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

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May 30, 2015

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 the cost of R&D. On average across US manufacturing firms, rising imports from China lead to slower sales growth and lower profitability. These effects are, however, significantly smaller for firms with a larger stock of R&D—by about half when moving from the 25th percentile to the 75th percentile of the R&D stock distribution. As a result, while the average firm in import-competing industries cuts capital expenditures and employment, R&D-intensive firms downsize considerably less.

*We thank seminar participants at INSEAD and conference participants at the Labex Ecodec Workshop at HEC Paris. We acknowledge financial support from the Investissements d'Avenir Labex (ANR-11-IDEX-0003/Labex Ecodec/ANR-11-LABX-0047).

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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 innovate and escape competition by climbing the quality ladder. 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. 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)

[1] This view underlies for instance the EU's Lisbon Strategy, which 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))

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 better 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 2 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 Return On Assets by 1 percentage point. 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 1 percentage point (i.e., about 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 2 percentage points and it reduces annual employment growth by 0.7 percentage points. Our estimates thus imply that the average labor adjustment to trade shocks is three times smaller than the average adjustment in fixed capital. This more sluggish reaction suggests that adjustment costs for labor are larger than for capital. Then, turning to the effect of R&D, we find that firms with a larger stock of R&D are significantly less affected by increased import competition. Moving from the 25th percentile to the 75th percentile of R&D capital offsets the reduction in capital expenditures by 1.3 percentage points of fixed assets (i.e., two-thirds of the average effect) and the reduction in employment growth by 0.7 percentage points (i.e., the same as the average effect).

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). 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.

Our paper makes several contributions to the literature. First, it adds to the literature studying the impact of import competition on firms in high-income economies (see, e.g., the survey by Bernard et al. (2012)). Most of these papers 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 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 revealed preference arguments, 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, the instruments, and the data. Section 3 presents the results. Section 4 provides robustness checks. Section 5 concludes.

[2] Amore and Zaldokas (2014) show that firms with better corporate governance fare better when import competition increases.

[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 depend on (endogenous) firm-level R&D but have no instrument at their disposal.

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 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

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

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 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 import 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 ($\rho_{s,t}$) 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 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 inventor(s). We measure the geographical distribution of firm i's R&D activity in year t based on the 10-year moving average share of its inventors located in each state s ($w_{i,s,t}$). The weighted average user cost of R&D for firm i in year t is thus $\rho_{i,t} = \sum_s w_{i,s,t}\rho_{s,t}$.

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 ($\rho_{i,t}$) and firm and year fixed effects. The coefficient on $\rho_{i,t}$ 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

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

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]

[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.

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

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

where $Y_{i,j,t}$ is an outcome variable for firm i operating in sector j in year t, $ImportPenetration_{j,t}$ is predicted import penetration from China at the industry-year level, and $R\&DStock_{i,j,t}$ 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-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.[10] 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.[11]

[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.[12]

[10] 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.

[11] 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).

[12] 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

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 (21 k$/worker) leads on average to a 2 percentage point decline in annual sales growth.[13] 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 1% 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 0.8 percentage points. When we include industry-year fixed effects, the effect becomes slightly larger (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 1 percentage point, that is, by half the average effect.

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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.

[13]Imports are in million USD per worker in Table 4. The effect of a one standard deviation increase in import penetration is thus $0.021 \times (-0.97) = -0.020$ change in sales growth.

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.

[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 (column (1)). The point estimate implies that a one standard deviation increase in import penetration from China leads on average to a 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 1% (column (2)). Moving from the 25th percentile to the 75th percentile of R&D stock reduces the negative effect on ROA by 1.1 percentage points, i.e., by the same magnitude as the average 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, 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 2% of fixed assets. Given that the average ratio capital expenditures over fixed assets is 38%, this effect amounts to a 5% 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 1.3% of fixed assets, i.e., by about two-thirds of the average 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 (column (1)). This result is consistent with the earlier literature that finds a negative effect of import competition shocks on employment (see for instance Acemoglu et al. (2014)). Our point estimate implies that a one standard deviation increase in China import penetration reduces employment growth by 0.7 percentage points. Comparing this effect to the effect on sales growth (Table 4, column (1)) reveals that employment decreases three times more slowly than sales. This slower reaction of employment may have two, non-exclusive explanations. First, since sales are measured in dollar amount, the decline in sales can come from a reduction in quantities or in prices or in 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.

The unconditional effect of import competition on employment growth can also be compared to the unconditional effect on capital expenditures (Table 6, column (1)). Since capital expenditures divided by lagged fixed assets can be interpreted as the growth rate of fixed assets (plus depreciation rate, which is absorbed by the constant in the regression), the estimated effects on employment growth and on capital expenditures over lagged fixed assets are thus directly comparable. This comparison reveals that the average adjustment in employment is three times smaller than the average adjustment in fixed capital. This more sluggish reaction suggests that adjustment costs for labor are larger than for capital.

We then investigate whether innovative firms reduce employment less. When we add the interaction term between import competition and the stock of R&D, this interaction term is positive and significant at 1% (column (2)). Employment in firms with a larger stock of R&D is thus less affected by increased import competition. 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 employment growth by 0.7 percentage points, i.e., by about the same amount as the average effect. This 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)). Innovative firms are therefore more likely to retain their labor force in industries exposed to import competition from China.

3.3 Arrow vs. Schumpeter

Economic theory actually make 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 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.[14] 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

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

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 regression 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.[15] We adopt our preferred 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 all four dependent variables. 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. For instance, 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 turns decreasing in

[15] 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.

import penetration above 80–90 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.

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" (see 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 9 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 (the $w_{i,s,t}$'s we used in Section 2.2 to locate firms' inventors). 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 9 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 10 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 10. They are similar to the results on the entire sample both in terms of statistical significance and economic magnitude. Standard errors on the interaction term between import penetration and R&D stock are on average 20% larger than when using the entire sample, which is due to the fact that the number of observations drops by 27%.[16] Regarding the economic magnitude, the point estimates are slightly smaller than on the entire sample for the effect on sales and profitability and slightly larger for the effect on capital expenditures and employment. 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

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

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 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 11 ABOUT HERE]

In Table 11 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 11 ABOUT HERE]

In Table 12 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 11, 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 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 as ours on employment growth measured from the CBP data and who find that the effect is imprecisely estimated and unstable in sign. In column (3) we study the unconditional effect on profitability. In this case, we obtain a positive effect of import competition in input markets and the coefficient is now significant at the 5% level. This is 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 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.[17] 55% of firms in our sample report more than one business segment. We compute for each firm-year (i,t) the fraction of sales in each segment j defined at the 4-digit SIC code level: $f_{i,t,j}$. 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: $\sum_j f_{i,t,j} Import_{j,t}$. 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 13 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 13 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 dependent variable, the size of the estimated effect using business segments ranges from the same as the estimated effect using the

[17]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.

main industry to one-third larger than this effect. 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. Overall, 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. Overall, our results suggest that innovative firms are better armed to face competition from China.

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.

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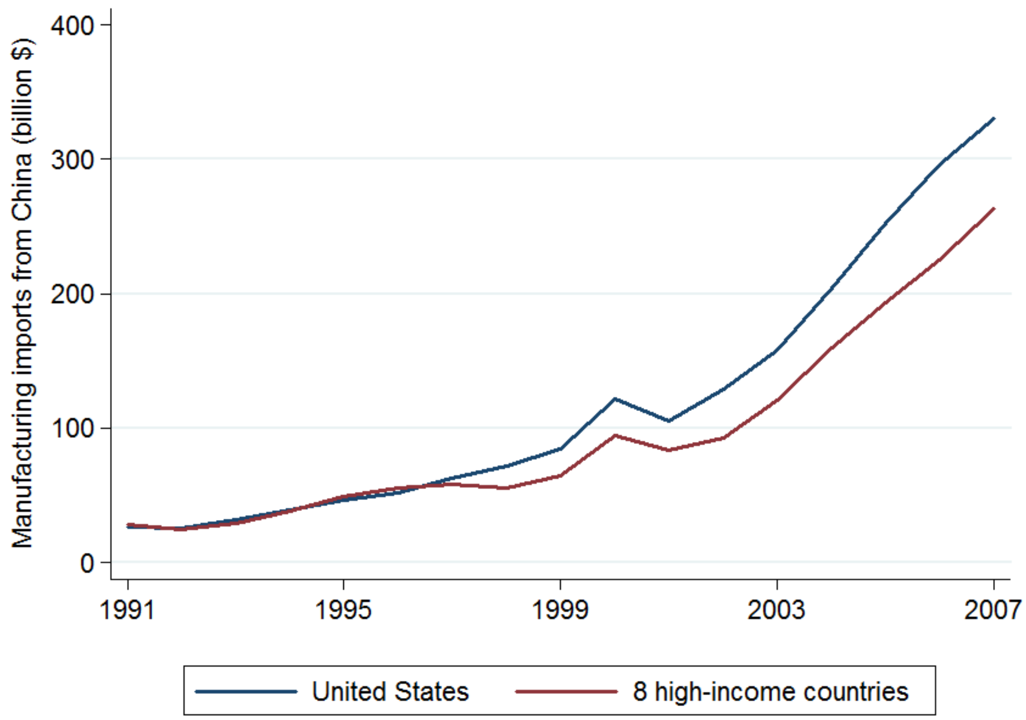
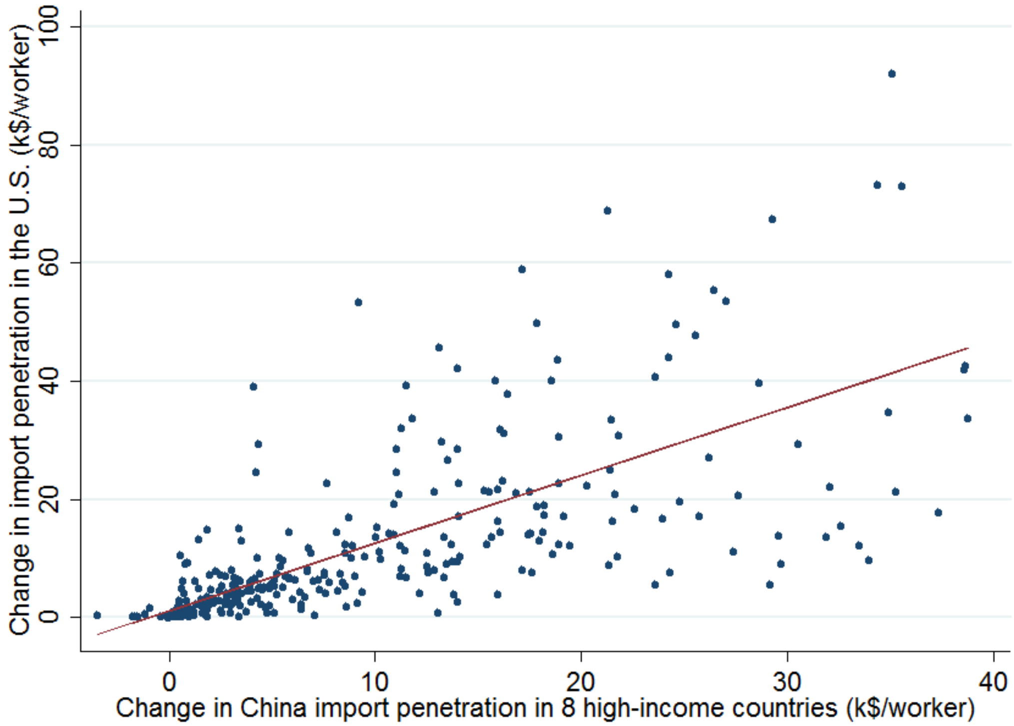
Figure 1: Manufacturing Imports from China to the US and to Other High-Income Countries



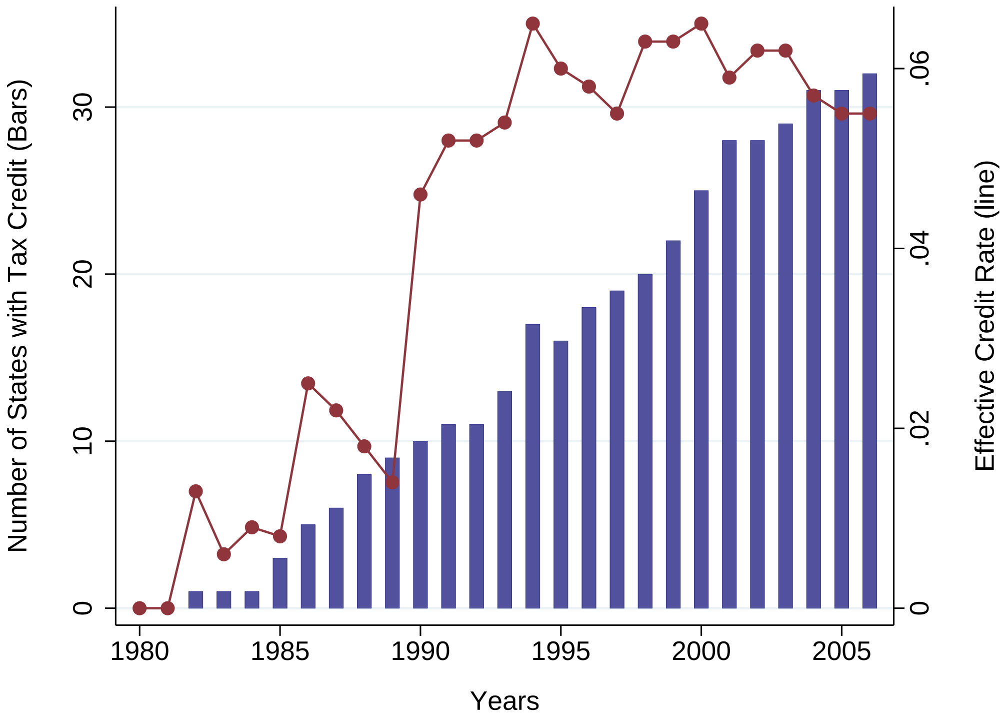
The figure plots total manufacturing imports (in 2007 billion USD) from China to the US (blue line) and to a group of 8 high-income countries (red line; Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland).

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 (million $/worker)	.0078	.021	.0000	.0012	.0055	25,494
R&D Stock/Total Assets	.38	.62	.042	.17	.43	25,494

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	-0.97***	-1.52***		
	(0.22)	(0.27)		
Import penetration × R&D Stock		1.02***	1.25***	1.26***
		(0.36)	(0.43)	(0.43)
Assets	0.01	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.20***	-0.24***	-0.22***	-0.23***
	(0.01)	(0.01)	(0.02)	(0.02)
R&D Stock		0.07***	0.06**	0.06**
		(0.02)	(0.02)	(0.02)
Import penetration × Age				-0.47
				(0.48)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	–	–
Industry-Year FE	No	No	Yes	Yes
Observations	24,753	24,753	24,753	24,753
R2	.23	.24	.32	.32

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) and 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**	-1.20***		
	(0.23)	(0.24)		
Import penetration × R&D Stock		1.41***	1.74***	1.74***
		(0.46)	(0.54)	(0.54)
Assets	0.07***	0.02**	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.07***	0.14***	0.15***	0.15***
	(0.01)	(0.02)	(0.02)	(0.02)
R&D Stock		-0.19***	-0.22***	-0.22***
		(0.02)	(0.03)	(0.03)
Import penetration × Age				0.04
				(0.44)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	–	–
Industry-Year FE	No	No	Yes	Yes
Observations	25,424	25,424	25,424	25,424
R2	.67	.68	.7	.7

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) and 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	-0.93**	-1.82***		
	(0.43)	(0.46)		
Import penetration × R&D Stock		1.62***	1.89***	1.90***
		(0.62)	(0.68)	(0.69)
Assets	0.03***	0.05***	0.05***	0.05***
	(0.01)	(0.02)	(0.02)	(0.02)
Age	-0.43***	-0.45***	-0.45***	-0.46***
	(0.02)	(0.03)	(0.03)	(0.03)
R&D Stock		0.03	0.03	0.03
		(0.03)	(0.04)	(0.04)
Import penetration × Age				-0.41
				(0.77)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	–	–
Industry-Year FE	No	No	Yes	Yes
Observations	25,210	25,210	25,210	25,210
R2	.33	.33	.39	.39

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 property, plant and equipment. All specifications include firm fixed effects, year fixed effects in columns (1) and (2) and 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	-0.34*	-0.82***		
	(0.19)	(0.30)		
Import penetration × R&D Stock		0.83**	1.02**	1.03***
		(0.34)	(0.40)	(0.40)
Assets	0.02***	0.07***	0.06***	0.06***
	(0.00)	(0.01)	(0.01)	(0.01)
Age	-0.20***	-0.25***	-0.25***	-0.25***
	(0.01)	(0.01)	(0.01)	(0.02)
R&D Stock		0.13***	0.12***	0.12***
		(0.02)	(0.02)	(0.02)
Import penetration × Age				-0.81*
				(0.43)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	–	–
Industry-Year FE	No	No	Yes	Yes
Observations	24,015	24,015	24,015	24,015
R2	.24	.24	.33	.33

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) and 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: Escape-Competition vs. Schumpeter

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Import penetration × R&D Stock	3.04**	4.08***	6.10***	3.42***
	(1.23)	(1.28)	(1.89)	(1.09)
Import penetration^2 × R&D Stock	-15.47*	-20.50**	-35.44***	-21.14**
	(8.96)	(8.73)	(13.41)	(8.31)
Assets	0.04***	0.01	0.05***	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.23***	0.16***	-0.46***	-0.25***
	(0.02)	(0.02)	(0.03)	(0.02)
R&D Stock	0.05**	-0.23***	0.01	0.11***
	(0.03)	(0.03)	(0.04)	(0.02)
Import penetration × Age	-0.83	0.68	-3.57**	-0.63
	(0.88)	(0.92)	(1.45)	(0.87)
Import penetration^2 × Age	4.02	-5.55	32.25***	-0.46
	(6.00)	(6.16)	(11.76)	(6.68)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	24,753	25,424	25,210	24,015
R2	.32	.7	.39	.34

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: Exogeneity of R&D Tax Credit Policy

	Change in State R&D Tax Credit ($t \rightarrow t+1$)		
	(1)	(2)	(3)
	$h = 1$	$h = 3$	$h = 5$
Change in GDP ($t - h \rightarrow t$)	-.0022	.0013	.0053
	(.0068)	(.0052)	(.0057)
Change in R&D ($t - h \rightarrow t$)	.0016	-.00068	-.0033
	(.0057)	(.0022)	(.0031)
Change in Number of Doctorates ($t - h \rightarrow t$)	-.0023	.0012	.0011
	(.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 10: Robustness: Excluding Californian Firms

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Import penetration × R&D Stock	1.18*	1.63***	2.85***	1.74***
	(0.62)	(0.61)	(0.92)	(0.56)
Assets	0.03***	0.01	0.04**	0.05***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.20***	0.14***	-0.40***	-0.22***
	(0.02)	(0.02)	(0.03)	(0.02)
Import penetration × Age	-0.47	-0.14	-0.08	-0.64
	(0.54)	(0.58)	(0.85)	(0.57)
R&D Stock	0.06**	-0.19***	-0.02	0.09***
	(0.03)	(0.03)	(0.04)	(0.02)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	18,092	18,524	18,358	17,570
R2	.32	.71	.39	.35

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 11: Robustness: Input-Adjusted Import Competition

	Sales Growth	ROA	Capital Expenditures	Employment Growth
	(1)	(2)	(3)	(4)
Input-adjusted import penetration	1.07	-1.84	11.89	7.94
	(5.80)	(4.31)	(9.18)	(8.76)
Input-adjusted import penetration × R&D Stock	1.43***	2.01***	1.69**	1.03**
	(0.52)	(0.63)	(0.77)	(0.45)
Assets	0.04***	0.01	0.05***	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)
Age	-0.23***	0.15***	-0.46***	-0.25***
	(0.02)	(0.02)	(0.03)	(0.01)
Input-adjusted import penetration × Age	-0.66	-0.18	-0.29	-0.75
	(0.54)	(0.51)	(0.81)	(0.48)
R&D Stock	0.07***	-0.21***	0.04	0.13***
	(0.02)	(0.03)	(0.04)	(0.02)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	24,753	25,424	25,210	24,015
R2	.32	.7	.39	.33

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 12: Robustness: Disentangling the Effect of Import Competition in Input Markets

	Sales Growth		ROA	
	(1)	(2)	(3)	(4)
Import penetration	-1.04***	4.00	-0.88**	5.53
	(0.25)	(150.77)	(0.35)	(248.83)
Input import penetration	0.48	-7.56	2.49**	-9.07
	(0.98)	(9.23)	(1.16)	(9.39)
Import penetration × R&D Stock		1.20**		1.76**
		(0.56)		(0.78)
Input import penetration × R&D Stock		0.62		0.21
		(2.23)		(3.47)
Assets	0.01*	0.04***	0.07***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.20***	-0.22***	0.07***	0.16***
	(0.01)	(0.02)	(0.01)	(0.02)
Import penetration × Age		-0.73		-0.30
		(0.54)		(0.52)
Input import penetration × Age		2.34		3.04
		(1.94)		(2.27)
R&D Stock		0.06**		-0.22***
		(0.03)		(0.03)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
Observations	24,753	24,753	25,424	25,424
R2	.23	.32	.67	.7

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 13: 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)
Import penetration × Age	-0.03	0.20	-0.04	-0.34
	(0.51)	(0.49)	(0.86)	(0.54)
R&D Stock	0.06**	-0.23***	0.02	0.13***
	(0.03)	(0.03)	(0.04)	(0.02)
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.