.0057)
Change in R&D $(t-h \to t)$	.0016	-.00068	-.0033
	(.0057)	(.0022)	(.0031)
Change in Number	-.0023	.0012	.0011
of Doctorates $(t-h \to t)$	(.0029)	(.0028)	(.0025)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,224	1,224	1,224
R2	.92	.92	.92

The sample is a balanced panel over 51 US states and the years 1982 to 2007. We estimate a linear regression model where the dependent variable is the one-year ahead change in the tax-induced user cost of R&D. All regressions include state and year fixed effects. The regressors are the change in state GDP, the change in state R&D, and the change in the number of doctorates awarded in the state. The changes in the regressors are measured over the past year in column (1), over the past three years in column (2), and over the past five years in column (5). Standard errors are clustered by state and year and reported in parenthesis. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 12: Robustness: Excluding Californian Firms

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Import penetration × R&D Stock	1.21**	1.41**	2.77***	1.75***
	(0.58)	(0.62)	(0.89)	(0.54)
Assets	0.03***	0.01	0.05***	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.20***	0.13***	-0.38***	-0.23***
	(0.02)	(0.02)	(0.03)	(0.02)
R&D Stock	0.08**	-0.19***	0.00	0.11***
	(0.03)	(0.03)	(0.04)	(0.02)
Import penetration × Age	-0.48	-0.24	-0.13	-0.49
	(0.55)	(0.45)	(0.77)	(0.44)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	17,471	17,876	17,712	16,970
R2	.35	.73	.42	.37

The sample is US manufacturing firms over 1991–2007 from Compustat, excluding firms that have more than 50% of their investors located in California. We estimate the same regression as in column (4) of Tables 4 to 7. 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 13: Robustness: Input-Adjusted Import Competition

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Net import penetration × R&D Stock	1.31***	1.74***	1.59**	0.92**
	(0.47)	(0.62)	(0.74)	(0.43)
Assets	0.03***	0.01	0.05***	0.07***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.23***	0.15***	-0.44***	-0.24***
	(0.02)	(0.02)	(0.03)	(0.02)
R&D Stock	0.08***	-0.21***	0.03	0.14***
	(0.03)	(0.03)	(0.04)	(0.02)
Net import penetration × Age	-0.80	-0.30	-0.15	-0.56
	(0.51)	(0.41)	(0.88)	(0.45)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	23,843	24,461	24,250	23,136
R2	.33	.72	.41	.35

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate the same regression as in column (4) of Tables 4 to 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. 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 14: Robustness: Disentangling the Effect of Import Competition in Input Markets

	Sales Growth		ROA	
	(1)	(2)	(3)	(4)
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 × R&D Stock		1.20**		1.67**
		(0.53)		(0.69)
Input market import penetration × R&D Stock		-0.24		-1.23
		(2.14)		(2.69)
Assets	0.01	0.03***	0.06***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.20***	-0.23***	0.06***	0.15***
	(0.01)	(0.02)	(0.01)	(0.02)
R&D Stock		0.07***		-0.21***
		(0.03)		(0.03)
Final good import penetration × Age		-0.85*		-0.39
		(0.51)		(0.45)
Input market import penetration × Age		1.45		1.55
		(1.86)		(2.16)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	–	Yes	–
Industry-Year FE	No	Yes	No	Yes
Observations	23,843	23,843	24,461	24,461
R2	.24	.33	.68	.72

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate the same regression as in column (4) of Tables 4 to 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.

Table 15: Robustness: Using Business Segments

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Import penetration × R&D Stock	1.51***	1.73**	2.56***	1.18**
	(0.56)	(0.72)	(0.82)	(0.47)
Assets	0.03***	0.01	0.05***	0.07***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.22***	0.16***	-0.43***	-0.24***
	(0.02)	(0.02)	(0.03)	(0.02)
R&D Stock	0.06**	-0.23***	0.02	0.13***
	(0.03)	(0.03)	(0.04)	(0.02)
Import penetration × Age	-0.03	0.20	-0.04	-0.34
	(0.51)	(0.49)	(0.86)	(0.54)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	22,271	22,888	22,699	21,620
R2	.33	.72	.4	.35

The sample is US manufacturing firms over 1991–2007 from Compustat. We estimate the same regression as in column (4) of Tables 4 to 7 except that we now identify firms' industries using Compustat business segments. The segment-based predicted import penetration variable is computed as the average predicted import penetration across all the segments of the firm weighted by the share of each segment. 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.