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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 costs. 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 (about half when moving from the bottom quartile to the top quartile of R&D). We provide evidence that this effect is explained by R&D allowing firms to increase product differentiation. As a result, while firms in import-competing industries cut capital expenditures and employment, R&D-intensive firms downsize considerably less.

THE RISE OF CHINA, TRIGGERED BY ITS transition to a market-oriented economy and rapid integration into world trade, has been identified as a major source of disruption for high-income economies, igniting the long-standing debate regarding the effect of trade with low-wage countries on firms and workers in the United States and Europe and regarding which firms are better able to absorb these stocks. In this context, innovation is often viewed as an effective shield against low-cost foreign competition by allowing firms to climb the quality ladder and differentiate their products from low-wage countries' exports. Because wage differences are so large, so the argument goes, competing on costs is bound to fail. Only firms that have invested in R&D and upgraded product quality are able to compete successfully against low-cost imports (e.g., Leamer (2007)).

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This view has had a large influence on public policies. In particular, it has provided further justification for R&D subsidies.[1]

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

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

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

In this paper, we adopt a direct approach to estimating the effect of R&D on firms' resilience to import competition. We test whether firm performance

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

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

as measured by sales growth or profitability is less adversely affected by an increase in import competition when the firm has invested more in R&D before the increase in import penetration. We conduct this test in the context of China's export boom and its effect on U.S. manufacturing firms. This allows us to estimate the effect of R&D as an ex ante moderating variable on the disruptive effects of trade with China.

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

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

Second, the accumulation of R&D capital is potentially endogenous to firms' productivity, management quality, and product demand. 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 U.S. federal R&D tax credit in 1981, U.S. states started to introduce R&D tax credits as well. In 2006, 32 states offered 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 variation in firms' R&D stock.

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

We show that China's import penetration has a sizable adverse effect on the unconditional (i.e., independent from the R&D level) performance of U.S. manufacturing firms. On average across U.S. manufacturing firms, a one-standard-deviation increase in import penetration reduces annual sales growth by 1.8 percentage points. This negative shock to sales triggered by increased import competition leads in turn to lower profitability. On average, a one-standard-deviation increase in import penetration reduces return on asset (ROA) by 1.1 percentage points. These preliminary results are consistent with the literature showing that U.S. manufacturing industries exposed to low-wage-country imports experience slower growth (Bernard, Jensen, and Schott (2006)), and validate the use of the Chinese export boom as a competition shock negatively impacting U.S. industries.

Next, we study how the effect of import competition on firm performance varies with firms' stock of R&D capital. We show that firms that have accumulated a higher stock of R&D capital are significantly less affected by import competition. Going from the 25^{th} percentile to the 75^{th} percentile of the distribution of R&D stock reduces the decline in annual sales growth by 0.9 percentage points (i.e., half the average effect) and reduces the decrease in ROA by 1 percentage point (i.e., about the same magnitude as the average effect).

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

The first channel is that the *benefit* of differentiation increases when import competition increases. This channel hinges on two ingredients: (i) firms that have invested more in R&D in the past have more differentiated products independent of the intensity of import competition, and (ii) the marginal benefit of product differentiation increases when import competition increases. Taken together, (i) and (ii) imply that the marginal benefit of a higher stock of R&D increases when import competition increases. Using Hoberg and Phillips (2016) text-based measure of product similarity vis-à-vis peer firms to proxy for differentiation, we provide evidence for (i) and (ii).

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

An ancillary prediction of these product differentiation mechanisms 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. We find that the effect of R&D is stronger in industries in which differentiation is more important. This result lends further support to the Sutton's (1991) argument that vertical differentiation is instrumental to absorb and escape competition shocks. Taken together, these results are consistent with the view that R&D makes firms more resilient to trade shocks because it allows them to climb the quality ladder and differentiate (ex ante and ex post) their products.

Finally, having shown that R&D has an economically meaningful effect on the resilience of firm performance to trade shocks, we explore the real effects on capital expenditures and employment. We find that, on average across firms, a one-standard-deviation increase in China's import penetration reduces growth in fixed capital by 1.6 percentage points. However, firms with a larger stock of R&D are significantly less affected. Moving from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ 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 for employment. Firms at the 25$^{\text{th}}$ percentile of the R&D distribution experience a significant 1.3 percentage point reduction in annual employment growth in response to a one-standard-deviation increase in import competition. In contrast, firms at the 75$^{\text{th}}$ percentile of the R&D distribution experience only a modest and statistically insignificant reduction in employment growth.

Our paper adds to the literature (surveyed by Bernard et al. (2012)) on the impact of import competition on firms in high-income economies. Most papers in this literature analyze the unconditional effect of trade shocks on various dimensions of firm performance such as output and survival (Bernard, Jensen, and Schott (2006)), cost of debt (Valta (2012)), leverage (Xu (2012)), capital expenditure (Frésard and Valta (2016)), and employment and outsourcing (Pierce and Schott (2016)). There is little evidence, however, as to which firms are better able to cope with trade shocks. A notable exception is Bernard, Jensen, and Schott (2006), who show that capital-intensive plants are more likely to survive and grow in the wake of import competition.[3] We complement this literature by showing that R&D-intensive firms are better able to cope 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.

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

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

The rest of the paper is organized as follows. Section I outlines the theoretical framework. Section II describes the empirical strategy and data. Section III presents the results on resilience to trade shocks, Section IV presents the results on product differentiation, and Section V presents the results on the real effects on capital expenditures and employment. Section VI provides robustness checks. Section VII concludes. Additional material can be found in the Internet Appendix.[4]

I. Theoretical Framework

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

A. 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 $c(R) = R + \theta R + \frac{\rho}{2} R^2$. The parameter 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. The parameter $\rho > 0$ also varies across firms and captures the extent of decreasing returns to R&D investment.

A firm exerting higher innovation effort has a higher probability of innovating. Let $I \in \{0, 1\}$ be a dummy variable equal to one if the firm's innovation effort is successful. We assume that $P[I = 1|R] = R$ and I conditional on R is independent of all other exogenous variables.[5]

Firms face import competition. We make two natural assumptions regarding the effect of import competition and innovation on firm performance.[6] First, higher import competition leads to lower performance whether the firm innovates or not. Denoting by T the intensity of import competition, where T

[4] The Internet Appendix may be found in the online version of this article.

[5] 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 innovation intensity such that $\mathrm{E}[I|R] = R$.

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

stands for Trade, firm performance when the outcome of the firm's innovation effort is $I \in \{0, 1\}$ is equal to[7]

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

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

Firm performance (1) can be rewritten as

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

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 noninnovators. When b_0 is high, import competition weighs heavily on the performance of noninnovators. This effect, identified by Arrow (1962) and referred to by Aghion et al. (2005) as the escape competition effect, implies that innovative firms are better able to escape competition than noninnovative firms and thus are more resilient to competition shocks. Conversely, when b_1 is high, import competition erodes the competitive edge of innovative firms as in Schumpeter (1943). In this case, innovative firms are relatively more sensitive to competition shocks.

Let $\alpha = a_0$, $\beta = -b_0$, $\gamma = a_1 - a_0$, and $\delta = b_0 - b_1$. Then, we can rewrite equation (2) as

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

The goal of this paper is to estimate δ, which tells us the effect of import competition on firm performance varies with the firm's level of innovation. In particular, we want to determine whether δ is positive (the Arrow effect dominates) or negative (the Schumpeterian effect dominates) as well as the economic magnitude of the net effect, that is, the degree to which R&D can (or cannot) mitigate the adverse effect of import competition.

~~*B. Import Penetration Scaled by 10-Year Lagged Employment*~~

In Internet Appendix I, we develop a simple model of product market competition with vertical differentiation to identify conditions under which δ may be positive or negative. The main insight is that δ depends on the relation between innovation and product differentiation. When innovation leads to increased product quality and enhanced product differentiation, it allows firms to preserve market shares and hence the Arrow effect dominates ($\delta > 0$). When

[7] In keeping with our focus on import competition, we assume that performance does not depend on the innovation outcome of other domestic firms. Allowing firm performance to depend on the average innovation of other domestic firms in the same industry would add an industry-specific constant term in equation (1) as well as equations (2), (3), and (5). In our empirical setting in panel data, this term would be absorbed by industry-year fixed effects, which we include in our preferred specification.

innovation increases productivity but does not enhance product differentiation, its positive effect on performance is eroded by competition and hence the Schumpeterian effect dominates ($\delta < 0$). We study empirically the role of product differentiation in Section IV.

C. Identification

C.1. Previous Literature

Previous studies address these questions by studying firms' endogenous choice of innovation in response to an exogenous competition shock (e.g., Scherer and Huh (1992), Aghion et al. (2005), Autor et al. (2016), and Bloom, Draca, and Van Reenen (2016), among many others).[8]

This approach has two main limitations to identifying δ. To see why, note that firms' choice of innovation effort is given by

$$R = \arg\max_{\tilde{R}} \mathrm{E}[\pi|\tilde{R}] - \left((1+\theta)\tilde{R} + \frac{\rho}{2}\tilde{R}^2\right) = \frac{1}{\rho}(\gamma + \delta T - (1+\theta)). \qquad (4)$$

As can be seen, firms conduct more R&D when the unconditional return to innovation is large (high γ), when the cost of R&D is low (low θ), when trade shocks are large and the Arrow effect dominates (high T and $\delta > 0$), or when trade shocks are small and the Schumpeterian effect dominates (low T and $\delta < 0$). Prior studies regress innovation choice (R) on instrumented competition (T). Equation (4) suggests that doing so provides only indirect, or even biased, information about δ.

First, even absent an endogeneity problem, regressing R on T can only identify δ/ρ. Since $\rho > 0$, the sign of δ can be determined. However, the value of δ cannot be pinned down because the cost parameter ρ is unknown to the econometrician. The economic intuition is that the sensitivity of R&D to competition depends on both the Arrow versus Schumpeterian effect trade-off (δ) and on the cost structure of R&D investment (ρ). Thus, the economic magnitude of the Arrow versus Schumpeterian effect trade-off cannot be identified from sensitivity of the R&D to competition alone.

Second, even if import competition is correctly instrumented, firms' endogenous innovation choices depend not only on returns to innovation ($\gamma + \delta T$) but also on various costs and frictions such as credit constraints and agency issues (captured by parameter θ in the model). For instance, if an increase in competition reduces firms' cash flows and tightens financing constraints, firms may respond to competition shocks by cutting investment in innovation not because innovation has negative net present value (NPV), but because the firms are constrained. Formally, the estimate of γ/ρ would be biased in this case because

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

θ is correlated with T. Crucially, the estimate would be biased even if T is instrumented because the correlation between T and θ comes from T causing θ, and thus this correlation would not be removed by instrumenting for T.

In sum, regressing R on T cannot identify δ, and may even lead to incorrect inference regarding the sign of δ. This may explain why papers that follow this approach generate conflicting results (e.g., Bloom, Draca, and Van Reenen (2016) find a positive effect while Autor et al. (2016) find a negative effect). A different approach is thus needed to estimate δ.

C.2. Our Approach

Our approach is to study directly how firm performance is affected by R&D, import competition, and the interaction between R&D and import competition. Specifically, we estimate

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

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

Estimating (5) with OLS may lead to biased estimates because both R&D and trade flows are endogenous. In Internet Appendix II.A, we study both sources of bias and show how to correct for them. Here, we summarize the main results of this analysis (Propositions IA1 to IA4):

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

(ii) Instrumenting for R&D using an exogenous cost shifter corrects these two biases. In the empirical analysis, the instrument that we use is the R&D tax credit.

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

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

II. Empirical Strategy and Data

To examine whether U.S. 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 I.C.2. Specifically, we compare the performance of high-R&D firms to low-R&D firms operating in industries that are highly exposed to import competition from China versus industries that are less exposed to import competition from China. This approach is valid if the amount invested in R&D at the firm level is instrumented by an exogenous cost shifter and China's import competition in the United States is instrumented using China's import penetration in countries comparable to the United States. We discuss the instrument for import penetration in Section II.A, the instrument for R&D in Section II.B, and the econometric specification in Section II.C.

A. Instrument for Import Penetration

To isolate the component of Chinese import penetration in the United States coming from Chinese productivity and trade cost shocks, we follow the approach of Autor, Dorn, and Hanson (2013) analyzed formally in Propositions IA3 and IA4 and we instrument imports from China to the United States using imports from China to other high-income markets. This strategy is valid if the common within-industry component of increasing Chinese imports to the United States and other high-income countries stems from rising productivity and falling trade costs in these sectors in China. 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 United States and other high-income countries. While we cannot categorically reject this possibility, evidence suggests that the surge in Chinese exports is strongly related to internal changes in China, which have 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 admission to the World Trade Organization (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, China's share of manufacturing imports grew sharply, from 6.7% to 25.0% in the United States and from 3.7% to 16.1% in other high-income countries. This is fast even compared to Mexico and Central America, which signed free trade agreements with the United States during that period and whose share grew from 9.8% to 13.8% over the same period.

Data on bilateral trade flows come from UN Comtrade. We use manufacturing imports from China both to the United States and to a group of eight high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) aggregated at the four-digit SIC level over the period 1991 to 2007.[9] Figure 1, Panel A, plots total manufacturing

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

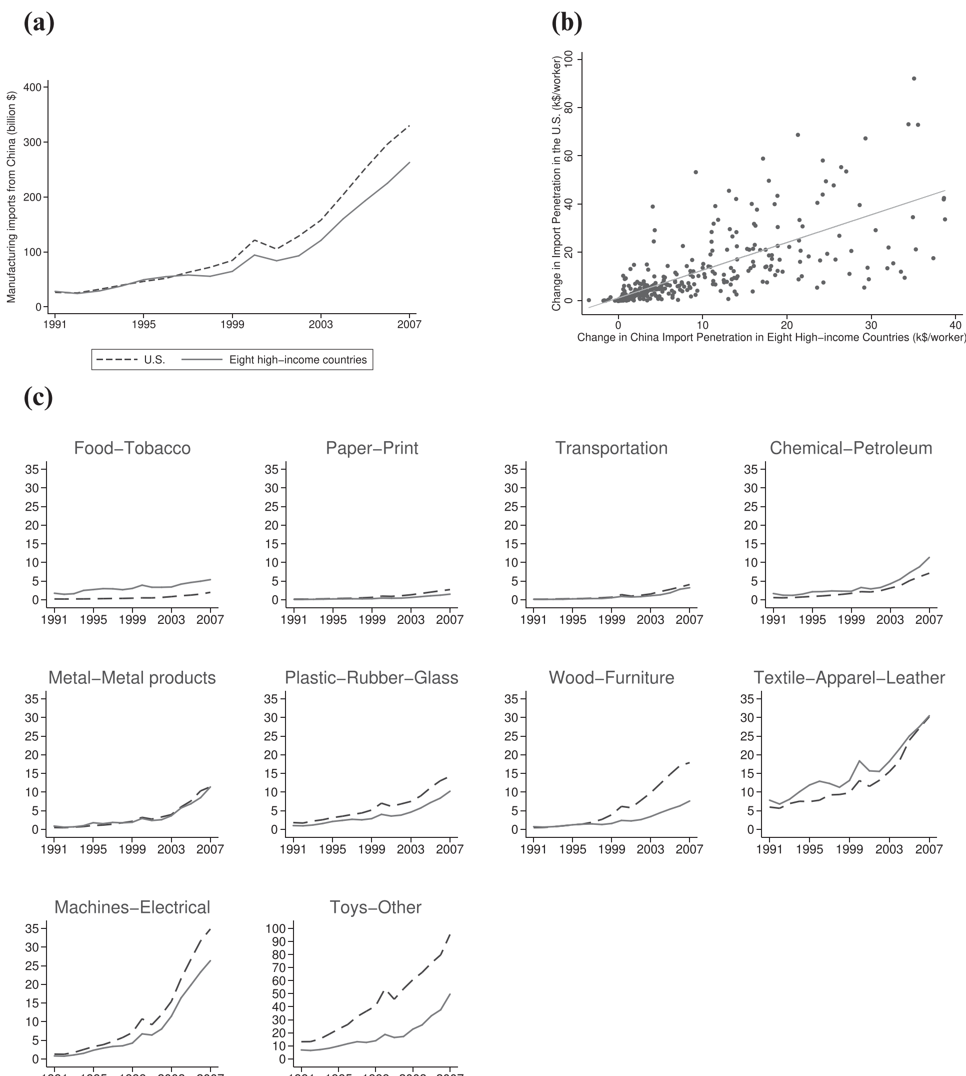

Figure 1. Manufacturing imports from China to the United States and to other high-income countries. Panel A plots total manufacturing imports (in 2007 billion USD) from China to the United States (blue line) and to a group of eight other high-income countries (red line: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Panel B plots China's import penetration in the United States (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$) from China in the industry divided by industry employment in 1990. Panel C plots the 1991 to 2007 change in China's import penetration in the United States on the *y*-axis against China's import penetration in a group of eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) on the *x*-axis. Each dot represents a four-digit manufacturing industry. For each industry, change in import penetration is measured as the change in imports (in 2007 k$) from China in the industry from 1991 to 2007 divided by industry employment in 1990.

Table I

Change in China's Import Penetration by Broad Industry

The table ranks two-digit manufacturing industries in descending order of the change in China's import penetration in the United States. For each industry, the 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.

Two-Digit SIC Industries		1991 to 2007 Change in China's 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

imports from China to the United States and to the other high-income countries. From 1991 to 2007, manufacturing imports from China increased 12-fold in the United States, suggesting an economically significant shock for American manufacturing firms. During the same period, Chinese manufacturing imports to other developed economies followed a similar pattern with a ninefold increase. The parallel evolution in the United States and in other high-income countries is consistent with our assumption that the surge in Chinese exports is due primarily to forces exogenous to the U.S. economy.

We define China's import penetration in the United States at the industry-year level as imports from China in a given 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.[10] Table I reports the 1991 to 2007 change in import penetration for each broad (two-digit SIC) manufacturing industry. Imports from China grew strongly in the textile, electronic, furniture, and industrial equipment industries, while tobacco, printing, food, and petroleum did not face increased Chinese competition.

[10] In Internet Appendix III.A, we show that our results are robust to scaling import penetration by employment 10 years before the beginning of the sample period (in 1980).

Table II

Instrument for Import Penetration: First-Stage Regression

The sample comprises four-digit industries over the 1991 to 2007 period. We estimate a linear regression model where the dependent variable is China's import penetration in the United States at the industry-year level. The dependent variable is China's import penetration in 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 includes industry and year fixed effects. Standard errors are clustered by industry and year. *** indicates statistically different from zero at the 1% level of significance.

	Import Penetration in the United States
Import penetration in other high-income countries	1.36***
	(0.12)
Industry FE	Yes
Year FE	Yes
Observations	2,885
Adjusted-R^2	0.94

We similarly define China's import penetration in the other high-income countries. Figure 1, Panel B, plots the evolution of import penetration in the United States and in the other high-income countries between 1991 and 2007 by broad industry. The figure shows that the increase in Chinese import penetration in the United States is concentrated in the same set of industries as in the other high-income countries.

Figure 1, Panel C, goes at a more granular level by plotting the change in import penetration from 1991 to 2007 in the United States against import penetration in the other high-income countries for each four-digit industry. The figure confirms that import penetration across industries is highly correlated between high-income economies. These patterns are consistent with the view that the surge in Chinese exports is due to rising productivity in China.

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

Importantly, our empirical strategy does not exclude the role of global production chains. During the sample period, about half of China's manufacturing exports are produced in export processing plants that import intermediate inputs from abroad and assemble them into the final goods that are exported

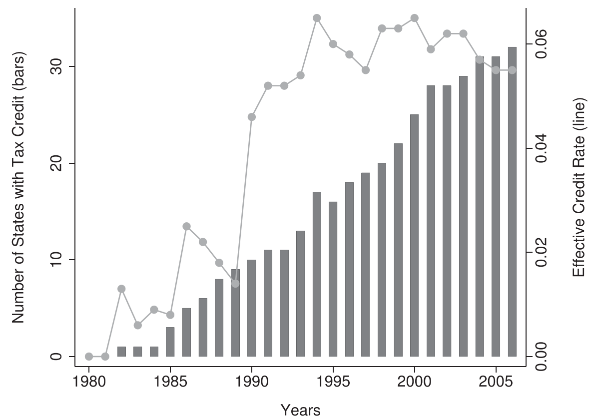

Figure 2. Number and average value of state R&D tax credits in the United States. Blue bars represent the number of U.S. states with R&D tax credits (left scale). Red dots plot the average effective R&D tax credit rate across the 50 states (right scale).

(Feenstra and Hanson (2005)). Our empirical strategy does not require that China contribute 100% to the value added of the goods that it ships abroad. Instead, we require that China's export growth be driven by internal shocks in China. These shocks may increase the supply of exported goods that are produced entirely 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 occurs in China. Both situations represent exogenous import competition shocks from the point of view of U.S. producers.

B. Instrument for R&D Capital Stock

To generate exogenous variation in R&D at the firm level, we exploit tax-induced changes to the user cost of R&D capital. After the introduction of the U.S. federal R&D tax credit in 1981, U.S. states progressively started to provide R&D tax credits to corporations. Figure 2 illustrates the staggered timing of changes in tax credit rates across U.S. states. The process began with Minnesota in 1982; as of 2006, 32 states provided tax credit. The average effective credit rate increased approximately fourfold over this period to equal roughly half of the value of the federal effective credit rate, and in some states the tax credit is considerably more generous than the federal credit (Wilson (2009)). These state-level 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 economic environment. While this possibility cannot be ruled out, 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 this issue in Internet Appendix III.B, where we examine whether changes in economic conditions predict R&D policies. We find no support for this effect.

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).[11] R&D expenses are eligible for 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 capture the location of a firm's R&D activity using the location of its inventors.[12] We obtain patent information using the NBER patent file (see Hall, Jaffe, and Trajtenberg (2001)) and inventor information using the Harvard Business School patent database (see Lai, D'Amour, and Fleming (2009)). These data provide us with a list of all patents filed by a firm and include 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 ensure that our results are not polluted by endogenous firm location, we rerun all of our tests using firms' initial locations instead of the 10-year moving average and obtain similar results.

Firm data come from Compustat. We consider U.S. firms operating in the manufacturing sector (SIC codes 2000 to 3999). We require that firms have nonmissing total assets and sales and that they have at least three consecutive years of data. Our instrument for R&D also imposes that we exclude firm-year observations for which a 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 locations of the firm's inventors. This leaves us with a sample of 3,334 firms and 41,860 firm-year observations over the 1982 to 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. Results of the first-stage regression are reported in Table III. The coefficient on ρ_{it} is equal to -0.11 with an F-statistic of 12.4 (standard errors

[11] The year t user cost of R&D capital in state s 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.

[12] R&D expenses can be offset against state-level corporation tax liabilities. State-level corporation tax liabilities are calculated by allocating total firm profits 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 a state is likely to be both liable for the state's corporation tax (due to its employees and property in the state) and eligible for an offsetting R&D tax credit. Inventor location thus provides a good proxy for state-level R&D tax credits eligibility. In Internet Appendix III.C, we show that our results are robust to measuring firms' exposure to state tax credits based on the location of their headquarters.

Table III

Instrument for R&D: First-Stage Regression

The sample comprises U.S. manufacturing firms over the 1973 to 2006 period 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 weights are based on the 10-year moving average of the share of the firm's inventors located in each state and the user cost of R&D at the state-year level comes from Wilson (2009) and is calculated using the Hall-Jorgenson formula as explained in Footnote 11. The regression includes firm and year fixed effects. Standard errors are clustered by industry. *** indicates statistically different from zero at the 1% level of significance.

	R&D
User cost of R&D	−0.11***
	(0.03)
Firm FE	Yes
Year FE	Yes
Observations	55,541
Adjusted-R^2	0.75

clustered at the industry level). Thus, a one-percentage-point decrease in the user cost of R&D capital increases R&D expenditures by 0.11% of total assets. Given that R&D expenditures over total assets are on average 8.4%, our estimate implies a price-elasticity of R&D of 1.3. This elasticity is in line with the estimates of Wilson (2009) and Bloom, Schankerman, and Van Reenen (2013a).

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). We initialize the R&D capital stock at zero in the first year the firm appears in Compustat or in 1982, whichever comes last.[13] One possible concern is that, even if the predicted value of R&D flow is exogenous, the predicted value of R&D stock is related to firm age. This could threaten our identification strategy if firms of different ages react differently to import competition. For instance, older firms may have better access to credit, which would allow them to better absorb negative shocks (Fort et al. (2013)). Alternatively, young firms may have higher productivity (Foster, Haltiwanger, and Syverson (2008)) or hold more cash, which would provide them an advantage when facing import competition shocks (Frésard (2010)). To account for such potential confounding effects, we control for firm age interacted with import penetration in the second-stage regression.

[13] Since states started to offer R&D tax credits in 1982, we can construct the instrumented R&D flow starting in 1982 even for firms that were in Compustat prior to 1982.

Table IV

Summary Statistics

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

	Mean	Std.Dev.	25^{th}	50^{th}	75^{th}	N
Sales growth	0.12	0.34	−0.032	0.079	0.23	24,753
ROA	0.023	0.37	−0.0095	0.12	0.2	25,424
Capex/PPE	0.38	0.53	0.12	0.22	0.41	25,210
Employment growth	0.063	0.26	−0.055	0.026	0.14	24,015
Import penetration (M$/worker)	0.0080	0.022	0.0000	0.0012	0.0056	24,598
R&D Stock/Total assets	0.38	0.62	0.042	0.17	0.43	25,494
Product differentiation	0.973	0.016	0.968	0.977	0.984	16,387

C. Econometric Specification

The sample period for the second-stage regression is 1991 to 2007, which corresponds to the rise of China illustrated in Figure 1, Panel A. Table IV reports summary statistics. Variables that can be positive or negative are winsorized at the 1% level in each tail while variables that can only be positive are winsorized at the 1% level in the upper tail.

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

$$\begin{aligned} Y_{i,j,t} = \alpha &+ \beta\ ImportPenetration_{j,t-1} + \gamma\ R\&DStock_{i,j,t-1} \\ &+ \delta\ ImportPenetration_{j,t-1} \times R\&DStock_{i,j,t-1} \\ &+ Controls_{i,j,t-1} + \nu_i + \omega_{j,t} + \varepsilon_{i,j,t}, \end{aligned} \tag{6}$$

where Y_{ijt} is an outcome variable for firm i operating in sector j in year t, $Import\ Penetration_{j,t-1}$ is the predicted import penetration from China at the industry-year level (where we use the historical four-digit SIC code to identify the a firm's industry),[14] and $R\&DStock_{i,j,t-1}$ is the 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. A positive δ would imply that an increase in the stock of R&D capital leads to an increase in the outcome variable in sectors with large import penetration relative to sectors with low import penetration.

ν_i are firm fixed effects, which absorb all time-invariant determinants of the outcome variable at the firm level. These firm fixed effects are important to

[14] 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 to not backfilling and instead using the current main SIC code. Results are also robust to using Compustat Business Segments data to construct a firm-level measure of import penetration as the average of predicted import penetration across all segments weighted by the share of each segment (see Internet Appendix III.D).

remove potential endogeneity coming from the unbalanced nature of the panel. For instance, if firms that are more resilient to import competition enter the sample period in states that offer generous R&D tax credits, 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 credits, then firms in import-competing industries with a high predicted stock of R&D will appear to have greater 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.

$\omega_{j,t}$ are industry-by-year fixed effects. They ensure that δ is identified by 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 a large number 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 comes from variations in firms' R&D tax credit rate within industry-years. Since a firm's R&D tax credit rate depends on its location, the specification with industry-year fixed effects requires that there be at least some geographic dispersion of firms within industry-years. This condition may not be satisfied for industries that are highly clustered geographically. To investigate whether this is the case, for each industry we rank states based on the share of R&D activity conducted in each state.[15] We then compute the average, across all industries, of the share of R&D conducted in the top state (which is not the same state for all industries), in the second state, and so on. Summary statistics are reported in Table V. 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 25% in the remaining states. These statistics suggest that while there is some clustering by industry, there is still significant geographic dispersion and hence we can implement the specification with industry-year fixed effects.[16]

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

[15] This share is computed using the weights we construct in Section II.B 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 the firm's inventors located in the state across all firm-years in the industry.

[16] A related concern is that California is the top state for 28% of industries. To check that the results are not driven by Californian firms, in Internet Appendix III.E we rerun the regressions after excluding firms that have more than 50% of their R&D activity in California. We obtain similar results.

Table V

Geographic Distribution of R&D by Industry

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.

Industry-by-Industry Ranking of States	Share of Industry R&D in the State
Top state	32.9%
Second state	17.2%
Third state	11.3%
Fourth state	8.2%
Fifth state	6.1%
Sixth state	4.7%
Seventh state	3.6%
Eighth state	2.9%
Ninth state	2.4%
10^{th} state	2.0%

predicted regressors. In all of our regressions, therefore, we report bootstrapped standard errors clustered by industry and year.[17]

III. Resilience to Import Competition

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

To assess whether a larger stock of R&D capital mitigates the negative effect of import competition on sales growth, we interact import penetration with the

[17] The bootstrap is conducted as follows. We first draw a random sample with replacement from the sample of industry-years used to predict imports, we run the first-stage regression for imports, and we generate the predicted imports in the United States. We then draw a random sample with replacement from 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 from the sample of firm-years used to estimate the second-stage regression (6); 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 of the firms from this industry-year), and we finally run our second-stage regression (6) on this sample. We repeat this procedure 500 times. The standard errors that we report correspond to the empirical distribution of the coefficients estimated.

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

Table VI

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

The sample comprises U.S. manufacturing firms over the 1991 to 2007 period 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), log of total assets, and log of firm age as controls. *ImportPenetration* is the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is the 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 *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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
R^2	0.24	0.24	0.34	0.34

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 hurt less by import competition shocks. The point estimate implies that going from the 25^{th} percentile to the 75^{th} 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 25^{th} percentile to the 75^{th} percentile of R&D stock reduces the effect of import competition by 0.9 percentage points, that is, by half the average effect.

One possible concern is that, even if the predicted value of R&D flow is exogenous, the predicted value of R&D stock is related to firm age. This is a problem if firms of different ages 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

Table VII

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

The sample comprises U.S. manufacturing firms over the 1991 to 2007 period 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 the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is the 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 *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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
R^2	0.68	0.68	0.72	0.72

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 nonmonotonic. In Internet Appendix III.F, we test for nonmonotonicity 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.

We turn to the effect on profitability in Table VII. 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).

When we interact import penetration with the stock of R&D, the interaction term is positive and significant at the 5% level (column (2)). Moving from the 25^{th} percentile to the 75^{th} percentile of R&D stock reduces the negative effect on ROA by 1 percentage point, that is, by the same magnitude as the average effect. The effect is slightly larger and significant at the 1% level when we include industry-year fixed effects (column (3)) and is 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, in terms of both growth and profitability.

IV. Product Differentiation

Through what mechanism does R&D moderate the effect of trade shocks on firm performance? Generally speaking, R&D can improve firm performance in two ways: by increasing product differentiation as in Sutton (1991), or by increasing productivity as in Grossman and Helpman (1991) and Aghion and Howitt (1992). A priori, however, it is unclear which channel is more important as import competition increases.

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

More specifically, the model identifies two potential channels. Under the first channel, the *benefits* of differentiation increase when import competition increases. The model prediction is that firms with ex ante more differentiated products are better shielded from import competition. Combined with the hypothesis that firms with a higher stock of R&D capital have more differentiated products independent of the intensity of import competition, this channel can explain why the benefits of R&D increase when import competition increases.

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

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

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

A. Channel 1: Higher Sensitivity of Performance to Differentiation

To study whether R&D makes firms more different and such differentiation becomes more important as import competition increases, we exploit the Text-based Network Industry Classification developed by Hoberg and Phillips (2016). Using the product description in firms' 10-Ks, Hoberg and Phillips (2016) compute pairwise word similarity scores for each pair of U.S. public firms. The similarity score ranges from zero to one and indicates the relative number of words that two firms share in their product description. Two firms are deemed to be closer in the product market space when their product similarity score is closer to one and more differentiated when their score is closer to zero. To ease exposition, we use one minus the similarity score and refer to this variable as product differentiation. For each firm-year, we compute the average product differentiation among the firm's U.S. peers. Average differentiation measures whether the firm sells more unique products that are less exposed to the competitive pressure. Because Hoberg and Phillips (2016) product similarity data start in 1996, the sample period in this analysis is from 1996 to 2007.

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

To test for (i), we regress product differentiation on instrumented R&D stock and the same set of controls and fixed effects as before. The results are reported in Table VIII. 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 effects. These results are consistent with the finding of Hoberg and Phillips (2016) that firms with higher (endogenous) R&D have more differentiated products.

To test for (ii), we regress firm performance on instrumented import penetration interacted with product differentiation as well as the noninteracted variables and the same controls and fixed effects as before. Note that we do not have an instrument for product differentiation.[19] In interpreting the results

[19] 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

Table VIII

Product Differentiation Becomes More Important (Channel 1)

The sample comprises U.S. manufacturing firms over the 1996 to 2011 period 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 (2016) product similarity index) from U.S. 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, 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 the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is the 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 the industry-year level and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	Differentiation		Sales Growth		ROA	
	(1)	(2)	(3)	(4)	(5)	(6)
R&D Stock	0.0015**	0.0011*				
	(0.00067)	(0.00062)				
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	0.00043**	−0.00044**	0.016	0.015	0.065***	0.07***
	(0.00022)	(0.00021)	(0.012)	(0.012)	(0.0088)	(0.0096)
Age	0.00031	0.00072	−0.21***	−0.2***	0.027*	0.027
	(0.00047)	(0.00046)	(0.031)	(0.031)	(0.015)	(0.016)
Differentiation ($t-1$)			−0.51	−0.73	0.02	−0.069
			(0.37)	(0.46)	(0.17)	(0.21)
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
R^2	0.83	0.84	0.25	0.35	0.74	0.77

one should keep in mind that variation in differentiation on the right-hand side might be endogenous if, for instance, 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 that this adjustment is imperfect.

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

Taken together, the evidence for (i) and (ii) indicates that R&D helps firms escape import competition by allowing them to differentiate their products, and that this mechanism becomes more important as competitive pressure from China increases.

B. Channel 2: Differentiation Increases

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

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

When we interact import penetration with the stock of R&D, we obtain a positive coefficient on the interaction term. Depending on the specification, the *p*-value is between 0.03 (when industry-year fixed effects are included, columns (3) and (4)) and 0.12 (when industry-year fixed effects are not included, column (2)). Moving from the 25$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile of R&D stock increases the effect of import penetration on differentiation by 25% of the unconditional effect. Thus, firms that invest more in R&D for reasons unrelated to competition are better able to increase differentiation when the competitive pressure intensifies and the benefits of differentiation increase.

Note that, ideally, we would measure differentiation from Chinese products. We cannot do this directly because the product similarity score is defined only for pairs of U.S. firms. Thus, our approach of looking at differentiation from

R&D. This approach would not allow us to identify whether the effect of R&D on resilience to trade shocks operates through higher sensitivity of performance to differentiation after trade shocks (channel 1) or through higher differentiation after trade shocks (channel 2).

Table IX

Product Differentiation Increases (Channel 2)

The sample comprises U.S. manufacturing firms over the 1996 to 2011 period 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 (2016) product similarity index) from U.S. 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), log of total assets, and log of firm age as controls. *ImportPenetration* is the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is firm-year-level predicted stock of R&D capital instrumented using firm-specific tax-induced user cost of R&D capital. Standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	Product Differentiation			
	(1)	(2)	(3)	(4)
Import penetration	0.035*	0.024		
	(0.02)	(0.018)		
Import penetration × R&D Stock		0.026	0.023**	0.023**
		(0.017)	(0.011)	(0.011)
Assets	−0.00082***	−0.00021	−0.00029	−0.00029
	(0.00026)	(0.00034)	(0.00034)	(0.00034)
Age	0.001**	0.00034	0.00058	0.0004
	(0.00052)	(0.00058)	(0.00059)	(0.00059)
R&D Stock		0.0018**	0.00087	0.00086
		(0.00088)	(0.00073)	(0.00073)
Import penetration × Age				−0.019
				(0.022)
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
R^2	0.78	0.78	0.83	0.83

U.S. competitors should be understood as using this variable as a proxy for differentiation from Chinese competitors, by capturing firms' ability to bring to market more unique products that are less subject to competition from (U.S. and Chinese) rivals. In Internet Appendix III.G, we follow a complementary approach and test whether a firm's products become more similar to the products of other U.S. 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 supports the view that R&D helps firms withstand import competition by improving their ability to differentiate when competition materializes.

C. Product Differentiation Across Industries

Another implication of the prediction that R&D helps firms overcome import competition through differentiation is that the effect of R&D on resilience to trade shocks should be stronger in industries in which product differentiation is more prevalent. To test this ancillary prediction, we proxy for the extent of

Table X

R&D Matters More in Industries with High Differentiation

The sample comprises U.S. manufacturing firms over the 1996 to 2011 period 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, 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 the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is the 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 (2016) product similarity index) of the industry is above the median of the sample distribution. All specifications include all the double and triple interactions between these three variables; noninteracted terms are also included but not reported. Standard errors are clustered at the industry-year level and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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
R^2	0.25	0.33	0.69	0.73

differentiation between firms at the industry level using the industry average of the firm-level differentiation measure used above and create the dummy *IndustryDifferentiation*, which we set 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 noninteracted terms and the same controls and fixed effects as before.

Table X reports the results. Columns (1) and (2) 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 similar findings in columns (3) and (4), where we use ROA to capture firm performance.

V. Capital Expenditures and Employment

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

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

In Table XI, we estimate equation (6) with capital expenditures normalized by lagged fixed assets as the dependent variable. First, we only include import penetration from China. We obtain a negative coefficient statistically significant at the 1% level (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 of capital expenditures to 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 Frésard and Valta (2016).

We next investigate whether this effect is mitigated for more innovative firms. Since innovative firms do not experience as much of a negative shock to sales and profits (see Tables VI and VII), we expect their investment opportunities will also shrink less. To test this prediction, we add the interaction term between import competition and R&D stock. We find that the interaction term is positive and significant at the 1% level (column (2)), which means that more innovative firms cut their capital expenditures less when import competition increases. The point estimate implies that moving from the 25th percentile to the 75th 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, that is, by almost as much as the unconditional effect. The effect is slightly more pronounced when we include industry-year fixed effects (column (3)) and is unchanged when we control for firm age interacted with import penetration (column (4)). Overall, while the average firms in industries exposed to Chinese competition cut capital expenditures, more innovative firms are able to continue investing in fixed capital. This result implies that the complementarity between R&D capital and fixed capital is amplified when competition intensifies.

In Table XII, we estimate equation (6) with employment growth as the dependent variable. When we only include import penetration from China (i.e., not interacted with R&D), we find that the unconditional effect of import

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

Table XI

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

The sample comprises U.S. manufacturing firms over the 1991 to 2007 period 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), log of total assets, and log of firm age as controls. *ImportPenetration* is the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is the 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 the industry-year level and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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
R^2	0.34	0.34	0.41	0.41

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 that on sales has two nonexclusive explanations. First, since sales are measured in dollars, the decline in sales can come from a reduction in quantity, a reduction in price, or both. Employment should decline only because of a drop in sales due to a drop in quantity. 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 25$^{\text{th}}$ of the R&D stock distribution reduces employment growth 0.7 percentage points (statistically significant at the 5% level) more than employment in firms at the 75$^{\text{th}}$ 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

Table XII

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

The sample comprises U.S. manufacturing firms over the 1991 to 2007 period 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), log of total assets, and log of firm age as controls. *ImportPenetration* is the industry-year-level import penetration from China in the United States instrumented using China's import penetration in eight other high-income markets. *R&DStock* is the 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 the industry-year level and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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
R^2	0.24	0.25	0.36	0.36

reduce employment growth by 1.3 percentage points (statistically significant at the 5% level). In contrast, firms at the top quartile reduce employment growth by a statistically insignificant 0.6 percentage points. The difference between firms with a high level and a low level of R&D is slightly larger when we include industry-year fixed effects (column (3)) and is unchanged when we control for firm age interacted with import penetration (column (4)). More innovative firms are therefore less likely to shrink their labor force in import-competing industries.

VI. Robustness

A. 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 United States that comes from changes in barriers to trade between China and the United States.

Following Pierce and Schott (2016), we exploit the fact that the United States changed its tariff agreement with China in 2000. Since the Smoot-Hawley Tariff of 1930, imports to the United States from nonmarket economies such as China have been subject to relatively high tariff rates, known as the non-Normal Trade Relations tariff (non-NTR). Starting in 1980, each year the President of the United States granted an annual waiver to China that needed to be approved by Congress. Following the agreement between China and the United States in 1999 governing China's eventual entry into the WTO, the United States granted China Permanent Normal Trade Relations (PNTR) status.[21]

This agreement has increased Chinese imports in the United States by reducing expected tariff rates and removing uncertainty about the U.S. trade policy vis-à-vis China. One key element of this agreement is that not all industries are affected in the same way, as the NTR tariff rate varies across industries. As such, the adoption of PNTR has led to a larger decline in the expected tariff rate in industries that have a high NTR tariff. We define the NTR gap for industry j 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 for industry j by PNTR: $\textit{NTR Gap}_j = \textit{Non-NTR Rate}_j - \textit{NTR Rate}_j$. Pierce and Schott (2016) show that industries facing a larger drop in expected tariffs experience a larger increase in Chinese imports.[22]

We first study the unconditional effect of the PNTR agreement on firm performance and investment decisions. Specifically, we regress each firm outcome variable on *NTR Gap* interacted with the dummy variable *Post*, which is equal to one after 2000, and the same controls and fixed effects as in the baseline regressions. The results are reported in the odd-numbered columns of Table XIII. Firms in industries with a higher NTR gap experience lower sale growth, lower profitability, lower capital expenditures, and lower employment growth. Moving from the 25$^{\text{th}}$ percentile (0.19) to the 75$^{\text{th}}$ percentile (0.38) of the NTR gap leads on average to a 2.2-percentage-point decline in annual sales growth ($-0.12 \times (0.38 - 0.19)$, significant at the 5% level, column (1)) and a 1.9-percentage-point decline in ROA (significant at the 1% level, column (3)).[23]

We next analyze how the effect depends on firms' R&D capital stock. To do so, we interact *NTR Gap* $\times$ *Post* with instrumented R&D stock and use our preferred specification with industry-year fixed effects.[24] The results are reported in the odd-numbered columns of Table XIII. For all four dependent variables, the interaction term is positive and statistically significant. The point estimates imply that going from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of the sample distribution of R&D stock reduces the negative effect of the interquartile NTR gap by 1.3 percentage points (significant at the 1% level, column (2)), that is,

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

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

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

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

Table XIII

Alternative Instrument for Import Competition

The sample comprises U.S. manufacturing firms over the 1991 to 2007 period from Compustat. We estimate a linear regression model on a firm-year panel. All specifications include firm fixed effects, year fixed effects, 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 onward. *R&DStock* is the 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 the industry-year level and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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		0.17***		0.09**		0.31***		0.15***
× R&D Stock		(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
R^2	0.24	0.33	0.71	0.75	0.35	0.42	0.24	0.34

by half of the unconditional effect, which is the same order of magnitude as what we obtain using the other instrument in Section III.[25]

B. Intermediate Inputs

Export growth from China leads not only to greater competition for U.S. producers but also to greater supply of intermediate inputs, which may offset the adverse effect of import competition in the final goods market. 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 goods market. We calculate import penetration in input markets as the average import penetration across all input markets weighted by the share of each input from the 1992 U.S. input-output table. For inputs coming from the manufacturing sector, import penetration is measured as imports per worker as above. For nonmanufacturing inputs, import penetration is taken to be zero. As before, input import penetration in the United States is instrumented by input import penetration in other high-income economies.

In columns (1) and (4) of Table XIV, 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 those obtained in Tables VI and VII, where we do not adjust for imports of intermediate inputs. Therefore, accounting for import competition in input markets does not affect our conclusion that a higher level of R&D allows U.S. producers to cushion trade shocks.

Next, we try to isolate the effect of input import competition by separately estimating the effects of import penetration in the final goods and intermediate input markets. Instead of netting the latter from the former, we now include the two variables in the regression. In column (2), we start by estimating the unconditional effect on sales growth of import competition in the final goods 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 goods market have a negative effect on sales growth. The coefficient on trade shocks in input markets is positive, suggesting a positive effect of positive supply shocks in input markets, but statistically insignificant. This result is consistent with Acemoglu et al. (2016), who estimate the effect of trade shocks in input markets measured in a similar way as our measure of employment growth based on the County Business Patterns data and find that the effect is imprecisely estimated and unstable in sign. In column (5), we study the unconditional effect on profitability. The effect of import competition continues

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

Table XIV

Controlling for Import Competition in Input Markets

The sample comprises U.S. manufacturing firms over the 1991 to 2007 period from Compustat. In columns (1) and (4), we estimate the same regression as in column (4) of Tables VI and VII 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 column (1) of Tables VI and VII 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 column (4) of Tables VI and VII except that we now use both import competition in the final markets and import competition in intermediate input markets. Standard errors are bootstrapped within industry-year clusters and reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	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
R^2	0.33	0.24	0.33	0.72	0.68	0.72

to be negative and strongly significant, while the effect of import competition in input markets is now positive and significant at the 10% level. These results are consistent with the view that positive supply shocks in input markets lead to cheaper inputs and higher profits, but we cannot detect significant effects of firms responding to cheaper inputs by expanding production, at least on average.

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

VII. Concluding Remarks

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

Our results have policy implications when viewed alongside previous work on how firms endogenously adjust R&D investment after trade shocks. The mixed evidence on this question (see Bloom, Draca, and Van Reenen (2016) vs. Autor et al. (2016)) suggests that firms may cut R&D investment not because its NPV becomes negative, but because trade shocks increase frictions such as credit constraints. In this case, public policies that aim to relax credit constraints may be better than R&D tax credits, which can distort firm investment choices, if not all firms have positive NPV R&D investment to undertake.

While we are cautious about generalizing 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 United States. More broadly, it is neither the first nor the last time that profitability and employment in the manufacturing sector in high-income countries face rising competition from low- and middle-income countries (Bernard, Jensen, and Schott (2006)). Second, the effect of the interaction between impact of import competition and R&D tax credit on firm performance is also relevant outside the United States as most high-income countries have introduced such tax credits to promote innovation.

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

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.