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

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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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1 Introduction

The rise of China, triggered by its transition to a market-oriented economy and rapid integration to world trade, has been identified as a major source of disruption for high-income economies. These developments have reopened the long-standing debate on the effect of trade with low-wage countries on firms and workers in the US and in Europe and on the best response for high-income economies.[1]

In this context, innovation is often viewed as a panacea against low-cost foreign competition. 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 climb the quality ladder and differentiate their products from low-wage countries' exports. Innovation plays a crucial role as it allows firms to increase product quality and differentiation, and thus escape competition. This view has largely influenced corporate and public policies. Import competition has induced firms to invest in technological change (Bloom, Draca and Van Reenen (2016)) and in product quality upgrading (Amiti and Khandelwal (2013)), while governments allocate large amounts of taxpayers money to subsidize R&D.[2] There is, however, little evidence that R&D does allow firms to better escape competition from low-wage countries.

In this paper, we test whether innovation allows US manufacturing firms to escape import competition from China. To guide the identification strategy, we first outline a model of the interplay between innovation and product market competition. The first insight is that the effect of innovation on firms' resilience to import competition is a priori ambiguous. It depends on whether competition reduces more pre-innovation performance or post-innovation performance. If limited competition allows non-innovative firms to make profit, an increase in competition will impair their activity while innovative firms can better absorb the competitive shock, resulting in an increase in the performance gap between innovative and non-innovative firms. This effect is consistent with the view of Arrow (1962) and called by Aghion et al. (2005) the "escape competition effect" of

[1]The debate arose in the wake of trade with Southeast Asian countries in the 1980s and with Mexico for the US after NAFTA's implementation in 1994 (Krugman (1997), Bernard et al. (2006), Leamer (2007), Krugman (2008)).

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

innovation. By contrast, the "Schumpeterian view" is that competition erodes the market power of innovative firms (Schumpeter (1943)). In this case, an increase in competition will reduce the performance gap between innovative and less innovative firms.

The second insight of the model is that estimating how the impact of import competition on a firm's performance depends on its level of innovation, by regressing firm performance on the interaction between import penetration and the firm's R&D capital, will be biased, because both trade flows and R&D investment are endogenous variables. We show that an unbiased estimate can be obtained by instrumenting both for import penetration and for R&D.

First, Chinese 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 Chinese import penetration in the US at the industry level using Chinese 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 variations across states and over time of the price of R&D, which in turn generates exogenous variations 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 (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 twenty-fifth percentile to the seventy-fifth percentile of the distribution of R&D stock reduces the drop in annual sales growth by 0.9 percentage points (i.e., half the average effect) and it reduces the drop in ROA by 1 percentage point (i.e., about the same magnitude as the average effect). 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 increase in Chinese import penetration reduces growth in fixed capital by 1.6 percentage points. However, firms with a larger stock of R&D are significantly less affected. Moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D capital offsets the reduction in capital expenditures by 1.4 percentage points of fixed assets (i.e., almost the same as the average effect). We find a similar pattern regarding employment. Firms at the twenty-fifth percentile of the R&D distribution experience a significant 1.3 percentage points reduction in annual employment growth in response to a one standard deviation increase in import competition.

In contrast, firms at the seventy-fifth percentile of the R&D distribution experience only a modest and statistically insignificant reduction in employment growth.

Fourth, we hypothesize that innovation makes firms more resilient to import competition because it allows them to differentiate. We test two distinct mechanisms related to product differentiation. First, we test whether R&D makes firms more responsive and improve their ability to increase differentiation when import competition increases. Using Hoberg and Phillips' (2015) text-based measure of product similarity vis-a-vis peer firms, we show that firms with a higher level of R&D react to import competition by increasing differentiation in a way that make their products more unique.

The second channel is that differentiation becomes more important as import competition increases. To provide evidence for this mechanism, we first show that higher R&D leads to greater product differentiation independently of the intensity of import competition. Next, we show that the sensitivity of firm performance to differentiation increases when import competition increases. Taken together, these findings imply that the marginal differentiation benefit brought about by R&D increases with import competition.

An ancillary prediction of mechanisms based on product differentiation is that the effect of R&D on firms' resilience to trade shocks should be stronger in industries in which product differentiation is more prevalent. To test this prediction, we proxy for the extent of differentiation at the industry level using the industry average of firm-level differentiation and find that the effect of R&D is stronger in industries in which differentiation is more important.[3]

We end the paper with several robustness checks. In particular, we show that the results are robust to exploiting an alternative source of exogenous variation in Chinese import penetration in the US. This shock is produced by changes in barriers to trade between China and the US that happened when the US granted China Permanent Normal Trade Relations status. The agreement led to a heterogeneous decline in expected tariff rates across industries (Pierce and Schott (2016)), which allows us to show that average firm performance deteriorates in industries that face a larger decrease in expected tariff

[3]In Appendix A, we show that these findings are consistent with a textbook model of product market competition with vertical differentiation. The key insight of this model is that the marginal benefit of differentiation increases when competition increases.

rates, but that this effect is mitigated for firms with a higher stock of R&D.

Our paper adds to the literature (surveyed by Bernard et al. (2012)) on the impact of import competition on firms in high-income economies. Most papers in this literature analyze the unconditional effect of trade shocks on various dimensions of firm performance such as output and survival (Bernard, Jensen and Schott (2006)), 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 (2016)). 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.[4] 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. The literature has focused on the effect of competition on incentives to innovate (Aghion et al. (2005), Aghion et al. (2009), and Bloom, Draca, and Van Reenen (2016)). By a revealed preference argument, firms' response to competition shocks indirectly informs us about firms' expectations regarding whether a higher level of innovation would mitigate or not the adverse effect of competition. However, as we show in Section 2, this approach cannot quantify the magnitude of the effect of R&D on firms' resilience to competition shocks. We follow a different approach and estimate directly how the effect of import competition on firm performance depends on their (exogenous) R&D capital stock.[5]

The rest of the paper is organized as follows. Section 2 outlines the theoretical framework. Section 3 describes the empirical strategy and the data. Section 4 presents the results on resilience to trade shocks and Section 5 the results on product differentiation.

[4]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 fare better when import competition increases.

[5]Bloom, Draca and Van Reenen (2016) study how firm performance depends on (endogenous) firm-level R&D but have no instrument at their disposal.

Section 6 provides robustness checks. Section 7 concludes. Additional materials can be found in the Online Appendix.

2 Theoretical Framework

This section outlines a model of the interplay between innovation and product market competition. We start from a reduced-form version of Aghion et al.'s (2005) model that captures the notion that competition may increase or decrease the returns to R&D. We adapt this framework to the case of import competition and use it to guide the empirical identification of the effect of innovation on firms' resilience to import competition.

2.1 Setup

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

A firm exerting higher innovation effort has a greater probability to innovate. Denoting by $I \in \{0, 1\}$ the dummy variable equal to one if the firm's innovation effort is successful, we assume $P[I = 1|R] = R$ and I conditional on R is independent from all other exogenous variables.[6]

Firms face import competition. We make two natural assumptions regarding the effect of import competition and of innovation on firm performance.[7] First, higher import competition leads to lower performance whether the firm innovates or not. Denoting by T the intensity of import competition, firm performance when the outcome of the firm's

[6] It is straightforward to impose additional parameter restrictions to ensure $R \in [0, 1]$ without affecting the rest of the analysis. Alternatively, and equivalently, I could be a continuous variable measuring the innovation intensity such that $E[I|R] = R$.

[7] Firm performance can be any measure of success in the product market, such as sales or profits.

innovation effort is $I \in \{0, 1\}$ is equal to:[8]

$$\pi_I = a_I - b_I T, \qquad \text{with} \quad b_0 > 0, \quad b_1 > 0. \tag{1}$$

Second, we assume that successful innovation increases performance at any level of import competition: $\pi_1 > \pi_0$ for all T.

Firm performance (1) can be rewritten as:

$$\pi = a_0 + (a_1 - a_0)I + \big[-b_0 + (b_0 - b_1)I\big]T. \tag{2}$$

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

We denote $\alpha = a_0$, $\beta = -b_0$, $\gamma = a_1 - a_0$, and $\delta = b_0 - b_1$, and rewrite equation (2) as follows:

$$\pi = \alpha + \beta\, T + \gamma\, I + \delta\, T\, I. \tag{3}$$

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

[8]In keeping with our focus on import competition, we assume that performance does not depend on the innovation outcome of other firms in order to abstract away from domestic competition, which is the focus of Aghion et al. (2005).

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

Previous literature has analyzed a related, yet different question. Aghion et al. (2005), Aghion et al. (2009), and Bloom, Draca, and Van Reenen (2016) study how investment in innovation reacts to competition shocks. In the model, firms choose innovation effort:

$$R = \arg\max_{\tilde{R}} E\big[\pi|\tilde{R}\big] - c\big(\tilde{R}\big) = \frac{1}{\rho}\big(\gamma + \delta T - (1+\theta)\big). \tag{4}$$

Firms do more R&D when the unconditional return to innovation is large (high γ); when the cost of R&D is low (low θ); and when trade shocks are large and the escape competition effect dominates (high T and $\delta > 0$) or when trade shocks are small and the Schumpeterian effect dominates (low T and $\delta < 0$). Regressing R&D (R) on competition (T) has allowed these authors to estimate γ/ρ.[9] Since $\rho > 0$, the sign of δ can be inferred. However, this approach cannot identify the value of δ because the cost parameter ρ is unknown to the econometrician. The economic intuition is that the sensitivity of R&D to competition depends both on the escape competition vs. Schumpeterian effect tradeoff (δ) and on the cost structure of R&D investment (ρ). Thus, the economic magnitude of the escape competition vs. Schumpeterian effect tradeoff cannot be quantified from the R&D-competition sensitivity alone. A different approach is needed to estimate δ.

Our approach is to estimate directly how firm performance depends on the interaction between R&D and import competition. In the next section, we analyze the potential biases in this approach and show how they can be corrected using instruments for R&D and for import competition.

[9]The estimator is unbiased under the exclusion restriction that T is not correlated with $\gamma - \theta$. The validity of this assumption is ensured in the literature by instrumenting competition shocks.

2.2 Identification

To study the identification of δ, suppose that firms differ in their opportunity cost of R&D (θ), baseline level of performance (α), resilience to trade shocks (β), and unconditional return to innovation (γ). Import competition (T) varies across industries, where industries are defined as non-overlapping sets of firms. All these variables may also be correlated with each other.

Consider an econometrician with data on performance (π) and R&D expenses (R) at the firm level and on import competition (T) at the industry level. In the data, variation in (π, R) is driven by variation in $(\theta, \alpha, \beta, \gamma, T)$ across firms and industries. The econometrician estimates the regression equation:

$$\pi = \alpha + \beta\, T + \gamma\, R + \delta\, T\, R + \epsilon. \tag{5}$$

Estimating (5) with OLS may be biased because both R&D and trade flows are endogenous. In order to isolate each source of bias, we proceed in two steps. In Section 2.2.1, we analyze the biases coming from endogenous R&D (abstracting from endogenous trade shocks) and show how to correct them by instrumenting for R&D. In Section 2.2.2, we analyze the bias arising when trade flows respond endogenously to domestic shocks and show how to correct it by instrumenting for imports. Finally, to facilitate the economic interpretation, we compute first-order Taylor approximations for small second-order moments of T, which enables us to obtain closed-form expressions for all the estimators of δ we analyze. All the proofs are relegated in Online Appendix B.

2.2.1 Endogenous R&D

To focus on the issue of endogenous R&D, we first consider the case where the econometrician can observe a measure of import competition (T) that is not correlated with $(\theta, \alpha, \beta, \gamma)$.[10] The following proposition analyzes the OLS estimator of (5) when endogenous R&D (R) is used as a regressor.

Proposition 1. *The expected estimator of δ in (5) when endogenous R&D is used as a*

[10] In Online Appendix C, we analyze the case where T is correlated with $(\theta, \alpha, \beta, \gamma)$.

regressor is:

$$E\Big[\hat{\delta}^{R\&D-ols}\Big] = \delta\Big(1 + \frac{Cov(\gamma, \gamma - \theta)}{V(\gamma - \theta)}\Big) + \frac{Cov(\beta, \gamma - \theta)}{V(\gamma - \theta)}\rho. \tag{6}$$

Proposition 1 shows that two biases arise in the OLS estimator. To highlight the economic intuition, we discuss here the case where θ is constant, in which case the expected OLS estimator is equal to $E\big[\hat{\delta}^{R\&D-ols}\big] = 2\delta + \dfrac{Cov(\beta, \gamma)}{V(\gamma)}\rho$.[11]

The first bias is that δ is estimated with an inflated factor of two. It arises because of unobserved heterogeneity in γ. The intuition is the following. Firms with a high benefit of innovation (high γ) do more R&D and, as a result, have higher performance. These firms also have higher performance at any level of R&D because they have higher returns to R&D. Thus, OLS estimates the sensitivity of performance to R&D with an upward bias. Because the bias is driven by unobserved heterogeneity in γ, the magnitude of the bias is proportional to the marginal effect of γ on performance, i.e., the bias is proportional to R&D. Now, δ measures how the performance-R&D sensitivity depends on import competition. If $\delta > 0$, industries exposed to higher competition have higher R&D and thus the estimated performance-R&D sensitivity is estimated with a larger upward bias in these industries relative to industries less exposed to import competition. Thus, δ is estimated with an upward bias. Conversely, if $\delta < 0$, industries exposed to higher competition have lower R&D and thus the estimated performance-R&D sensitivity is estimated with a smaller upward bias in these industries. Thus, δ is estimated with a downward bias. In both cases, the OLS estimator of δ is biased away from zero.

The second bias arises when the resilience to trade shocks (β) is correlated with the benefit of innovation (γ). For instance, if firms that are better managed are more resilient to trade shocks and also do more R&D, then there will be a spurious positive correlation between R&D and resilience to trade shocks that does not reflect the causal effect of R&D.

The next proposition shows that these biases can be corrected by instrumenting for R&D. Suppose we have at our disposal a variable z that shifts the cost of R&D (θ) and is orthogonal to other exogenous variables. In the empirical analysis, z will be the R&D

[11] Similar mechanisms are at work with heterogeneous θ.

tax credit. Proposition 2 analyzes the IV estimator of equation (5) when we instrument (T, R, RT) using (T, z, zT).

Proposition 2. *The expected estimator of δ in (5) when R&D is instrumented by an exogenous cost shifter is:*

$$E\left[\hat{\delta}^{R\&D-iv}\right] = \delta. \tag{7}$$

Thus, the biases in the OLS estimator stemming from the endogeneity of the R&D decision are eliminated when R&D is instrumented by an exogenous cost shifter.

2.2.2 Endogenous trade flows

In the previous section, the econometrician was assumed to observe directly productivity shocks in the foreign country. We now analyze the case where the econometrician can only observe trade flows from the foreign country to the domestic country and try to infer from them the underlying productivity shocks in the foreign country.

In any theory of international trade, trade flows depend both on productivity in the exporting country and on productivity in the domestic country. The latter can threaten the identification of δ, because innovation shocks in the domestic country can generate a spurious correlation between imports and the performance of innovative firms. Intuitively, positive innovation shocks in the domestic country raises aggregate domestic productivity and thus lowers imports, and they also increase the productivity of innovative firms.

More formally, the econometrician observes imports at the industry level. Imports depend on the gap between foreign productivity and domestic productivity. In our simple framework, we proxy for domestic productivity A_j in industry j as the average performance that firms in this industry would experience in the absence of international trade (i.e., setting $T_j = 0$ in equation (3)). Thus, $A_j = \frac{1}{|j|}\sum_{i\in j}\left(\alpha_i + \gamma_i I_i\right)$ and imports in industry j are equal to:

$$Imports_j = T_j - \lambda A_j, \tag{8}$$

where $\lambda > 0$ parameterizes the sensitivity of imports to domestic productivity.

We assume that shocks to the innovation outcome do not perfectly average out at the industry level: $\frac{1}{|j|}\sum_{i\in j} I_i \neq \frac{1}{|j|}\sum_{i\in j} E[I_i|R_i]$. This assumption captures the notion that industries are granular, breaking the Law Of Large Numbers (LOLN) (Gabaix (2011)).

If the LOLN held, aggregate innovation at the industry level would be a deterministic function of aggregate R&D in the industry. From an econometric perspective, it would mean that R&D is a perfect measure of innovation at the industry level. Instead, we assume that the LOLN does not apply, which implies that innovation can vary across industries even for the same level of R&D. Formally, we assume there are industry-level innovation shocks, μ_j, that make firm-level innovation correlated with industry-level innovation conditional on R&D:[12]

$$\text{for } i \in j, \quad P[I_i = 1 | R_i, \mu_j] = \mu_j R_i. \tag{9}$$

Finally, to focus on the endogeneity of trade flows in relation with innovation shocks, we make the simplifying assumption that the distribution of $(\alpha, \beta, \gamma, \theta)$ across firms is the same in all industries.

The following proposition calculates the estimator of δ equation (5) when R&D is instrumented by an exogenous cost shifter (such that endogeneity of R&D is no longer a problem) and imports are used as a proxy for foreign productivity shocks (T).

Proposition 3. *The expected estimator of δ in (5) when R&D is instrumented by an exogenous cost shifter and foreign productivity is measured using domestic imports is:*

$$E\left[\hat{\delta}^{import-ols}\right] = \delta - \kappa\, \lambda\, V(\mu), \tag{10}$$

where $\kappa > 0$ is reported in equation (B.3) in the online appendix.

A first observation from Proposition 3 is that, when imports do not depend on domestic productivity ($\lambda = 0$), we are back to the case where the estimator is unbiased. However, when imports depend on domestic productivity ($\lambda > 0$), the OLS estimator is downward biased. When domestic firms successfully innovate (high realized μ_j), the realized returns to R&D are large and, at the same time, imports are low because domestic productivity is high relative to foreign productivity. This mechanism generates a spurious negative relation between realized returns to R&D and realized imports, creating a

[12]Since μ_j is interpreted as a (non-zero) average of idiosyncratic shocks that are assumed to be independent from other exogenous variables, we assume that μ_j is also independent from other exogenous variables. It then follows from $P[I_i = 1|R_i] = R_i$ and Bayes law that $E[\mu_j] = 1$.

downward bias in the estimate of δ.

The next proposition shows that this bias can be eliminated by extracting foreign productivity shocks from foreign imports to a third country that has a similar economic structure as the domestic country. Consider a third country (or group of third countries) described by equations mirroring the ones for the domestic country. Namely, in the third country, firm performance is given by equation (3), firm innovation is given by equation (9) where μ_j is replaced by μ_j^* representing the part of the idiosyncratic shocks that fails to average out across firms belonging to industry j in the third country, and imports by the third country ($Imports_j^*$) are given by equation (8) where A_j is replaced by A_j^* defined as before as average firm performance in the third country's industry j that would prevail in the absence of international trade.

Proposition 4 analyzes the estimator of equation (5) when $(Imports, R, R.Imports)$ is instrumented using $(Imports^*, z, z.Imports^*)$ and innovation shocks in the domestic country and the third country are not correlated.[13]

Proposition 4. *Assume μ and μ^* are not correlated. The expected estimator of δ in (5) when R&D is instrumented by an exogenous cost shifter and domestic imports are instrumented by the third country's imports is:*

$$E\left[\hat{\delta}^{import-iv}\right] = \delta. \tag{11}$$

Proposition 4 shows that the downward bias stemming from the endogeneity of trade flows to innovation shocks in the destination country is eliminated when we use imports to a third country to estimate the returns to innovation in the domestic country. Since the bias was always downwards in Proposition 3, it implies that using imports by the third country as a regressor leads to a higher (and unbiased) estimate of δ than when using imports by the domestic country.

[13] The case where μ and μ^* are correlated is analyzed in Online Appendix D.

3 Empirical Strategy and Data

We seek to test whether US firms that are more innovative perform better in the wake of import competition from China. We follow the difference-in-difference approach analyzed in Section 2 and compare the performance of firms with a high stock of R&D relative to firms with a low stock of R&D, operating in industries that are highly exposed to import competition from China relative to industries that are less exposed to import competition from China. The approach is valid if the invested amount of R&D at the firm level is instrumented by an exogenous cost shifter and Chinese import competition in the US is instrumented using Chinese import penetration in countries comparable to the US. We present the instrument for import penetration in Section 3.1, the instrument for R&D in Section 3.2, and the econometric specification in Section 3.3.

3.1 Instrument for Import Penetration

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

Data on bilateral trade flows are from UN Comtrade. We use manufacturing imports from China both to the US and to a group of eight high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) aggregated at the 4-digit SIC level for the years 1991 to 2007.[14] Figure 1a plots total manufacturing imports from China to the US and to the other high-income countries. From 1991 to 2007, manufacturing imports from China have increased 12-fold in the US, suggesting an economically significant shock for American manufacturing firms. During the same period, Chinese manufacturing imports to other developed economies have followed a similar pattern with a 9-fold increase. The parallel evolution in the US and in other 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 FIGURES 1a AND 1b ABOUT HERE]

We define Chinese 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 data.[15] Table 1 reports the 1991–2007 change in import penetration for each broad (2-digit SIC) manufacturing industry. Imports from China grew strongly in textile, electronic, furniture, industrial equipment, while tobacco, printing, food, and petroleum did not face increased Chinese competition.

[INSERT TABLE 1 ABOUT HERE]

We define similarly Chinese import penetration in the other high-income countries. Figure 1b plots the evolution of import penetration in the US and in the other high-income countries between 1991 and 2007 by broad industry. It reveals that the increase

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

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

in Chinese import penetration in the US is concentrated in the same set of industries as in the other high-income countries.

Figure 2a goes at a more granular level by plotting the 1991–2007 change in import penetration in the US against import penetration in the other high-income countries for each 4-digit industry. It confirms that import penetration across industries is highly correlated between high-income economies. These patterns are consistent with the assumption that the surge in China's exports originates from rising productivity in China.

[INSERT FIGURES 2a AND 2b ABOUT HERE]

To further check that the cross-industry correlation of import penetration apparent on Figure 2a reflects changes that happens at the same time in the US and in the other high-income countries, we repeat the analysis by splitting the sample into four subperiods: 1991–1995, 1995–1999, 1999-2003, and 2003–2007. Figure 2b confirms that the change in import penetration is correlated across industries within each subperiod.

To construct the predicted value for import penetration in the US, we regress at the 4-digit industry-year level Chinese import penetration in the US on Chinese import penetration in the eight other high-income countries and a full set of industry and year fixed effects. The result of the first stage regression is reported in Table 2. We obtain a positive and statistically significant coefficient of 1.36 (standard error 0.12 clustered by industry and year). The F-test is equal to 127, indicating that our instrument is a strong predictor of imports in the US. We then use the predicted value of this regression to construct the predicted Chinese import penetration in the US that we will use in the second stage. We denote this predicted variable $ImportPenetration$.

[INSERT TABLE 2 ABOUT HERE]

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

3.2 Instrument for R&D Capital Stock

To generate exogenous variations in R&D at the firm level, we exploit tax-induced changes to the user cost of R&D capital (this corresponds to the variable z in Proposition 2). 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 Online Appendix G where we look for, and find no statistical evidence that changes in economic conditions predict R&D policies.

We use the state-by-year tax-induced changes in user cost of R&D capital (z_{st}) for the years 1982 to 2006 from Wilson (2009).[16] 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

[16]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.

the location of a firm's R&D activity using the location of its inventors.[17] 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 inventors. We measure the geographical distribution of firm i's R&D activity in year t based on the 10-year moving average share, w_{ist}, of its inventors located in each state s. The weighted average user cost of R&D for firm i in year t is thus $z_{it} = \sum_s w_{ist} z_{st}$. The advantage of computing the weighted average user cost of R&D based on the firm's "average location" over the past 10 years is that it alleviates concerns that firms might be moving to states offering more generous tax credits. To further make sure that our results are not polluted by endogenous firm location, we have re-run all our tests using firms' initial locations instead of the 10-year moving average and obtained similar results.

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

We predict R&D expenditures normalized by total assets using the firm-specific user cost of R&D (z_{it}) and controlling for firm and year fixed effects. The result of the first stage regression is reported in Table 3. The coefficient on 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

[17] 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. In Online Appendix H, we show that our results are robust to measuring firms' exposure to state tax credits based on the location of their headquarters.

estimates of Wilson (2009) and Bloom, Schankerman and Van Reenen (2013).

[INSERT TABLE 3 ABOUT HERE]

The innovation of a firm depends on its current and past R&D expenditures. To account for this, we use the predicted value of R&D expenditures to create a predicted value of R&D capital stock ($R\&DStock$) using the perpetual inventory method. We use a depreciation rate of R&D capital of 15% as suggested by Hall, Jaffe and Trajtenberg (2005).[18] We initialize the R&D capital stock at zero in the first year the firm appears in Compustat or in 1982, whichever comes last.[19] One possible concern is that, even if the predicted value of R&D flow is exogenous, the predicted value of R&D stock is related to firm age. It may threaten our identification strategy if firms of different age react differently to import competition. For instance, older firms may have better access to credit, which allows them to better absorb negative shocks, whereas young firms tend to be more pro-cyclical (Fort, Haltiwanger, Jarmin, and Miranda (2013)). On the other hand, young firms may have higher productivity levels (Foster, Haltiwanger and Syverson (2008)) or hold more cash, which provides them with an advantage when facing import competition shocks (Fresard (2010)). To account for such potential confounding effects, we will control for firm age interacted with import penetration in the second stage regression.

3.3 Econometric Specification

The sample period for the second stage is 1991–2007, which corresponds to the rise of China illustrated in Figure 1a. Table 4 reports summary statistics. Variables that can be positive or negative are winsorized at 1% in each tail and variables that can only be positive are winsorized at 1% in the upper tail.

[INSERT TABLE 4 ABOUT HERE]

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

[19] 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:

$$\begin{aligned} Y_{i,j,t} = \alpha + \beta\ \mathit{ImportPenetration}_{j,t-1} + \gamma\ \mathit{R\&DStock}_{i,j,t-1} \\ + \delta\ \mathit{ImportPenetration}_{j,t-1} \times \mathit{R\&DStock}_{i,j,t-1} \\ + \mathit{Controls}_{i,j,t-1} + \nu_i + \omega_{j,t} + \varepsilon_{i,j,t}, \end{aligned} \quad (12)$$

where Y_{ijt} is an outcome variable for firm i operating in sector j in year t, $\mathit{Import\ Penetration}_{j,t-1}$ 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,[20] and $\mathit{R\&DStock}_{i,j,t-1}$ is predicted stock of R&D capital at the firm-year level. Controls include log of total assets, log of firm age, and log of firm age interacted with predicted import penetration. The variable of interest is 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.

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

[20] 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.

$\omega_{j,t}$ are industry-by-year fixed effects. They 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.[21] We then compute the average, across all industries, of the share of R&D conducted in the top state (which is not the same state for all industries), in the second state, and so on. These summary statistics are reported in Table 5. The average industry has 33% of its R&D activity in the top state, 17% in the second state, 11% in the third state, 8% in the fourth state, 6% in the fifth state, and thus 25% in the remaining states. These statistics suggest that while there is some clustering by industry, this clustering is far from perfect and there is still significant geographic dispersion that allows us to implement the specification with industry-year fixed effects.[22]

[INSERT TABLE 5 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.[23]

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

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

[23]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

4 Results: Resilience to Import Competition

4.1 Firm Performance

[INSERT TABLE 6 ABOUT HERE]

We first estimate equation (12) using sales growth as the dependent variable and report results in Table 6. To begin with, we only include predicted import penetration from China (not interacted with R&D capital stock). The coefficient on imports is negative and significant at the 1% level (column (1)). The point estimate implies that a one standard deviation increase in import penetration from China (22 k$/worker) leads on average to a 1.8 percentage point decline in annual sales growth.[24] This result is consistent with previous literature showing that US manufacturing industries exposed to low-wage-country imports grow more slowly (Bernard, Jensen and Schott (2006)).

In order to assess whether a larger stock of R&D capital mitigates this negative effect of import competition on sales growth, we interact import penetration with the predicted stock of R&D. The interaction term is positive and significant at the 5% level (column (2)), which implies that more innovative firms are less hurt by import competition shocks. The point estimate implies that going from the twenty-fifth percentile to the seventy-fifth percentile of the sample distribution of R&D stock (i.e., from 4% to 43% of total assets) reduces the negative effect of a one standard deviation increase in import competition on sales growth by 0.7 percentage points. When we include industry-year fixed effects, the effect becomes slightly larger and significant at the 1% level (column (3)). In this case, moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock reduces the effect of import competition by 0.9 percentage point, that is, by half the average effect.

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 (12); 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 (12) on this sample. We repeat this procedure 500 times, and the standard errors we report correspond to the empirical distribution of the coefficients estimated.

[24]Imports are in million USD per worker in Table 6. The effect of a one standard deviation increase in import penetration is thus $0.022 \times (-0.84) = -0.018$ 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.

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

[INSERT TABLE 7 ABOUT HERE]

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

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

The next section investigates the real effects on capital expenditures and employment.

4.2 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 8 ABOUT HERE]

In Table 8, we estimate equation (12) with capital expenditures normalized by lagged fixed assets as the dependent variable. First, we only include import penetration from China and obtain a negative coefficient statistically significant at 1% (column (1)). The point estimate implies that following a one standard deviation increase in import competition, firms reduce their capital expenditures on average by 1.6% of fixed assets. Given that the average ratio capital expenditures over fixed assets is 38%, this effect amounts to a 4.2% decline in capital expenditures. This unconditional negative effect of import competition on capital expenditures is consistent with the results of Fresard and Valta (2016). We now investigate whether this effect is mitigated for more innovative firms.

Since innovative firms do not experience as much of a negative shock on sales and profits (see Tables 6 and 7), we expect that their investment opportunities will also shrink less. To test whether this is true, we add the interaction term between import competition and R&D stock. The interaction term is positive and significant at 1% (column (2)), which means that more innovative firms cut less their capital expenditures when import competition increases. The point estimate implies that moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock reduces the negative effect of a one standard deviation increase in import competition on capital expenditures by 1.4% of fixed assets, i.e., by almost as much as the unconditional effect. The effect is slightly larger when we include industry-year fixed effects (column (3)) and unchanged when we 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 9 ABOUT HERE]

In Table 9, we estimate equation (12) with employment growth as the dependent variable. When we only include import penetration from China (not interacted with R&D), we find that the unconditional effect of import penetration on employment is negative and not statistically significant (column (1)). The result that the average effect on employment is weaker (both economically and statistically) than the effect on sales has two, non-exclusive explanations. First, since sales are measured in dollar amount, the decline in sales can come from a reduction in quantities or a reduction in prices or both. Employment should decline only because of the drop in sales coming from the drop in quantities. Second, labor adjustment costs can make employment more sticky than sales.

When we add the interaction term between import competition and R&D, we find that the effect on employment depends significantly on the stock of R&D (column (2)). Employment in firms at the twenty-fifth percentile of the R&D stock distribution reduces employment growth by 0.7 percentage points (statistically significant at 5%) more than firms at the seventy-fifth percentile of the R&D stock distribution when hit by a one standard deviation increase in import penetration. The coefficient estimates imply that firms at the bottom quartile of R&D reduce employment growth by 1.3 percentage points (statistically significant at 5%). In contrast, firms at the top quartile reduce employment growth by a statistically insignificant 0.6 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.

5 Product Differentiation

In this section, we study how R&D via differentiation helps firms escape import competition. A first potential channel is that R&D makes firms more responsive and improve their ability to increase differentiation when import competition increases. A second potential channel is that higher R&D leads to more differentiation independently of the intensity of import competition and that differentiation becomes more important as competition increases. We provide evidence for the first channel in Section 5.1 and for the second channel in Section 5.2. In Section 5.3, we present additional evidence that the effect of R&D on resilience to import competition operates through differentiation by showing that the effect is stronger in industries in which product differentiation is more important.

In Appendix A, we show that these predictions emerge naturally in a textbook model of product market competition with vertical differentiation in which innovation may enhance vertical differentiation or reduce costs. The model shows that the marginal benefit of differentiation increases when competition increases ("second channel"), which gives firms incentives to increase differentiation when competition increases ("first channel"). The model also predicts that the effect of R&D on resilience to trade shocks is stronger in industries in which differentiation-enhancing innovation is more prevalent.

5.1 Channel 1: Differentiation Increases

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.

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 (12) 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 10 ABOUT HERE]

Results are reported in Table 10. In column (1) we only include import penetration not interacted with R&D and obtain a positive and statistically significant coefficient. Thus, an increase in import competition leads firms to become more differentiated. The point estimate implies that a one standard deviation increase in import competition leads to an increase in product differentiation of 0.05 standard deviations. In line with the model in Appendix A, firms have more incentives to increase differentiation when competition increases.

When we interact import penetration with the stock of R&D, we obtain a positive coefficient on the interaction term. Depending on the specification, the *p*-value is between 0.03 (when industry-year fixed effects are included, column (3) and (4)) and 0.12 (when industry-year fixed effects are not included, column (2)). Moving from the twenty-fifth percentile to the seventy-fifth percentile of R&D stock increases the effect of import penetration on differentiation by 25% of the unconditional effect. Thus, firms that have invested more in R&D for reasons unrelated to competition are better able to increase differentiation when the competitive pressure tightens and the benefits from differentiation increase.

Our second approach is described in Online Appendix K for the sake of space. 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. The results are in line with those reported here. Overall, the evidence lends support to the notion that R&D helps firms withstand import competition by improving their ability to differentiate when competition materializes.

5.2 Channel 2: Differentiation Becomes More Important

The second potential channel is that differentiation becomes more important as import competition increases. This mechanism relies on a combination of two ingredients: (a) higher R&D leads to greater product differentiation independently of the intensity of import competition and (b) the impact of differentiation on firm performance increases as import competition increases.

[INSERT TABLE 11 ABOUT HERE]

To test for (a), we regress the same measure of product differentiation as in Section 5.1 on instrumented R&D stock and the same set of controls and fixed effects as before. The result is reported in Table 11. In column (1), the positive and statistically significant coefficient on R&D stock indicates that a higher level of R&D leads to more differentiated products. In column (2), the effect is robust to controlling for industry-year fixed effect. These results are consistent with the finding of Hoberg and Phillips (2015) that firms with higher (endogenous) R&D have more differentiated products.

To test for (b), we regress firm performance on instrumented import penetration interacted with product differentiation as well as the non-interacted variables and the same controls and fixed effects as before. Note that we do not have an instrument for product differentiation.[25] The results should thus be interpreted while keeping in mind that variation in differentiation on the right-hand side might be endogenous, for instance if firms more exposed to trade shocks try harder to increase differentiation. To alleviate such reverse causality concerns, we lag differentiation by one year while acknowledging this is of course imperfect.

[25] Instrumenting differentiation using our instrument for R&D would boil down to running our baseline regression of firm performance on instrumented imports interacted with instrumented R&D. This approach does not allow one to identify whether the effect of R&D on resilience to trade shocks operates through higher differentiation after trade shocks (what we called "channel 1") or through higher sensitivity of performance to differentiation after trade shocks ("channel 2").

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

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

5.3 Product Differentiation Across Industries

Another implication of the hypothesis that R&D help firms overcome import competition through differentiation is that the effect of R&D on resilience to trade shocks should be stronger in industries in which product differentiation is more prevalent. To test this prediction, we proxy for the extent of differentiation between firms at the industry level using the industry average of the measure of firm-level differentiation used in Sections 5.1 and 5.2 and create a dummy *Industry differentiation* equal to one if the average score of the industry is above the sample median. To test whether the effect of R&D on resilience to trade shocks is stronger in industries in which differentiation is more important, we regress firm performance on the triple interaction between R&D stock, import penetration, and industry-level importance of differentiation, as well as on the simple interaction and non-interacted terms and the same controls and fixed effects as before.

[INSERT TABLE 12 ABOUT HERE]

Columns (1) and (2) of Table 12 focus on the effect on sales growth. The coefficient on the triple interaction term is positive and significant whether industry-year fixed effects are included or not. Therefore, the effect of R&D on firms' ability to escape foreign competition is stronger in industries in which product differentiation is more important. We obtain a similar result in columns (3) and (4) where we use ROA as a measure of firm performance.

6 Robustness

6.1 Alternative Instrument for Trade Shock

In this section, we show that our results are robust to using an alternative source of variation in China's import penetration in the US, which comes from changes in barriers to trade specifically between China and the US. We follow Pierce and Schott (2016) and exploit the fact that the US changed its tariff agreement with China in 2000. Since the Smoot-Hawley Tariff of 1930, imports to the US from nonmarket economies such as China are subject to relatively high tariff rates, known as "non-Normal Trade Relations tariff" (non-NTR). Since 1980, the President of the US granted a waiver to China on a annual basis, that needed to be approved every year by Congress. Following the agreement between China and the US in 1999 governing China's eventual entry into WTO, the US granted China "Permanent Normal Trade Relations" (PNTR) status.[26]

This agreement has a positive effect for Chinese imports in the US by eliminating potential tariff increases on Chinese imports, as it reduces expected tariff rates and removes uncertainty about the US trade policy vis-a-vis China. One key element of this agreement is that all industries are not affected in the same way, as NTR tariff rate varies across industries. As such, the adoption of PNTR leads to a larger drop in expected tariff in industries that have high NTR tariff. We define the NTR gap as the difference between the non-NTR rate to which tariffs would have risen if annual renewal had failed and the NTR tariff rate that is locked in by PNTR for industry j: $NTR\,Gap_j = Non\,NTR\,Rate_j - NTR\,Rate_j$. Pierce and Schott (2016) show that industries facing a larger drop in expected tariffs experience a larger increase in Chinese imports.[27]

[INSERT TABLE 13 ABOUT HERE]

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

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

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

controls and fixed effects as in the baseline regressions. Results are reported in odd-numbered columns of Table 13. Firms in industries with a higher NTR gap experience lower sale growth, lower profitability, lower investment in physical asset, and lower employment growth. Moving from the twenty-fifth percentile (0.19) to the seventy-fifth percentile (0.38) of the NTR gap leads on average to a 2.2 percentage points decline in annual sales growth ($-0.12 \times (0.38 - 0.19)$, significant at 5%, column (1)) and a 1.9 percentage point decline in ROA (significant at 1%, column (3)).[28]

Then, we analyze how the effect depends on firms' R&D capital stock. We interact $NTR\,Gap \times Post$ with instrumented R&D stock and use our preferred specification with industry-year fixed effects.[29] Results are reported in odd-numbered columns of Table 13. For all four dependent variables, the interaction term is positive and statistically significant. The point estimates imply that going from the twenty-fifth to the seventy-fifth percentile of the sample distribution of R&D stock reduces the negative effect of the interquartile NTR gap by 1.3 percentage point (significant at 1%, column (2)), that is, by half the unconditional effect, which is the same order of magnitude that we obtained using the other instrument in Section 4.1.[30]

6.2 Intermediate Inputs

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

[28]The effect on the production factors is to decrease capital expenditures by 2.7% of fixed assets (significant at 5%, column (5)) and employment growth by 1 percentage point (column (7), p-value of 0.15).

[29]Results are similar using the specification without industry-year fixed effects.

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

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

[INSERT TABLE 14 ABOUT HERE]

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

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

Finally, we study whether firms respond differently to these supply shocks in input markets depending on their level of R&D capital. Theory makes no clear prediction on whether innovation and intermediate inputs are complements or substitutes. 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 (3) and (6) we interact import competition in the final good market and in input markets with R&D stock. As in the baseline specification, we find that the interaction term between import competition in the final good market and R&D stock is positive and significant. In contrast, the interaction term between import competition in intermediate input markets is insignificant and close to zero. Therefore, it does appear that more innovative firms benefit either more or less from import competition shocks in their input markets.

6.3 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 Chinese 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.[31] 55% of firms in our sample report more than one business 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 Chinese 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 Chinese import penetration

[31]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.

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 (12) 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 6 to 9. 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, 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.

7 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 Chinese 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. First, we show that R&D improve firms' ability to increase differentiation when import competition increases. Second, we find that differentiation becomes more important as competition increases and that the effect of R&D on resilience to import competition is stronger in industries in which product differentiation is more important.

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

An open issue left for future research pertains to general equilibrium effects. What would happen if all US firms 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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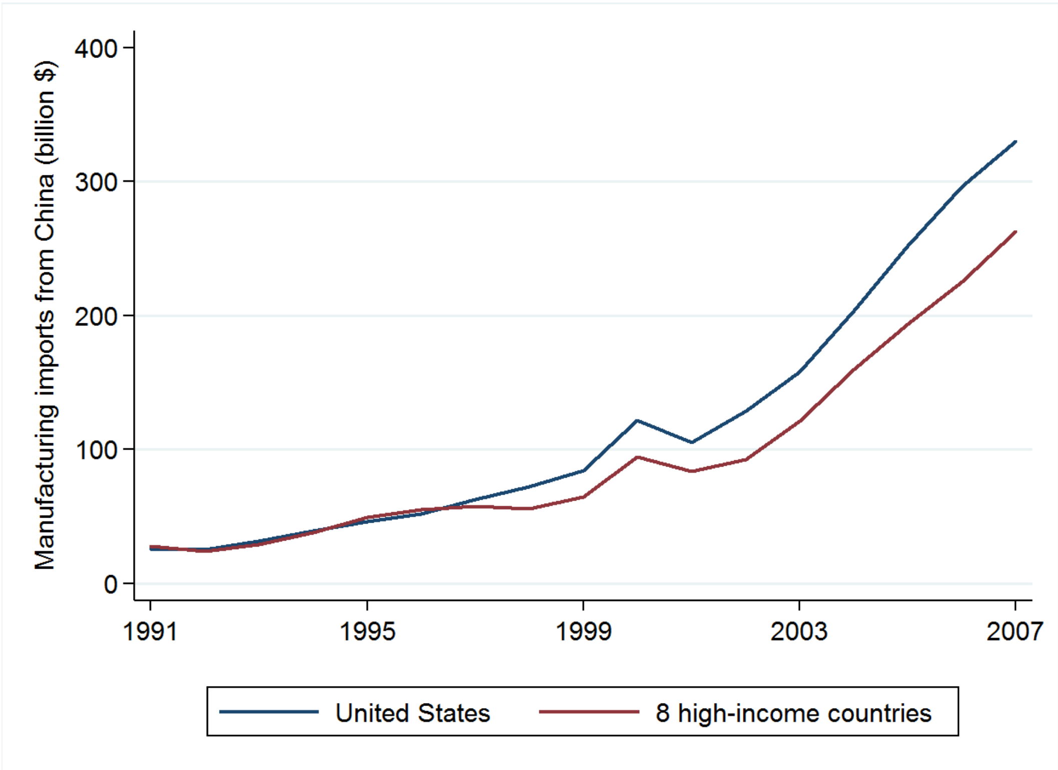
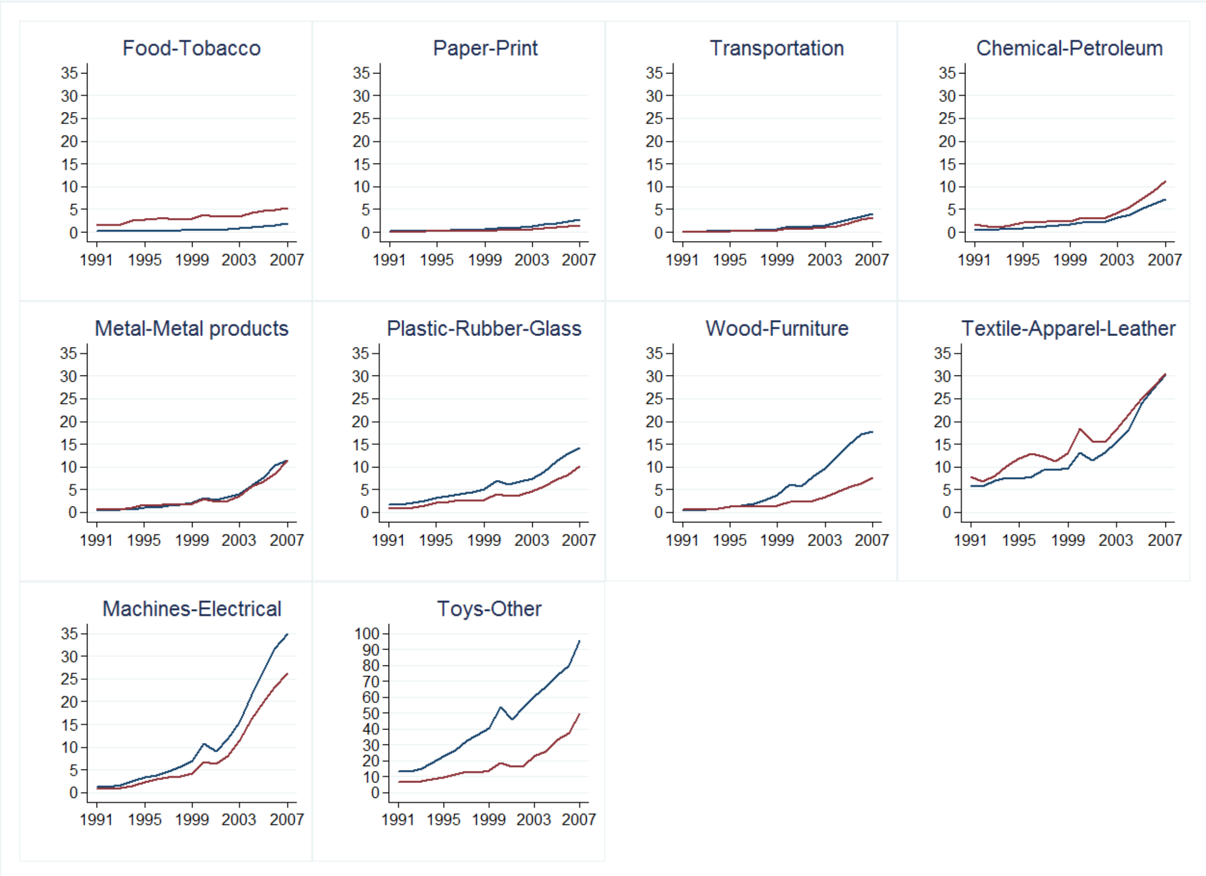
Figure 1a: Manufacturing Imports from China to the US and to Other High-Income Countries



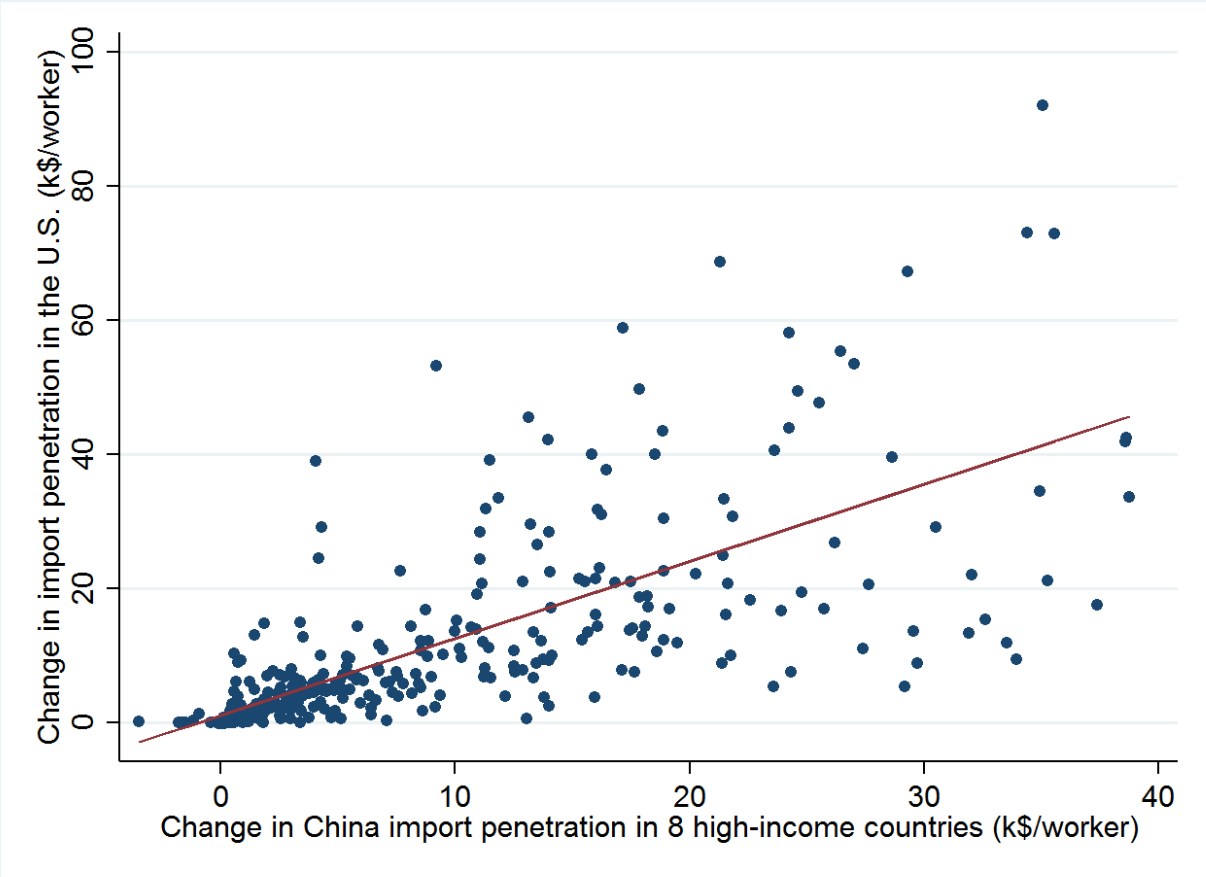
The figure plots total manufacturing imports (in 2007 billion USD) from China to the US (blue line) and to a group of eight other high-income countries (red line; Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland).

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



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

Figure 2a: Change in Chinese import Penetration by Industry in the US vs. Other High-Income Countries

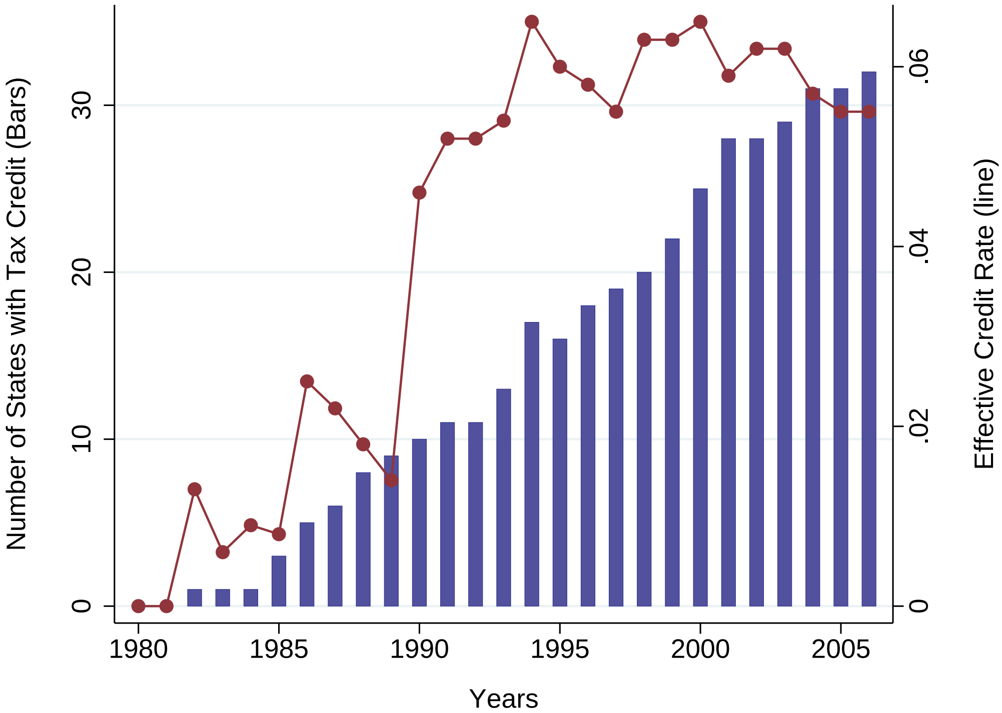


The figure plots the 1991–2007 change in Chinese import penetration in the US on the y-axis against Chinese import penetration in a group of eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) on the x-axis. Each dot represents a 4-digit 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 2b: Change in Chinese import Penetration by Industry in the US vs. Other High-Income Countries

The four graphs plot the change in Chinese import penetration in the US on the y-axis against Chinese import penetration in a group of eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) on the x-axis for four subperiods: 1991–1995 (top-left graph), 1995–1999 (top-right), 1999–2003 (bottom-left), and 2003–2007 (bottom-right). 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 over the period 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 Chinese import penetration in the US. For each industry, change in import penetration is measured as the change in imports (in 2007 k$) from China in the industry from 1991 to 2007 divided by industry employment in 1990.

Table 2: Instrument for Import Penetration: First Stage Regression

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

The sample is 4-digit industries over 1991–2007. We estimate a linear regression model where the dependent variable is Chinese import penetration in the US at the industry-year level. The dependent variable is Chinese import penetration a group of eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Import penetration is measured as imports (in 2007 k$) from China divided by industry employment in 1990. The regression include industry fixed effects and year fixed effects. Standard errors are clustered by industry and year. *** means statistically different from zero at the 1% level of significance.

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

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

The sample is US manufacturing firms over 1973–2006 from Compustat. We estimate a linear regression model on a firm-year panel where the dependent variable is R&D expenses over total assets. User cost of R&D at the firm-year level is calculated as the weighted average of state-year-specific user of cost of R&D to which the firm is eligible, where the weights are based on the 10-year moving average of the share of firm's inventors located in each state and the user cost of R&D at the state-year level is from Wilson (2009) and calculated using Hall-Jorgenson formula as explained in footnote 16. The regression include firm fixed effects and year fixed effects. Standard errors are clustered by industry. *** means statistically different from zero at the 1% level of significance.

Table 4: Summary Statistics

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

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

Table 5: Geographic Distribution of R&D by Industry

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

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

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

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

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

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

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

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

Table 9: 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 Chinese import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at industry-year and reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5, and 1% levels of significance.

Table 10: Channel 1: Product Differentiation Increases

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

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

Table 11: Channel 2: Product Differentiation Becomes More Important

	Differentiation		Sales growth		ROA	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D Stock	.0015**	.0011*				
	(.00067)	(.00062)				
Import penetration			-16**		-9.7***	
			(7.2)		(3.7)	
Import penetration × Differentiation(t-1)			16**	15*	9.4**	12***
			(7.4)	(9.2)	(3.9)	(4.5)
Assets	-.00043**	-.00044**	.016	.015	.065***	.07***
	(.00022)	(.00021)	(.012)	(.012)	(.0088)	(.0096)
Age	.00031	.00072	-.21***	-.2***	.027*	.027
	(.00047)	(.00046)	(.031)	(.031)	(.015)	(.016)
Differentiation(t-1)			-.51	-.73	.02	-.069
			(.37)	(.46)	(.17)	(.21)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	–	Yes	–	Yes	–
Industry-Year FE	–	Yes	–	Yes	–	Yes
Observations	15,637	15,637	12,767	12,767	12,767	12,767
R2	0.83	0.84	0.25	0.35	0.74	0.77

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

Table 12: R&D Matters More in Industries with High Differentiation

	Sales growth		ROA	
	(1)	(2)	(3)	(4)
Import penetration × R&D Stock	0.25	0.48	0.01	0.21
	(0.35)	(0.40)	(0.62)	(0.64)
Import penetration × R&D Stock	1.55*	1.88**	2.43***	3.13***
× Industry differentiation	(0.90)	(0.97)	(0.92)	(1.00)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	–	Yes	–
Industry-Year FE	–	Yes	–	Yes
Observations	23,074	23,074	23,710	23,710
R2	0.25	0.33	0.69	0.73

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

Table 13: Alternative Instrument for Import Competition

	Sales growth		ROA		Capital expenditures		Employment growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NTR Gap × Post	-0.12**		-0.10***		-0.14**		-0.05	
	(0.06)		(0.03)		(0.06)		(0.04)	
NTR Gap × Post × R&D Stock		0.17***		0.09**		0.31***		0.15***
		(0.05)		(0.04)		(0.06)		(0.04)
Assets	0.03***	0.03***	0.01	0.00	0.04***	0.04***	0.06***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.24***	-0.23***	0.06***	0.08***	-0.33***	-0.32***	-0.24***	-0.22***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
R&D Stock	0.08***	0.05*	-0.14***	-0.18***	0.03	-0.03	0.15***	0.12***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	–	Yes	–	Yes	–	Yes	–
Industry-Year FE	–	Yes	–	Yes	–	Yes	–	Yes
Observations	23,471	23,471	23,471	23,471	23,471	23,471	22,234	22,234
R2	0.24	0.33	0.71	0.75	0.35	0.42	0.24	0.34

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

Table 14: Controlling for Import Competition in Input Markets

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

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

Table 15: Measuring Import Penetration From 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 6 to 9 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.

A A Simple IO Model

There are two ways by which innovation can translate into higher product market performance. The one traditionally considered in the innovation and growth literature is that innovation leads to an increase in productivity.[32] Second, innovation may improve product market performance through vertical differentiation (Tirole (1988, Chapter 2), Sutton (1991)).

The distinction between the two types of innovation is important because they lead to different empirical implications. In this appendix, we work out a textbook model of competition with vertical differentiation showing that, while both types of innovation lead to an unconditional increase in firm profit, they have opposite effects *conditional* on the intensity of competition. Importantly, the distinction between productivity improvement and vertical differentiation has relevant empirical content. Hoberg and Phillips (2015) develop a methodology to measure the similarity between firms' products based on the textual analysis of product descriptions in firms' 10-K, which can be used to identify industries in which products are more homogeneous (and innovation is more about improving productivity) and industries in which products are more differentiated (and innovation is more about increasing vertical differentiation).

Setup[33] There is a mass one continuum of consumers with heterogeneous valuation ξ for quality. ξ is uniformly distributed on $[0,1]$. Each consumer consumes one or zero units of a good. A consumer with valuation ξ for quality derives utility $\xi q - p$ from purchasing a good of quality q at price p, or u_0 if he does not purchase the good. We assume that u_0 is low enough such that all consumers purchase the good in equilibrium.

There is one domestic firm and a competitive fringe of foreign firms. The domestic firm and foreign firms have marginal cost c and c^*, respectively, and they produce goods of quality q and q^*, respectively. We assume that the domestic firm is initially more efficient than foreign firms on both the productivity dimension and the quality dimension: $c < c^*$ and $q > q^*$. To focus on interesting cases, we also assume that the cost differential

[32]See for instance Tirole (1988, Chapter 10) for a presentation of the early innovation literature, Aghion and Howitt (1992) for an application to endogenous growth, and Aghion et al. (2005) on the interaction with product market competition.

[33]The setup follows closely the presentation in Tirole (1988, Chapter 2).

between domestic and foreign firms is not too large to ensure that the demand addressed to both types of firms is nonzero in equilibrium: $c^* - c < q - q^*$.

Since foreign firms are competitive and produce homogeneous products, they charge a price $p^* = c^*$. The domestic firm faces the demand function:

$$D(p) = \begin{cases} 1 & \text{if } p \leq c^*, \\ 1 - \frac{p-c^*}{q-q^*} & \text{if } p \in [c^*, c^* + q - q^*], \\ 0 & \text{if } p \geq c^* + q - q^*. \end{cases}$$

Its profit $\pi(p) = (p - c)D(p)$ is maximized for a price $p \in [c^*, c^* + q - q^*]$ such that the first order condition $\pi'(p) = 0$ holds. It implies $p = \frac{1}{2}\big((q - q^*) + (c + c^*)\big)$ and equilibrium profit for the domestic firm is equal to:

$$\Pi(c, q, c^*, q^*) = \frac{\big((q - q^*) + (c^* - c)\big)^2}{4\big(q - q^*\big)}. \tag{A.1}$$

$\Pi(c, q, c^*, q^*)$ is decreasing in c and increasing in q. Thus, both productivity-enhancing innovation and vertical differentiation-enhancing innovation lead to higher performance for the domestic firm.

Increase in import competition We model an increase in import competition as a reduction in foreign firms' marginal cost c^*. The impact on the performance of the domestic firm is given by:

$$-\frac{\partial \Pi}{\partial c^*} = -\frac{(q - q^*) + (c^* - c)}{2(q - q^*)} < 0. \tag{A.2}$$

Thus, import competition weighs on the domestic firm's profits. More important to us is whether the negative effect of foreign competition is stronger or weaker when the domestic firm has done more productivity-enhancing innovation (i.e., it has lower c) and when it has done more vertical differentiation-enhancing innovation (i.e., it has higher q).

Consider first the case of productivity-enhancing innovation. The adverse effect of import competition given by (A.2) is stronger (more negative) when c is lower. It reflects the Schumpeterian effect by which the benefit of higher productivity is eroded by competition. In the language of the model presented in Section 2, δ is negative for productivity-enhancing innovation.

In the case of vertical differentiation-enhancing innovation, the adverse effect of import competition given by (A.2) is lower (less negative) when q is higher. It reflects the effect by which vertical differentiation allows firms to escape import competition. Thus, δ is positive for vertical differentiation-enhancing innovation.

These results have the following implications:

Implication 1. *An increase in competition has a less adverse effect on firms with more differentiated products.*

We test Implication 1 in Section 5.2.

Implication 2. *If R&D allows firms to choose between increasing productivity or increasing differentiation, then an increase in competition shifts the optimal choice towards increasing differentiation.*

We test Implication 2 in Section 5.1. The last implication relies on the idea that the extent to which innovation allows firms to increase productivity or to increase differentiation varies across industries.

Implication 3. δ *is higher (more positive) in industries in which innovation is differentiation-enhancing relative to industries in which innovation is productivity-enhancing.*

We test Implication 3 in Section 5.3, where we proxy for the importance of vertical differentiation as the average distance between firms' products in the industry.