Innovation Spillovers in Production Networks: The Role of Supply Chain Complementarities

Preliminary and Incomplete (Link to Most Recent Version)

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Abstract

How does innovation propagate through production networks? I show that partnerships along the production network influence R&D expenditure and, conversely, innovation plays a crucial role in the formation of supply chain partnerships. Empirically, I document that firms' R&D intensity increases with the R&D intensity of their partners, and this relationship is robust to instrumenting R&D expenditure on exogenous R&D tax credits. I introduce a novel dynamic heterogeneous firm model where price-setting firms across two sectors, linked through the production network, invest in innovation. In the model, product complementarity produces the sorting and feedback in R&D investment across supply chain partners observed in the data, and predicts that innovation shocks predominantly benefit highly innovative upstream and downstream firms. I validate these predictions using unanticipated increases in market value attributed to patent issuances, and find these innovative firms experience increases to equity returns, sales, profits, and R&D following innovation shocks from their suppliers and customers. Finally, I show the impact of R&D tax credits is U-shaped in size: increases to innovation from R&D tax credits are greatest for the least and most productive firms.

Keywords: Innovation, supply chains, product complementarity, spillover effect

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1 Introduction

Innovation, the generation and advancement of products and ideas, is a key source of long-run economic growth. Consequently, understanding the incentives driving firm innovation is first order. While the literature has largely focused on how horizontal strategic interactions between competitors impact innovation and rents (Grossman and Helpman [1993], Aghion and Howitt [1992], Aghion et al. [2005], Klette and Kortum [2004]), the role of vertical relationships between supply chain partners on innovation is less understood. Indeed, business historians and firms emphasize the importance of their supply chain partners: for example, Steve Jobs often heralded Apple's partnership with Corning Glass in the success of the first iPhone. [1][2] Most recently, while advances in artificial intelligence have been largely attributed to increases in the market capitalization and sales of computer chip producer Nvidia, these gains were not shared by its close competitor, Intel.[3]

Supply chain partnerships, the firms' relationships with their suppliers and customers, are integral to modern production. Moreover, these economic linkages often spanning several periods and are a crucial source of firm and sector-specific shocks (Cohen and Frazzini [2008], Foerster et al. [2011], Barrot and Sauvagnat [2016], Carvalho and Tahbaz-Salehi [2019], Dou et al. [2022]). Hence, it is natural to consider how these partnerships not only impact production, but also innovation—the development and advancement of new products. In this paper, I interrogate the role of supply chain relationships on innovation and the propagation of innovation shocks, and vice versa, shed light on innovation impacts the formation and persistence of supply chain linkages.

[1]Bajarin, T. (2017, November 10). How Corning's crash project for Steve Jobs helped define the iPhone. Fast Company.

https://www.fastcompany.com/40493737/how-cornings-crash-project-for-steve-jobs-helped-define-the-iphone

[2]Hetler, A. (2024, November 7). What's going on with Nvidia stock and the booming AI market?. TechTarget.

https://www.techtarget.com/whatis/feature/Whats-going-on-with-Nvidia-stock-and-the-booming-AI-market

[3]Gallagher, D. (2025, February 3). Intel shows why Nvidia is still hard to beat. The Wall Street Journal.

https://www.wsj.com/tech/intel-shows-why-nvidia-is-still-hard-to-beat-92344c34

I begin by documenting empirical evidence for a new mechanism governing the transmission of innovation across the supply chain. While the growth literature, inspired by Romer [1986] and others, has largely focused on the transmission of innovation shocks through technology diffusion—-new ideas building on existing ideas—-with a focus on horizontal competition and technology diffusion through the citation network (Bloom et al. [2013], Acemoglu et al. [2016]), I show empirically that the supply chain also plays an important role in innovation transmission. Specifically, using Compustat and the supply chain relationships from Compustat and Factset, I document a positive relationship in research and development (R&D) intensity, as defined as R&D expenditure divided by lagged sales, and R&D growth between firms and their supply chain partners. An 1 p.p. increase to the R&D intensity of its major customers corresponds to an increase in a firm's own R&D intensity of 38 b.p. This relationship holds even after controlling for sector fixed effects, suggesting the firms' individual supply chain relationships play an important role in firm investment in innovation. Since identification of spillover effects are subject to endogeneity concerns, using firm-level relationships and exogenous exposure to R&D tax credits (Wilson [2009], Bloom et al. [2013]), I show this relationship is not only correlative, but causal: firms increase their R&D expenditure and patenting activity when their partnered firms on average increase their R&D expenditure.

Second, I present evidence that innovation intensity plays a role in the realization of supply chain linkages. Firms are more likely to be linked with partners of similar R&D intensity and size. Specifically, sorting firms by percentile of R&D intensity within its sector, a firm's percentile of R&D intensity within its sector is increasing in the percentile of R&D intensity of its partners but not in percentile of R&D intensity of non-partners in the same sector. This evidence suggests that not only do existing supply chain relationships impact innovation, but innovation impacts the formation of the supply chain network.

Moreover, I show that supply chain relationships play an important role in the diffusion of

technology. Not only do firms increase their innovation along with their supply chain partners but, using data on patenting from the USPTO, I find firms are also more likely to cite their supply chain partners and cite more recent patents by their partners, and that the proportion of citations of their supply chain partners and the similarity of their patenting increases with the duration of their relationship. This is consistent with upstream and downstream innovation actively influencing not only the magnitude of innovation, but, also the direction of innovation, in contrast to a more passive diffusion arising from the nonrivalry of ideas. Finally, using expanded data on innovation shocks from Kogan et al 2017, I find that downstream and upstream innovation shocks (increases to market value corresponding to announcements of patent approval) predict increases to R&D expenditure and the number of patents filed over subsequent years.

Next, to illustrate how upstream and downstream innovation shocks can propagate to firm R&D expenditure, markups, and valuation, I propose a dynamic heterogeneous agent model of firm innovation where firms operate along a vertical supply chain and innovate along a quality ladder to compete horizontally. In the model, a continuum of downstream firms use intermediate inputs supplied by the upstream sector to produce differentiated final goods. Demand for final goods depends on the quality of the final good which is an aggregate of not only the downstream firm's value added, but the quality of its chosen intermediate input. Given their own quality, downstream firms compete a la Cournot, and their static profit maximizing decision is to choose their price and the quality of their intermediate input to maximize profits, subject to household demand and the price schedule of intermediate inputs of varying quality. In this model, consistent with the sorting of firms across size observed in the data, complementarity of inputs along the supply chain means that the quality of the chosen intermediate input is increasing in quality of the downstream firm. For example, for computer producers requiring inputs of computer chips, firms producing better computers optimally chose a more powerful computer chips.

Each period, upstream firms compete a la Bertrand, taking their own quality as given, and each setting their prices to maximize profits given demand from downstream firms. As described earlier, demand from downstream firms depends on their own productivity and hence the profit maximizing price and resulting profits of an upstream firm's static problem depends not only on its own quality but the distribution of quality of downstream firms. To extend the analogy, a computer chip producer can charge higher prices to increase profits if the quality of computer producers increase, since not only do they demand more units but they place a greater premium on higher quality chips. In the baseline case where downstream firms have the choice among two upstream inputs, a lower quality generic or a higher quality input produced a firm with access to quality improving innovation, the profit maximizing price of the high quality upstream firm bifurcates the market, such that the higher quality intermediate inputs are sold to a subset of high quality downstream firms.

In the context of the model, productivity shocks propagate heterogeneously across the supply chain. In particular, due to product complementarity, higher quality downstream firms predominantly benefit from quality-improving shocks to the upstream producer. In contrast, for lower quality downstream firms, the accompanying increase in input costs eventually outweighs benefits from upstream quality improvement. Similarly, when downstream producers experience quality improvements, they increase their preference for higher quality intermediate inputs, shifting demand away from lower quality inputs, overwhelmingly benefiting higher quality suppliers.

In addition to their static profit maximizing decision, both upstream and downstream firms have access to decreasing returns to scale productivity-improving innovation investment. The model provides a mechanism by which supply chain relationships and product complementarity induces complementarity to returns on innovation. In one direction, improvements to downstream quality enable supplier firms to optimally increase prices and profits. Indeed, the marginal return of

upstream innovation is constrained by the distribution of downstream productivity and increases with downstream quality advances. In the other direction, when intermediate input quality is fixed, product complementarity constrains returns from quality innovations by downstream firms. In the model, increases to upstream innovations, enables downstream productivity advances to be profit maximizing. This innovation complementarity produces positive feedback between upstream and downstream innovation.

I validate the main predictions of my model using data from Kogan et al. [2017] on individual patent valuations, aggregated to the monthly and annual frequency for each firm, I show that firms real outcomes respond heterogeneously depending on their own innovation activities to exogenous upstream and downstream innovation shocks. First, defining innovation shocks as the percent of market value over the year or month attributed to patent values and using Jorda local projections (Jorda [2005]), I show firms which themselves invest in R&D benefit from innovation shocks in their supply chain, increase their sales, gross profits, capital expenditure, and employment. In contrast, firms which did not invest in R&D experienced declining or stagnant real outcomes. In addition, I show after innovation shocks in their supply chain, firms increase their own R&D over the subsequent five years, consistent with the complementarity in R&D investment produced in the model and with the results of the quasi natural experiment where firm R&D increases with exogenous changes to their partners' R&D expenditure arising from R&D tax credits. Furthermore, defining innovation shocks at the monthly level, I show that, consistent with the model, while upstream and downstream innovations are largely associated with increase in firm excess returns, the benefits accrue most to firms which are more R&D intense.

Finally, I consider the impact on R&D tax credits on innovation, profits, and the distribution of firms. Compared to the baseline stationary distribution, firms in an economy with R&D tax credits increase their innovation intensity. However, this increase is heterogenous and U-shaped,

with the least productive and most productive firms innovating the most. Indeed, if we estimate empirically how firms' relative size within their sector in Compustat impacts the effectiveness of R&D tax credits, we see that the largest relative firms increase innovation more in response to R&D tax credits. Moreover, this produces a distributional effect, increasing the dispersion of firm size in the downstream sector, as the largest firms become larger.

Section 2 describes the data, presents the motivating facts, and the results of the R&D tax credit exercise. Section 3 describes the model and the implications of the model to upstream and downstream pricing, profits, and innovation. Section 4 validates the predictions of the model using evidence from innovation shocks. Section 5 considers the impact of R&D tax credits within the model and in the data.

2 Empirics

Motivating Facts

Using data from over 80,000 annual observations of supply chain linkages between public US firms spanning 1980 to 2018, I document a strong relationship in innovation intensity between firms and their major supply chain partners. In this sample, the correlation between a firm's annual R&D intensity (as defined as R&D expenditure divided by the previous year's R&D expenditure) and the average R&D intensity of its reported customers (downstream partners) is 47 percent. Conversely, the correlation between a firm's annual R&D intensity and the average R&D intensity of its observed suppliers (upstream partners) is 37 percent. Panel A of Figure 1 provides a graphical representation of the positive relationship between firm R&D intensity and the average R&D intensity of its customers, sorting firms into 100 bins based on their customers' average R&D intensity and controlling for year fixed effects. I winsorize R&D intensity and the average R&D intensity

of its customers at the 5 percent level to limit the impact out outliers. Panel B similarly presents the positive relationship between firm R&D intensity and the average R&D intensity of known suppliers. The relationship between a firm's R&D intensity and their upstream and downstream suppliers is robust to including including year by sector (3-digit SIC) fixed effects and firm fixed effects, suggesting that the variation in firm R&D intensity is not only explained by sector-level variations, but depend largely on individual supply chain relationships.

Furthermore, I present evidence of assortative matching in innovation intensity across supply chain partners. Since sectors vary in average R&D intensity, I first sort firms with positive R&D expenditure by R&D intensity within each 3-digit SIC sector, and then, as shown in Panel A of Figure 4 for each link compare how each firm's rank compares with the rank of their upstream/downstream partner. I find that a 10 point increase in the rank of a firm's downstream partner (customer) is on average associated with a 1 point increase in rank of the firm. As a placebo, Panel B shows little relationship between a firm's R&D intensity percentile and the R&D percentile of firms which are not customers operate in the same sector as the firm's customers. This evidence suggests that not only might firms' investment in innovation depend on their supply chain partners' investment in innovation, as discussed earlier, but moreover, that innovation and product quality play important roles in the formation of supply chain partnerships.

Quasi Exogenous Variation from R&D Tax Credits

Since supplier and customer firms R&D investment decisions may coincide for many reasons, including changes to the technology space, this poses an identification challenge. One might be concerned that the positive correlation in R&D intensity between firms and their supply chain partners may not be causal, since spillover effects between partners would be a violation of the stable unit treatment value assumption (SUTVA) (Rubin [2007], Manski [1993, 2013]). in order to

identify the spillover from the existing supplier customer relationship, I exploit exogenous firm-level to the user cost of R&D investment arising from differential firm exposure to state and federal R&D tax credits, following Wilson [2009], Bloom et al. [2013], Arque-Castells and Spulber [2022] , and others. I use a two stage approach, where I first instrument each firm's R&D intensity on its state and federal user cost of R&D, and then regress the firm's R&D intensity on its customers' predicted R&D intensity. I focus on the impact of downstream R&D intensity due to the nature of data. While firms are required to report important customers, they are not required to report critical suppliers. Hence the measured impact from downstream partners should be subject to less noise.

Firms are differentially exposed to state R&D tax credits due to differences in state-level corporate income taxes and R&D subsidies rates in conjunction with firm-level differences in exposure to each state. I follow Bloom, et. al. 2013, and assume each firm's state user cost of R&D , ρ_{sit}, is proportional to a weighted average of the state-level user cost of capital, $\tilde{\rho}_{st}$, weighted by, θ_{kst}, the firm's R&D exposure to state k. To measure θ_{kst}, I use the the proportion of unique inventors located in state k corresponding to patents produced by the firm i in the previous 5 years. That is, the firm's state user cost of R&D, ρ^s_{it}, is the weighted

$$\rho^s_{it} = \log\left(\sum_{k=1}^{50} \theta_{kst}\tilde{\rho}_{st}\right)$$

While federal corporate tax rates and subsidies vary across time, firms also have different federal R&D user costs cross sectionally due to non-linearies in the percentage of R&D which qualifies for the credit. Since the goal of this tax credit was to induce additional R&D investment, the subsidy was applied to R&D only above the firm's tax applicable base, which at different points in time was a function of either past R&D or past sales. Moreover, the subsidy was not available to R&D exceeding twice the base. These rules, among others, induced differences in a firm's user cost of

R&D arising from federal R&D tax credits, ρ^f_{it}, due the firm's past sales and R&D differences, as well as changes to the tax code over time. I largely follow Bloom et al. [2013] and Arque-Castells and Spulber [2022] in their estimation of firms' R&D user cost from federal R&D tax credits.

Table 3 presents the first stage of the analysis, where log R&D expenditure is regressed on user cost of R&D arising from variations in state and firm level tax credits. As expected, an increase in the user cost, corresponds to decrease in R&D expenditure. With the state and federal user costs in hand, in the first stage, I project each firm's R&D expenditure and R&D intensity as predicted by the state and federal user costs.

$$lxrd_{it} = \gamma_0 + \gamma_{1t}\rho^s_{it} + \gamma_{2t}\rho^f_{it} + lsale_{it-1} + \delta_i + \eta_{it} \Rightarrow \widehat{lxrd_{it}}$$

$$\widehat{rdintensity_{it}} = \frac{\widehat{xrd_{it}}}{sale_{it-1}}$$

I define a firm's instrumented customer R&D intensity as the average predicted R&D intensity of its customers $k = 1, ..., N$

$$\widehat{customer_rdintensity_{it}} = \frac{1}{N}\sum_{k=1}^{N} \widehat{rdintensity_{kt}}$$

In the second stage, to estimate the role of customer R&D on a supplier's R&D, I regress a firm's R&D intensity on the average predicted R&D intensity of its customers. I control for the firm's own exposure to state and federal R&D user costs, include firm fixed effects δ_i, and to capture changes to the industry environment which may impact innovation, I include for industry (SIC3) by year fixed effects η_{it}.

$$rdintensity_{it} = \beta_0 + \beta_1 \widehat{customer_rdintensity_{it}} + \beta_2\rho^s_{it} + \beta_3\rho^f_{it} + \delta_i + \eta_{it} + \epsilon_{it}$$

Table 2 presents the coefficients of the regression. Columns 1 to 3 present the analog to Panel A of Figure 1 with year fixed effects, firm and year fixed effects, firm and year-by-sector fixed effects, respectively. Column 4 presents the regression coefficients where average customer R&D intensity instrumented by state and federal R&D tax credits. Here a 1 p.p. increase in the average customer R&D intensity induced by exogenous changes to R&D user cost due to changes in tax policy results in a 2.30 b.p. increase to a firm's R&D intensity, after controlling for the firm's own exposure to R&D tax credits and year-by-sector fixed effects. Column 5 and 6 present the regression coefficients where average customer R&D intensity is instrumented only by R&D user cost arising from state and federal tax credits, respectively, and show a 1 p.p. increase to the R&D intensity of the average customer induces a 3.60 and 3.99 p.p. increase to the firm's R&D intensity. These results suggest that the relationships between firms' innovation and their partners' innovation is not only merely correlative but firms's R&D investment increases with exogenous increases in R&D investment of their downstream partners.

Evidence on Product and Patent Similarity

I find evidence that supply chain relationships impact not only the magnitude of R&D invested, by firms, but also play a role in the direction of innovation and the development of products. First, using data on supply chain relationships, we can define the *Relationship Age* as the number of years from the first year ($RelationshipAge = 1$) the relationship was reported and measure how cross-firm citations evolve over the relationship tenure. Fore each observed relationship, Panel A of Figure 5, plots the percentage of cross firm citations attributed to the partner in the first ten years of the relationship and in the preceding ten years. On average firms, before the relationship is reported, 1.5 percent of firms' citations are to the eventual downstream partner. This increases steadily as the relationship continues, with on average 3.5 percent of firms' citations being attributed

to a single downstream partner of ten years. A very similar pattern emerges in the other direction with firms increasing citations to upstream partners throughout the relationship. Moreover, Panel B of Figure 5 considers the pairwise cosine similarity of firms' patent portfolios, defined as the set of patents issued by the firm each year. Cosine similarity is measured by first calculating a vector representing the distribution of patents across CPC patent classes and patent subgroups, and then for each pair of firms in a given year, measuring the cosine similarity of the firm's patent portfolios. Panel B shows that, not only do firms tilt their innovations increasingly towards their supply chain partners throughout the relationship, but the increase in cosine similarity proceeds the onset of the observed relationship.

3 Model

In this section I consider an infinite horizon dynamic quality ladder model of innovation with two vertically-oriented sectors, where downstream firms use intermediate inputs from upstream firms in the production of differentiated goods and both upstream and downstream firms invest in innovation to improve productivity. In the model, product complementarity in value-added across supply chain partners endogenously produces assortative matching in supply chain relationships between upstream and downstream firms, as observed in the data. Also consistent with the empirical observations, supply chain relationships are critical to the passthrough of productivity innovations and firm-level shocks. These supply chain relationships produces economic synergy between upstream and downstream innovations, particularly for the most productive firms: Downstream innovations not only increase demand for intermediate inputs but also increase the demand for higher quality intermediate inputs. Upstream innovations which increase the quality of intermediate inputs, increase demand of downstream products by households, but come at the cost of more expensive intermediate inputs; hence the relative gains accrue to more productive downstream firms, increasing

incentives to innovate.

3.1 Static Model

Household consumption and downstream profits

In the spirit of Grossman and Helpman [1993] and Aghion and Howitt [1992] , the representative household consumes aggregate $X = \left(\int_0^1 z_i x_i^{\frac{\epsilon-1}{\epsilon}} di\right)^{\frac{\epsilon}{\epsilon-1}}$ of differentiated goods x_i, which have elasticity of substitution $\epsilon$and vary in quality z_{it}. Production spans two sectors: the upstream sector S and the downstream sector C. Differentiated goods indexed by i are produced by a continuum of downstream firms in sector C which compete monopolistically using blueprints of quality z_i^C and constant returns to scale technology production with marginal cost $\psi^C z_i^C$, reflecting the notion that more advanced blueprints are more expensive. In addition, each unit produced by the downstream firm requires a unit of intermediate input supplied by sector S. We can think of this as analogous to computer firms requiring computer chips as intermediate inputs in their production or electric vehicle producers requiring lithium ion batteries.

Let Z^S be the set of intermediate input qualities available to the downstream firm. The downstream firm has the choice over intermediate input quality $z_i^S \in Z^S$and faces increasing price schedule $g\left(z_i^S\right)$ where $g' > 0$ and $g'' \geq 0$ (Better quality intermediate inputs are increasingly more expensive). The household's demand for good i is a function of not only price p_i^C, but critically also a function of aggregate $z_{it} = \left(\kappa_C \left(z_i^C\right)^{\frac{\nu-1}{\nu}} + \kappa_S \left(z_i^S\right)^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}}$ of both the downstream quality z_i^C and the upstream input z_i^S chosen by the downstream firm. A downstream firm with blueprint quality z_i^C hence chooses p_i^C and z_i^C to solve static profit maximizing problem

$$\pi^C\left(z_i^C\right) = \max_{p_i^C, z_i^S \in Z^S} x\left(z_i^C, z_i^S, p_i^C\right)\left[p_i^C - \psi^C z_i^C - g\left(z_i^S\right)\right]$$

given household demand $x_i = x\left(z_i^C, z_i^S, p_i^C\right) = X\left(\left(\kappa_C\left(z_i^C\right)^{\frac{\nu-1}{\nu}} + \kappa_S\left(z_i^S\right)^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}}\right)^{\epsilon}\left(\frac{p_i^C}{P}\right)^{-\epsilon}$ and increasing price schedule $g\left(z_i^S\right)$ for the intermediate input. Intuitively, demand for the downstream firm's product increases with the quality of the intermediate input z_i^S; however, higher quality inputs are more expensive ($g' > 0$). The first order condition with respect to z_i^S for an interior solution reflects this tradeoff:

$$\underbrace{p_i^C z_i^{\frac{1-\nu}{\nu}} \kappa_S \left(z_i^S\right)^{-\frac{1}{\nu}}}_{MR_{z^S}} = g_{z^S}$$

Namely, given downstream quality z_i^C, the marginal return from a higher quality input z^S, MR_{z^S}, must justify the additional per unit cost g_{z^S}. Indeed, substituting the profit maximizing price $p_i^C = \frac{\epsilon}{\epsilon-1}\left[\psi^C z_i^C + g\left(z_i^S\right)\right]$, we evaluate how MR_{z^S} changes with downstream quality z_i^C.

$$\frac{dMR_{z^S}}{dz_i^C} = z_i^{\frac{1-\nu}{\nu}} \kappa_S \left(z_i^S\right)^{-\frac{1}{\nu}} \left[\frac{\epsilon}{\epsilon-1}\psi^C\right] + \frac{1-\nu}{\nu} p_i^C z_i^{-2} \kappa_S \kappa_C \left(\frac{z_i^S}{z_i}\right)^{-\frac{1}{\nu}} \left(\frac{z_i^C}{z_i}\right)^{-\frac{1}{\nu}}$$

If the blueprints across the supply chain are complementary, $\nu < 1$, then $\frac{dMR_{z^S}}{dz_i^C} > 0$, meaning downstream firms with higher quality blueprints z_i^C place greater value on higher quality intermediate inputs z_i^S.

Positive Assortative Matching

Consider the special case where a downstream firm i has the static choice between two upstream intermediate inputs of quality, a generic supplier with input quality z_0^S which produces at cost $\psi^S z_0^S$ and an innovating supplier with quality $z_1^S > z_0^S$, with prices $p_1^S > p_0^S$, respectively. A downstream firm of quality z_i^C which chooses intermediate input quality z_j^S earns profits

$$\pi^C\left(z_i^C, z_j^S\right) = X\left(\frac{1}{P}\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon} \frac{1}{\epsilon-1} z_{ij}^{\epsilon} \left(\psi_{ij}^C\right)^{1-\epsilon}$$

where $z_{ij} = \left(\kappa_C\left(z_i^C\right)^{\frac{\nu-1}{\nu}} + \kappa_S\left(z_j^S\right)^{\frac{\nu-1}{\nu}}\right)^{\frac{\nu}{\nu-1}}$, $\psi_{ij}^C = \psi^C z_i^C + p_j^S$, and $p_i^C = \frac{\epsilon}{\epsilon-1}\psi_{ij}^C$.

Hence there exists cutoff price $p_1^{S*}\left(z_i^C\right)$ below which firm i of quality z_i^C will choose the higher quality intermediate input

$$p_1^{S*}\left(z_i^C, z_1^S\right) = \left(\frac{\kappa_C\left(z_i^C\right)^{\frac{\nu-1}{\nu}} + \kappa_S\left(z_1^S\right)^{\frac{\nu-1}{\nu}}}{\kappa_C\left(z_i^C\right)^{\frac{\nu-1}{\nu}} + \kappa_S\left(z_0^S\right)^{\frac{\nu-1}{\nu}}}\right)^{\frac{\epsilon}{\epsilon-1}\frac{\nu}{\nu-1}} \left(\psi^C z_i^C + p_0^S\right) - \psi^C z_i^C$$

Observe that for $\nu \leq 1$, meaning productivities are complementary across the supply chain, $\frac{dp_1^{S*}\left(z_i^C, z_1^S\right)}{dz_i^C} > 0$. That is, for a given intermediate input quality z_1^S, higher quality downstream firm z_i^Cwill value the intermediate input more and have a higher reservation price p_1^{S*}. We can also show that $\frac{d^2 p_1^{S*}\left(z_i^C, z_1^S\right)}{dz_i^C z_1^S} > 0$. Intuitively, as the higher quality intermediate input,z_1^S, improves, the gap between what a lower quality downstream firm and a higher quality downstream firm is willing to pay widens. Figure 7 depicts this graphically, showing (1) reservation price $p_1^{S*}\left(z_i^C, z_1^S\right)$ is increasing in downstream productivity z_i^C and (2) for higher quality z_S, reservation price $p_1^{S*}\left(z_i^C, z_1^S\right)$ increases more rapidly for higher quality downstream customer z_i^C.

Upstream Firms

The non generic upstream firm with quality z_1^Stakes the distribution of downstream firms $\Phi\left(z_i^C\right)$ and their outside option z_0^S with price p_0^S as given, and chooses price p_1^S to maximize profits

$$\pi^S\left(z_1^S\right) = \max_{p_1^S} \int_0^1 \left(p_1^S - \psi^S z_1^S\right) x\left(z_i^C, z_1^S, p_i^C\right) \mathbf{I}\left\{p_1^S \leq p_1^{S*}\left(z_i^C, z_1^S\right)\right\} d\Phi\left(z_i^C\right)$$

Observe that since $p_1^{S*}\left(z_i^C, z_1^S\right)$ increasing in z_i^C, there exists cutoff z^{C*} such that if $p_1^S = p_1^{S*}\left(z^{C*}, z_1^S\right)$, then for all $z_m^C \geq z^{C*}$, $p_1^{S*}\left(z_m^C, z_1^S\right) \geq p_1^S$. Hence the upstream firm's problem can be defined equivalently as follows.

$$\pi^S\left(z_1^S\right) = \max_{p_1^S} \int_{\Phi(z^{C*})}^1 \left(p_1^S - \psi^S z_1^S\right) x\left(z_i^C, z_1^S, p_i^C\right) d\Phi\left(z_i^C\right)$$

Figure 8 plots the upstream profits across different prices, p_1^S, and for different productivities, z_1^S, assuming the upstream firm faces a downstream sector of firms distributed according to a Pareto distribution, $z_i^C \sim Pareto\,(1, 1.5)$, and given an assumption for generic quality, z_0^S, and price, $p_0^S = \psi^S z_0^S$. For a given z_1^S, increasing p_1^S initially rapidly increases upstream firm's profits since the supplier's price is substantially below downstream firm's reservation price. However as p_1^S increase, not only does each downstream firm demand fewer units, but downstream firms, beginning with the least productive, substitute away to the generic. Moreover, while higher productivity suppliers charge higher prices, p_1^S, we see that the downstream distribution restricts the increases to profits—that is, the returns to innovation—accrued to a higher quality upstream. Not only are returns diminishing, but when the downstream distribution is unchanged, a sufficiently high z_1^S actually receives lower profits, because the increased costs to producing a higher quality blueprint are not enough to offset the reduction in demand. Figure 9 presents the upper convex envelope of profits depicted in Figure 8, showing profits, $\pi^S\left(z_1^S\right)$, for as a function of upstream productivity, z_1^S. In addition, as z_1^S increases, optimal price p_1^S and markup p_1^S/ψ_1^S also increase, while quantity produced falls, as the more productive supplier chooses to target a more rarified customer base. Finally, Figure 10 shows that as the downstream distribution of z_i^C elongates right, not only do profits increase for all $z_1^S > z_0^S$, but the profit function $\pi^S\left(z_1^S\right)$ becomes steeper.

Downstream Profits

Given the non-generic supplier's best response $p_1^S\left(z_1^S\right)$ to distribution $\Phi\left(z^C\right)$, we can ask how profits vary across profit-maximizing downstream firms of different productivities, z_i^C, along the distribution, and how these profits change when the supplier productivity, z_1^S, changes.

First, the downstream firm has choice over intermediate input quality $\left\{z_0^S, z_1^S\right\}$ and associated price $\left\{p_0^S, p_1^S\right\}$. Following a similar argument to before, for $\nu \leq 1$ there exists cutoff z^{C*} such that for all $z_i^C \geq z^{C*}$, firms will optimally choose the higher quality input since $\pi^C\left(z_i^C, z_1^S, p_1^S\right) \geq$

$\pi^C\left(z_i^C, z_0^S, p_0^S\right)$, and below which firms will choose the generic input.

Next, conditional on choice z_j^S and price p_j^S, we can evaluate the derivative of downstream profits $\pi^C$with downstream productivity z_i^C.

$$\frac{d\pi^C\left(z_i^C, z_j^S\right)}{dz_i^C} = X\left(\frac{1}{P}\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon}\left(\frac{z_{ij}}{\psi_{ij}^C}\right)^{\epsilon}\left[\frac{\epsilon}{\epsilon-1}\left(\frac{\psi_{ij}^C}{z_i^C}\right)\underbrace{\frac{dz_{ij}/z_{ij}}{dz_i^C/z_i^C}} - \psi^C\right]$$

Note that derivative is increasing in the elasticity to the firm's own productivity, $\frac{dz_{ij}/z_{ij}}{dz_i^C/z_i^C} = \kappa_C\left(\frac{z_i^C}{z_{ij}}\right)^{\frac{\nu-1}{\nu}}$. Indeed, for $\nu < 1$ and sufficiently small z_i^C,

$$\frac{\epsilon}{\epsilon-1}\left(\psi^C + \frac{p_1^C}{z_i^C}\right)\underbrace{\frac{dz_{ij}/z_{ij}}{dz_i^C/z_i^C}} \geq \psi^C$$

and hence downstream profits are increasing in z_i^C.

We can see this reflected in Figure 11: for a given upstream productivity z_1^S and price p_1^S, the profit function $\pi^C\left(z_i^C\right)$ has two regions: In the first region, lower quality downstream firms select the generic. However, as their productivity z_i^C increases, their chosen intermediate input does not increase z_0^S, therefore profits fall as increases to z_i^C do not translate into sufficient increases in household demand to compensate for the increasing blueprint cost $\psi^C z_i^C$. This continues until an inflection point, z^{C*}, is reached where $p_1^{S*}\left(z^{C*}\right) = p_1^S$ (such downstream firm is indifferent between choice of intermediate inputs) and downstream firms switches to the non-generic, higher quality input. After this point, profits again increase with quality, z_i^C, eventually reaching a maximum, after which profits fall as before.

We can ask next how downstream profits vary with upstream productivity z_j^S, assuming the

firm does not switch.

$$\frac{d\pi^C\left(z_i^C, z_j^S\right)}{dz_j^S} = X\left(\frac{1}{P}\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon}\left(\frac{z_{ij}}{\psi_{ij}^C}\right)^{\epsilon}\left[\frac{\epsilon}{\epsilon-1}\left(\frac{\psi_{ij}^C}{z_j^S}\right)\underbrace{\frac{dz_{ij}/z_{ij}}{dz_j^S/z_j^S}} - \frac{dp_j^S}{dz_j^S}\right]$$

When productivity, z_j^S, improves, the upstream firm is able to charge higher price p_j^S. Hence profits are increasing provided the following holds

$$\frac{\epsilon}{\epsilon-1}\left(\frac{\psi^C z_i^C + p_1^C}{z_j^S}\right)\underbrace{\frac{dz_{ij}/z_{ij}}{dz_j^S/z_j^S}} \geq \frac{dp_j^S}{dz_j^S}$$

where elasticity $\frac{dz_{ij}/z_{ij}}{dz_j^S/z_j^S} = \kappa_S\left(\frac{z_i^S}{z_{ij}}\right)^{\frac{\nu-1}{\nu}}$. Observe for $\nu \leq 1$ and z_i^C sufficiently large, product complementarity means that the benefit from the increased demand exceeds the accompanying per unit cost $\frac{dp_j^S}{dz_j^S}$. Moreover, for these firms, $\frac{d\pi^C\left(z_i^C, z_j^S\right)}{dz_j^S}$ is increasing in z_i^C.

Finally, if z_0^S and p_0^S do not change, to understand how threshold z_C^* varies with upstream productivity z_1^S, since $\pi^C\left(z^{C*}, z_0^S, p_0^S\right)$ is unaffected, it is sufficient to evaluate $\frac{d\pi^C\left(z^{C*}, z_1^S\right)}{dz_1^S}$. If $\frac{d\pi^C\left(z^{C*}, z_1^S\right)}{dz_1^S} < 0$ then the threshold increases with productivity improvements, $\frac{dz^{C*}}{dz_1^S} > 0$ as the marginal downstream firm z^{C*} and a neighborhood around it substitute away from the higher quality input. This occurs if the ability of the upstream firm to raise prices, $\frac{dp_1^S}{dz_1^S}$, is high, which depends on downstream distribution, $\Phi\left(z_i^C\right)$.

In summary, due to product complementarity, the upstream quality z_1^S limits the commercial feasibility of downstream productivity z_i^C: the z_i^C which attains the global maximum profits $\pi^C\left(z_i^C\right)$, increases with upstream productivity z_1^S, and for sufficiently high z_i^C, returns to increasing downstream productivity z_i^C increase with upstream productivity. Finally, quality improvements to z_1^S have a heterogeneous impact on downstream profits $\pi^C\left(z_i^C\right)$, with three distinct regions: (1) on one end, the lowest quality z_i^Cwhich continue to use the generic and are unaffected (2) on the other

end, the highest quality z_i^C for which profits increase, and (3) the intermediate subset for which the accompanying increase to the intermediate price may or may not sufficiently compensate for increased household demand.

3.2 Innovation, Feedback, and Model Equilibrium

Innovation

The previous section presented a static model of strategic interaction between two sectors of price-setting upstream and downstream firms. I now consider how these strategic interactions between these two sectors which are connected through the supply chain impact the decision to innovate in each sector. Following, previous models of innovation and growth, I suppose the non-generic upstream firm has access to productivity improving, decreasing returns to scale, innovation technology such that advances to productivity, z_{1t}^S, is increasing in proportional spending on innovation investment η_{1t}^S and subject to constant rate of depreciation δ.

$$z_{1t+1}^S - z_{1t}^S = \chi \left(\frac{\eta_{1t}^S}{z_{1t}^S} \right)^{\xi} z_{1t}^S - \delta z_{1t}^S$$

Given downstream distribution $\Phi\left(z_t^C\right)$, the upstream firm chooses investment η_{1t}^S to maximize its discounted future value and solves the below value function.

$$V^S\left(z_{1t}^S, \Phi\left(z_t^C\right)\right) = \max_{\eta_{1t}^S} \pi^S\left(z_{1t}^S, \Phi\left(z_t^C\right)\right) - \eta_{1t}^S + \beta V^S\left(z_{1t+1}^S, \Phi\left(z_{t+1}^C\right)\right)$$

Similarly, I suppose each downstream firm has access to innovation technology η_{it}^C. A firm with initial quality z_{it}^Cdraws stochastic $\hat{z}_{it+1}^C$ such that

$$\hat{z}_{it+1}^C - z_{it}^C = \chi z_{it}^C d\Theta_{it}^C - z_{it}^C d\Theta^D$$

where $d\Theta^D$ is Poisson process with average δ^C and $d\Theta^C_{it}$ is Poisson process with average $\left(\frac{\eta^C_{it}}{z^C_{it}}\right)^{\xi}$. Since profits $\pi^C\left(z^C_{it}\right)$ are non monotonic in z^C_{it}, if firms had to operate at $\hat{z}^C_{it+1}$ they may not innovate altogether to avoid decreasing profits. Instead, I suppose as follows that $\hat{z}^C_{it+1}$ represents an upper bound: the downstream firm chooses the $z^C_{it+1} \leq \hat{z}^C_{it+1}$ to maximize its future valuation given expectations on future upstream productivity, z^S_{1t+1}, and the distribution of downstream productivities, $\Phi\left(z^C_{t+1}\right)$.

$$z^C_{it+1} \in \arg \max_{z^C_{it+1} \in \left[z^C_{it} - z^C_{it} d\Theta^D, z^C_{it} + \chi z^C_{it} d\Theta^C_{it} - z^C_{it} d\Theta^D\right]} V^C\left(z^C_{it+1} \mid z^S_{1t+1}, \Phi\left(z^C_{t+1}\right)\right)$$

I furthermore assume each downstream firm has exogenous probability ϕ^C of exiting. The value function is hence defined as below with the downstream firm choosing innovation investment, η^C_{it}, to maximize expected future valuation.

$$V^C\left(z^C_{it+1} \mid z^S_{1t+1}, \Phi\left(z^C_{t+1}\right)\right) = \max_{\eta^C_{1t}} \pi^C\left(z^C_{it}, z^S_{1t}, \left\{z^C_{it}\right\}\right) - \eta^C_{it} + E_t\left[\beta\left(1-\phi^C\right) V^C\left(z^C_{it+1} \mid z^S_{1t+1}, \Phi\left(z^C_{t+1}\right)\right)\right]$$

Product complementarity and the supply chain relationship leads to complementarity in R&D investment. As illustrated earlier, upstream profits $\pi^S\left(z^S_{1t}, \Phi\left(z^C_t\right)\right)$ are a function not only of the upstream firm's own productivity but the distribution of downstream productivities, $\Phi\left(z^C_{t+1}\right)$ and profits, and hence returns to innovation, increase as $\Phi\left(z^C_{t+1}\right)$ extents rightward. Similarly, downstream profits $\pi^C\left(z^C_{it}, z^S_{1t}, \Phi\left(z^C_t\right)\right)$, and hence returns to innovation, are a function of upstream productivities, and for sufficiently large z^C_{it}, downstream profits are increasing in upstream productivities. Together, this produces complementarity in investments in innovation: quality-improving downstream innovation increases returns to upstream innovation and vice versa upstream innovation feeds back, incentivizing downstream innovation for high quality downstream firms.

Horizontal Feedback

In the model, vertical strategic interactions also have implications for horizontal competition. It is well understood that competitor quality improvements and innovations negatively impact firms, supplanting existing profits, eroding margins, and capturing market share. In the model, supply chain dynamics interact with and sometimes amplify the impact of horizontal innovation shocks. First, quality improvements to downstream firms enable the non-generic supplier to optimally increase the price of its intermediate input, weakly raising marginal costs for downstream firms which did not innovate. Second, as discussed previously, quality improvements to the higher quality upstream firm may cause some downstream firms to optimally reallocate to the benefit of the generic supplier. In contrast, an increase to the productivity of the generic, pulls demand away from the higher quality upstream supplier, but the magnitude depends largely on the downstream distribution: higher quality downstream firms will still optimally choose the higher quality intermediate input.

Model Equilibrium

The stationary equilibrium can be characterized as non-generic supplier quality z_1^{S*}, price p_1^{S*}, and innovation investment η_1^{S*}plus downstream distribution $\Phi^* \left(z^C\right)$ and investment function $\eta^{C*} \left(z^C\right)$ across the distribution such that

1. Given downstream distribution $\Phi^* \left(z^C\right)$ and investment $\eta^{C*} \left(z^C\right)$, p_1^{S*} solves the upstream non-generic supplier's static problem and η_1^{S*} solves its dynamic investment decision.

2. For each downstream firm z_i^{C*}, $\eta^{C*} \left(z_i^C\right)$ solves its dynamic problem, assuming downstream profits reflects supplier quality $z_1^{S*}$and price p_1^{S*} in perpetuity.

3. Distribution $\Phi^* \left(z^C\right)$ evolves according to $\eta^{C*} \left(z_i^C\right)$, exit rate ϕ^C, and exogenous initial distribution $\Phi_{new} \left(z^C\right)$.

Figure 13 presents the resulting stationary downstream distribution and scaled innovation rates η_i^{C*}/z_i^{C*} for each productivity level z_i^{C*}. We see little to no innovation for draws of z_i^C that elect to use the intermediate input since any innovation is unlikely to increase profits. As alluded to from observations of profits, for intermediate quality z_i^C which use the higher quality input, we initially see higher levels of innovation, which decline increases to costs $\psi^C z_i^C + p_1^{S*}$ outweigh the joint benefits of $z_1^{S*}$and a higher z_i^C.

4 Impact of Innovation Shocks

Section 2 provides empirical evidence that supply chain partnerships play an important role in firm innovation: firms' R&D investment respond to the R&D investment of their supply chain partners. Section 3 provides a mechanism by which upstream and downstream quality improvements induce increases to R&D investment. In this section one can ask how firms respond to realized innovation shocks across their supply chain, given that these innovation shocks should correspond to future quality improvements. To define a firm innovation shock, I lean on the data of patent valuations from Kogan et al. [2017] which use daily firm level increases to equity prices around the issuance of new patents to estimate the market value of each individual patents. A key assumption is that each patent's issuance reflects new information on the realization of firm innovation not previously reflected in the firm's market value. For each firm i, I define a firm's innovation shock in period t, $InnovShock_{it}$, as the market value sum of all patents issued to firm i in year t, $PatentValue_{it}$, divided by the market value of firm i as of the beginning of the year, $MarketValue_{it-1}$, and winsorize at the 1 percent level.

$$InnovShock_{it} = \frac{PatentValue_{it}}{MarketValue_{it-1}}$$

Figure 6 presents the distribution of firm innovation shocks for the set of firms who were issued at least one patent during the period. On average firms experience a monthly innovation shock of 1.7 percent. The distribution is naturally right skewed with the firm's innovation shock reflecting the change in the firm's market value attributed to patent issuances.

I define a firm i's exposure to downstream/customer innovation shocks, $CustomerInnovShock_{it}$ as the average of the innovation shocks experienced in year t of all known customers $j \in J$ of firm i for year t.

$$CustomerInnovShock_{it} = \frac{\sum_{j \in J} Innovsk_{jt}}{|J|}$$

Firm i's exposure to upstream/supplier innovation shocks, $SupplierInnovShock_{it}$, is similarly defined using the set of known suppliers. Intuitively, this measure reflects the magnitude of realized innovation to a firm's downstream and upstream partners, respectively.

Real Impact

What is the real impact of innovation shocks across the supply chain? To understand how downstream/customer innovation shocks impact real firm investment and outcomes, I utilize Jorda local projections, regressing annual firm dependent variables $\log(y_{it+h})$ for years $h = 0, ..., 5$ on the firm's exposure to a customer innovation shock in year t, $CustomerInnovShock_{it}$, and controlling for the lagged variable $\log(y_{it+h})$, a firm's own innovation shock $InnovShock_{it}$, and firm and year-by-sector fixed effects, δ_i and η_{it}, respectively.

$$\log(y_{it+h}) = \beta_0 + \beta_1 CustomerInnovShock_{it} + \beta_2 Shock_{it} + \beta_3 \log(y_{it-h}) + \delta_i + \eta_{it} + \epsilon_{it}$$

First, the model provides a mechanism by which upstream and downstream innovation shocks propagate. Specifically, when downstream firms experience innovation shocks, increases to their

productivity, mean that they not only demand more intermediate inputs, but demand higher quality inputs. This increases the incentives of upstream/supplier firms to innovate. Consistent with the predictions of the model, Figure 15 shows that downstream/customer innovation shocks correspond to elevated R&D growth on the year of the shock and over the subsequent 5 years and an increase to the number of patents filed over the next couple years. We can also consider how downstream innovation shocks impact sales, gross profits, capital expenditure and employment. With the context of the model in mind, I consider separately firms that innovate and those that do not. As shown in Figure 17, following a customer innovation shock, innovating firms increases to both sales and gross profits. In contrast, non-innovating firms experience declines to both sales and gross profits, with the decline in gross profits exceeding the declines to sales, suggestions that non innovating firms are also cutting margins after a downstream shock. Moreover, if we consider the impact over a 5 year horizon on forward looking variables such as capital expenditure and employment in Figure 16, we again find a different response between innovating and non-innovating firms: innovating firms experience significant increases to capital expenditure and employment over the 5 year horizon, where as non-innovating firms experience decreases to capital expenditure and non-significant impact to employment. This is consistent with downstream innovation shifting demand to higher quality intermediate inputs.

Next we can conversely consider the impact of upstream/supplier innovation shocks on real firm outcomes, by estimating the impact of supplier innovation shocks, $SupplierInnovShock_{it}$, which reflect the average increase to market value due to patent issuance for a firm's observed suppliers.

$$\log(y_{it+h}) = \beta_0 + \beta_1 SupplierInnovShock_{it} + \beta_2 Shock_{it} + \beta_3 \log(y_{it-h}) + \delta_i + \eta_{it} + \epsilon_{it}$$

As before, the model suggests that due to product complementarity, increases to supplier produc-

tivity increase incentives of downstream/customer firms to innovate. Consistent with the model predictions, Figure 18 shows that a supplier innovation shock increases firm investment in R&D. Moreover, the model predicts supplier innovation shocks also differentially impact firms, with the highest quality customers benefitting most from productivity improvements. If we again compare the impact of supplier innovation shocks on innovating and non innovating firms in Figure 19, we see that, consistent with the model, a differential impact: an upstream shock corresponds to positive growth in sales and gross margins for innovating firms (those with positive R&D) and little significant impact on growth of sales and gross margins of non-innovating firms.

Equity Prices

Given that new on patent issuances are reflected in changes to firms' own market valuations, and these shocks have real consequences to upstream and downstream capital and R&D investment and firm outcomes, it is natural to think that the upstream and downstream impact of innovation news should also be priced. Indeed, I show that this is the case. Measuring customer innovation shocks are before, as the average percent change over the month attributed to a firm's customers' patents, I can regress downstream/customer innovation shocks on firm monthly excess returns, where excess returns reflect idiosyncratic returns after accounting for the firm's market beta.

$$ExcessReturn_{it} = \beta_0 + \beta_1 CustomerInnovShock_{it} + \epsilon_{it}$$

Column 3 of Table I presents the results of this regression. On average a 1 p.p. customer innovation shock corresponds to a 24 b.p. increase to a firm's excess return. Interacting the customer innovation shock with a dummy where $PosRD_{it} = 1$if firm i invests in R&D in the previous fiscal year in Column 4 suggests that most of positive excess return, 20 b.p., due to downstream innovation shocks accrues to firms which themselves innovate. As before, this suggests that a firm's own

innovation plays an important role in the extent which a firm benefits from downstream innovation. I investigate this further, in Column 5, where I estimate a positive coefficient between the customer innovation shock and the firm's own previous year's R&D intensity. Indeed in Column 6, I include an interaction with the firm's own innovation shock in the same month.

$$\begin{aligned} ExcessReturn_{it} &= \beta_0 + \beta_1 CustomerInnovShock_{it} + \beta_2 InnovShock_{it} \\ &\quad + \beta_3 CustomerInnovShock_{it} \times InnovShock_{it} + \epsilon_{it} \end{aligned}$$

The resulting positive coefficient on the interaction term is consistent with the complementarity in returns to innovation investment observed in the model. Firms benefit most from downstream innovations which coincide with their realizations to their own innovations. Finally Figure 14 presents an an analog to Column 5. Consistent with the R&D activity impacting a firm's response to downstream innovation, I divide innovating firms into quantiles according to their R&D intensity within the preceding year, and run the previous regression of excess returns on customer innovations shocks for each quantile, as well as the set of non-innovating firms. Figure 14 presents the coefficients for each groups: Firms which are more R&D intense response more positively to downstream innovation shocks.

Next, to evaluate the equity pricing response of upstream innovation shocks, I similarly regress firm excess returns on the average innovation shocks of their suppliers for each month.

$$ExcessReturn_{it} = \beta_0 + \beta_1 SupplierInnovShock_{it} + \epsilon_{it}$$

Column 3 of Table II finds that a 1 p.p. supplier innovation shock corresponds to a 24 b.p. increase in excess returns. Column 4 suggestions returns largely accrue to innovating firms, and have little impact on non innovating firms. Furthermore, consistent with the model and previous evidence

on the real impact of supplier innovation shocks, Column 5 which reports the coefficients to the interaction between supplier innovation shocks and a firm's own innovation shocks, suggest that the impact of supplier innovation shocks on excess returns is amplified by firms' own innovations, and when firms do not benefit from patent issuances in the month, they on average experience a negative impact of suppliers innovation shocks. This would be consistent with the market anticipating supplier innovations outpacing the downstream firm such that the upstream innovations reflect increased cost which are not compensated by increases to demand.

5 R&D Tax Credits

Counterfactual Horizontal Economy

In this section, I consider the impact of two important trends from the 1980s: the increase in state and federal R&D tax credits and the decline in real interest rates.

We can contrast the paper's model with a standard quality ladder model with only firms which compete monopolistically and innovate. In this model, given a firm with productivity z_i, a household will demand $x(z_i) = Xz_i^{\epsilon}\left(\frac{p_i}{P}\right)^{-\epsilon}$. The firm will optimally choose price $p_i = \frac{\epsilon}{\epsilon-1}\psi z_i$ where ψz_i is the per unit cost. Hence, without a supply chain, profits scale linearly with productivity.

$$\pi(z_i) = \frac{XP^{\epsilon}\psi^{1-\epsilon}}{\epsilon - 1} z_i$$

If a firm with productivity z_{it} chooses innovation intensity η_t to maximize firm value

$$V(z_{it}) = \max_{\eta_{it}} \frac{XP^{\epsilon}\psi^{1-\epsilon}}{\epsilon - 1} z_{it} - \theta\eta_{it} + \beta EV(z_{it+1})$$

where θ is the gross tax or subsidy on R&D, and productivity is a stochastic process

$$\frac{dz_{it+1}}{z_{it}} = \chi d\Theta_{it} - \delta$$

where $d\Theta_{it}$ follows Poisson process with average $\left(\frac{\eta_{it}}{z_{it}}\right)^{\xi}$, then it is straightforward to show that innovation intensity $i_{it} = \frac{\eta_{it}}{z_{it}}$ is homogenous of degree zero in z_{it} and value $V(z_{it})$ is linear with z_{it}. Taking first order conditions and applying the envelope condition, the solution can be characterized by a system of two equations

$$\theta = K^* \beta \chi \left(i^*\right)^{\xi - 1} \xi$$

$$A - \theta i^* + \beta K^* \left(1 + \chi i^{*\xi} - \delta\right) = K^*$$

where $i^* = \frac{\eta_{it}}{z_{it}}$ and $K^* = \frac{V(z_{it})}{z_{it}}$. Consequently, under this horizontal model, the impact of R&D tax credits to innovation and valuations, $\frac{di^*}{d\theta}$ and $\frac{dK^*}{d\theta}$, and the impact of an exogenous change to discount rates, $\frac{di^*}{d\beta}$ and $\frac{dK^*}{d\beta}$, are invariant to productivity z_{it}.

R&D Tax Credits

R&D tax credits were introduced at the federal level in through the 1981 Economic Recovery Tax Act (ERTA), and have increased steadily since.[4] Section 2 presents evidence that these R&D tax credits propagate through the production network, by increasing the incentive of supply chain partners to innovate in anticipation of future productivity improvements. However, as illustrated through the model in Section 3 and empirically in Section 4 the impact of productivity improvements is heterogenous, largely benefiting the highest quality, most productive firms.

Figure 20 compares the baseline economy with one where R&D costs fall by 10 percent due as consistent with a tax credit. The top panel shows that as the equilibrium supplier quality increases,

[4]Figure 21 shows the R&D user cost over time has fallen as tax credits have increased.

downstream profits as a function of productivity z_i^C change. As before, the most productive firms experience an increase to profits, firms using the generic experience no change, and there is an intermediate region which is worse off. The top panel also plots that innovation intensity, η_i^C/z_i^C. As expected, firms increase their innovation intensity. However, if we calculate how innovation intensity increase with the tax credit along z_i^C, as in the middle panel, we see that innovation intensity is U-shaped. This is in contrast to the counterfactual model with only a single sector and horizontal competition, where firms of all size increase innovation intensity equally. On one end lowest quality downstream firms who still benefit from innovation increase their innovation. On the other end, we see that the increase to innovation intensity is greatest for the most productive firms.

Indeed, Table III shows that in the data, if we sort firms by their size percentile for each firm by 3-digit sector group, we observe that it is the largest firms (analogously the most productive in the model) which decrease their R&D expenditure more for each increase to R&D user cost (decrease to R&D tax credits). Finally, the bottom panel of Figure 20 plots the stationary distribution of the downstream firm under the baseline economy and the economy with the tax credit. The tax credits have a distributional consequence, increasing the dispersion of sales across the downstream sector.

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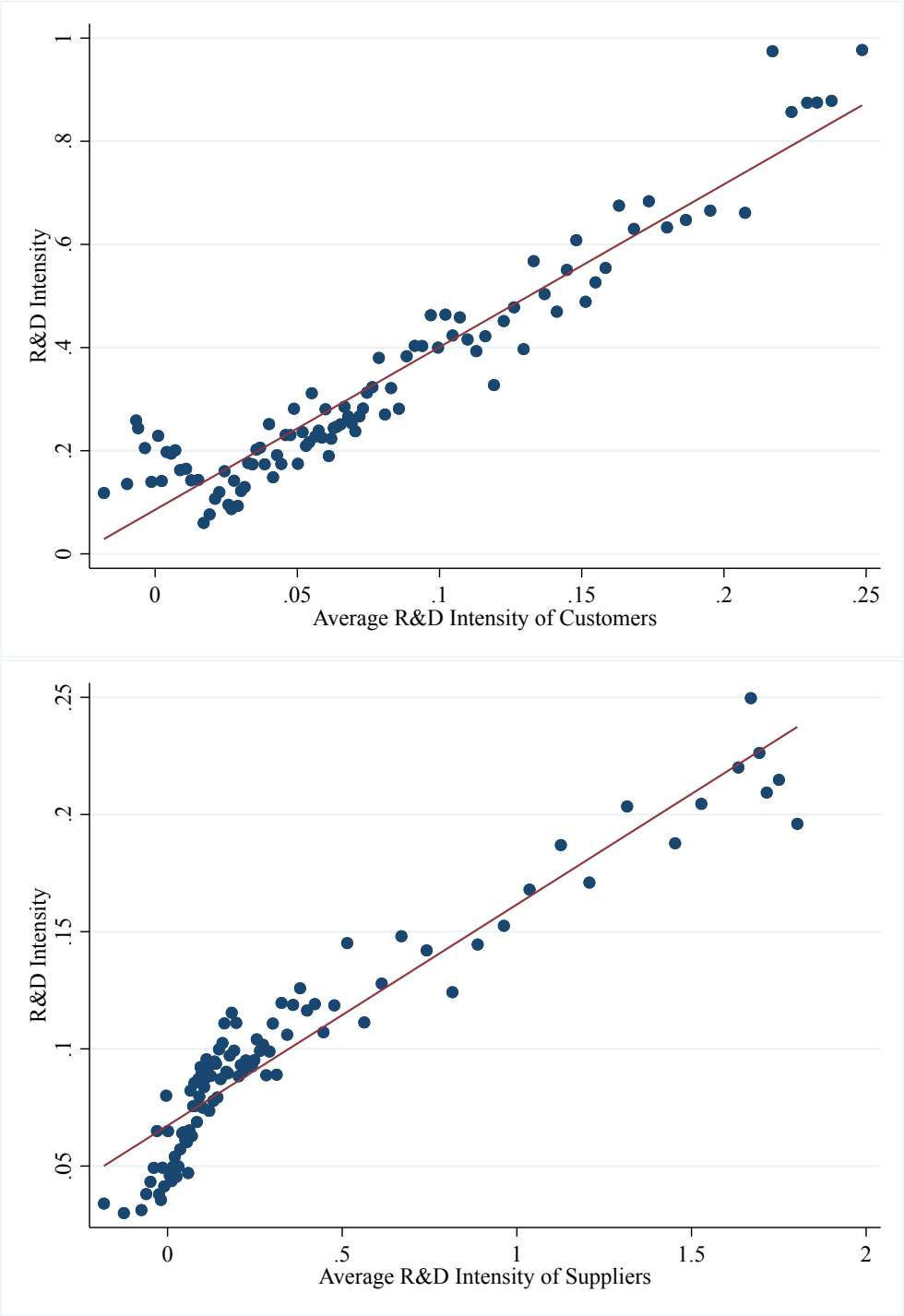
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Tables and Figures

FIGURE 1 – Firm R&D Intensity is Increase in the R&D Intensity of its Partner



Note: This figures shows the relationship between firm R&D intensity (R&D expenditure/lagged sales) and the average R&D intensity of its known customers and suppliers. The top panel collects firm-year observation into 100 bins sorted by the average R&D intensity of the downstream customers, including year fixed effects, and plots the average R&D intensity of firms within each bin. The bottom panel similarly presents the average firm R&D for each bin, 100 bins defined by the upstream R&D intensity of the firm's suppliers.

Figure 2 – R&D Tax Credit Results

	(1) rdintensity	(2) rdintensity	(3) rdintensity	(4) rdintensity	(5) rdintensity	(6) rdintensity
customer_rdintensity	2.461***	0.420***	0.384***			
	(107.71)	(16.83)	(13.88)			
customer_rdintensity_pred				2.300***		
				(3.98)		
customer_rdintensity_predS					3.601***	
					(3.73)	
customer_lrdintensity_predF						3.990***
						(5.66)
r2	0.233	0.866	0.880	0.900	0.902	0.877
n	42666	41192	38811	6852	8877	17747
F	11600.8	283.2	192.7	5.282	7.544	20.08
Fixed Effects	Year	Firm, Year	Firm, YearXSector	Firm, YearXSector	Firm, YearXSector	Firm, YearXSector

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This figure presents the results of the R&D tax credit exercise in Section 2. Specifically, it shows that not only does downstream (customer) R&D intensity predict firm R&D intensity, even including firm and sectorXyear fixed effects, but Column 4 finds the result is robust to instrument downstream R&D on exogenous variation in state and federal R&D tax credits, and controlling for a firm's own exposure to R&D tax credits. Column 5 and 6 instrument downstream R&D on only variation in state and federal R&D tax credits, respectively.

Figure 3 – R&D Tax Credits, First Stage

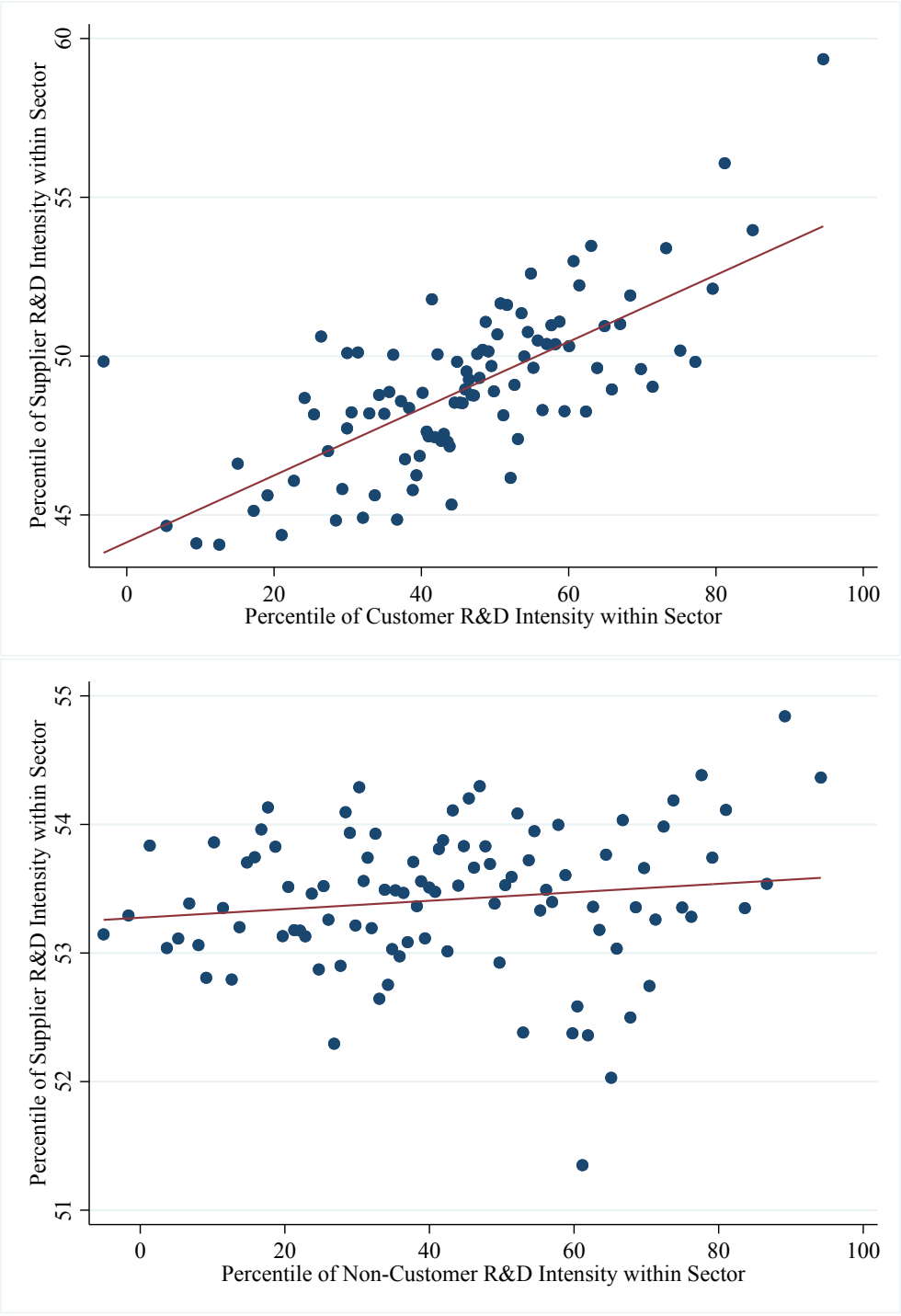
	(1) lxrd	(2) lxrd	(3) lxrd	(4) lxrd	(5) lxrd	(6) lxrd
r2	0.0714	0.940	0.0482	0.919	0.0852	0.940
n	49835	47806	65972	63976	147090	143758
F	1916.9	742.7	3340.2	24.53	13703.4	4640.9
Fixed Effects	None	Firm YearXSector	None	Firm YearXSector	None	Firm YearXSector

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

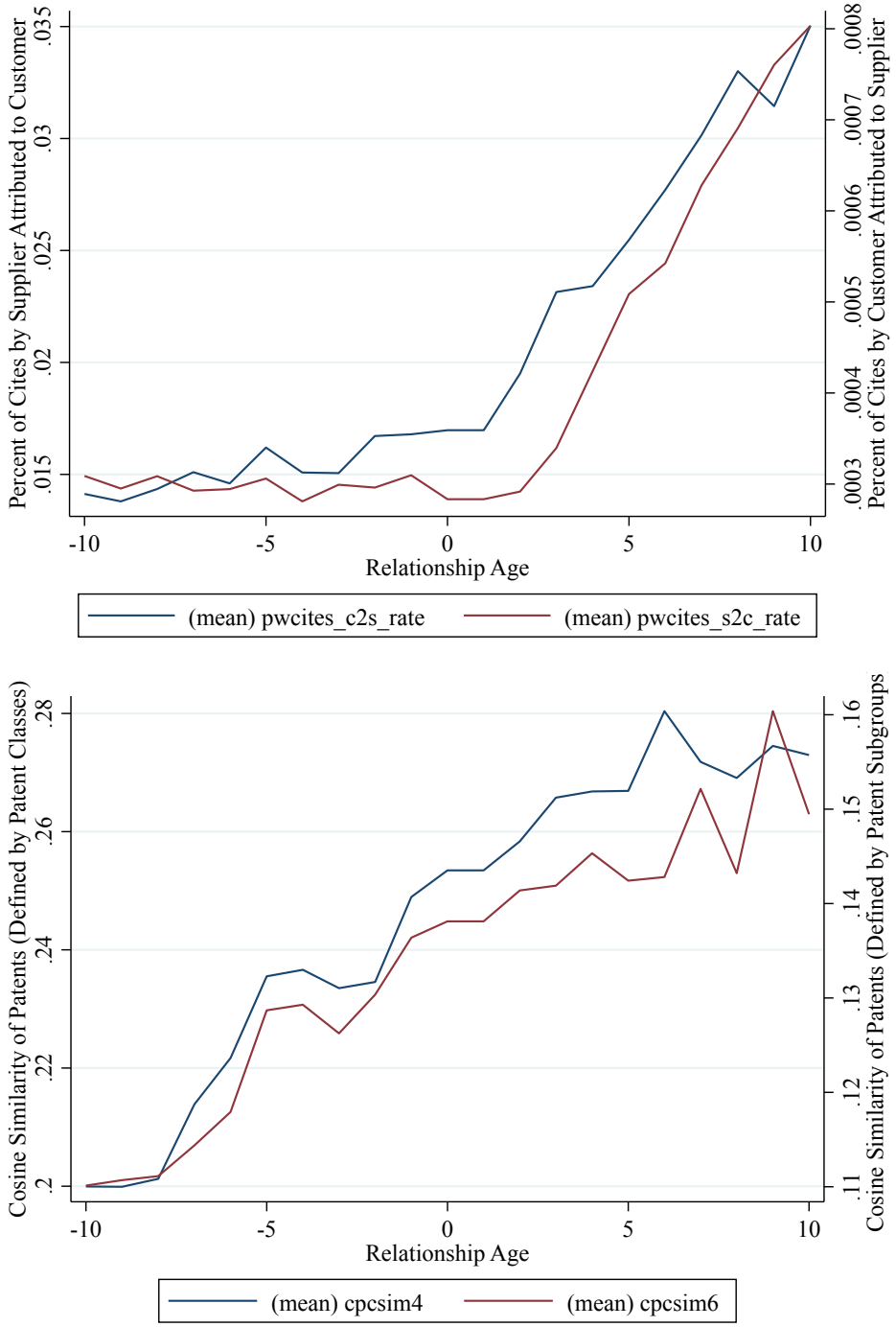
Note: This figure presents the first stage of the R&D tax credit exercise in Section 2, finding that an increase in the R&D user cost of capital implied by variations in state and federal tax credits corresponds to decreased R&D expenditure.

FIGURE 4 – Firms Choose Similarly Innovative Supply Chain Partners



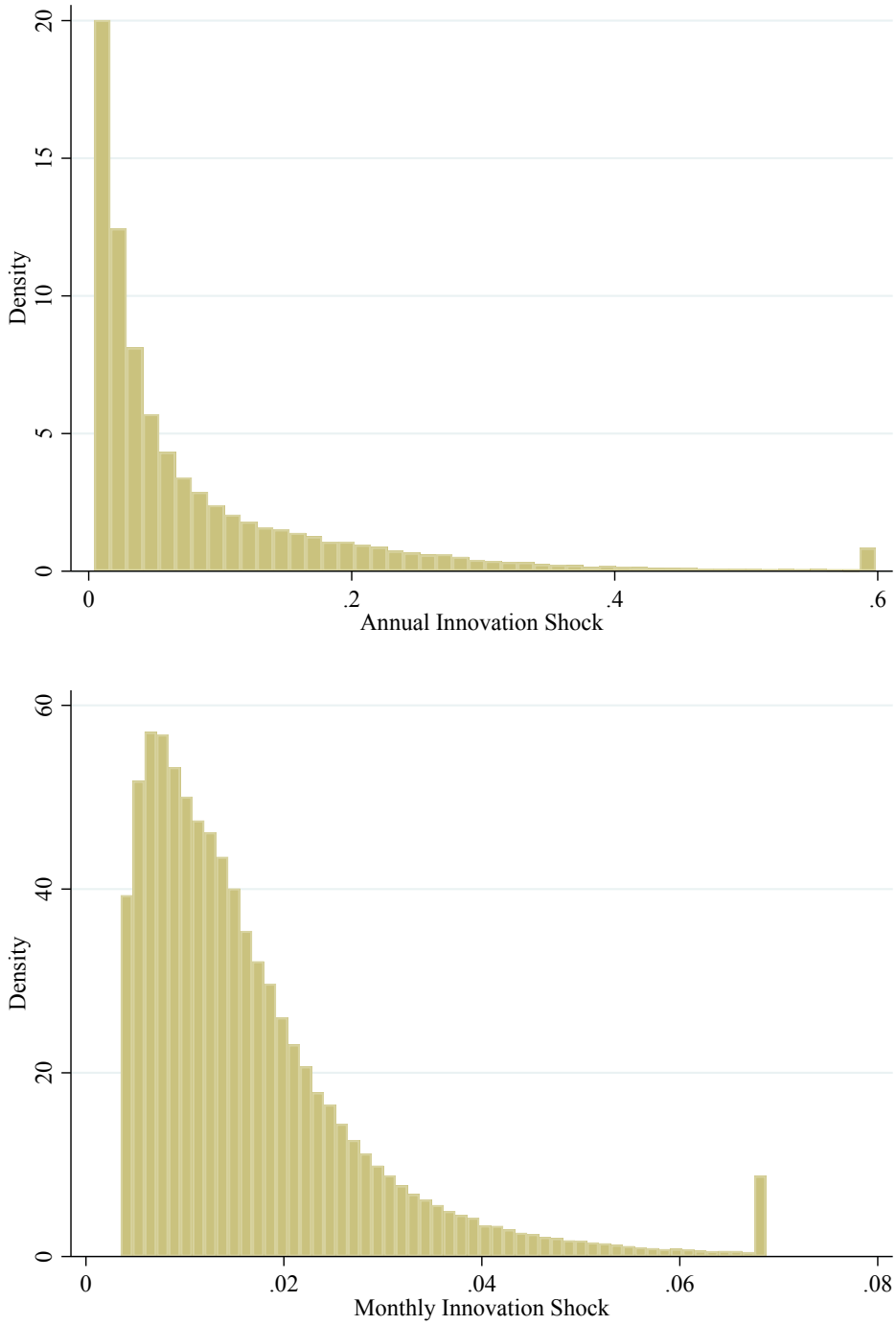
Note: Since typical R&D intensity varies by sector, in this graph, the percentile of a firm's innovation, as defined as R&D intensity (R&D expenditure / sales), is measured within each year and sector (3-digit SIC). A firm's average percentile is compared to the R&D intensity of its (downstream) customers. The top panel presents a bin-scatter of the relationship, showing that high R&D intense customer, relative to their sector, tend to match to high R&D intense suppliers, relative to their sector. In contrast, the bottom panel presents a binscatter comparing firm's R&D intensity percentile to the percentile of R&D intensity of downstream firms, not connected, but in the same sector as a firm's customer.

FIGURE 5 – Firms Increase Citations of Supply Chain Partners and File Similar Patents



Note: For each pairwise relationship, the top panel plots the average percent of citations by customer firms to the supplier and vice versa, over the tenure of the relationship. The bottom panel shows the average cosine similarity of the patents filed between supplier-customer pairs over the relationship tenure. For each firm-year, I measure a vector of patents filed in the year by USPTO class and subgroup, and then measure the cosine similarity of these vectors for each relationship pair.

FIGURE 6 – Distribution of Firm Innovation Shocks



Note: This plots the winsorized distribution of firm's annual and monthly innovation shocks as defined as the sum of the valuation of patents issued to a firm during the period divided by the market value of the firm as of the beginning of the period. Patent valuations are estimated using Kogan et al. [2017].

FIGURE 7 – Downstream Reservation Price for High Quality Intermediate Inputs

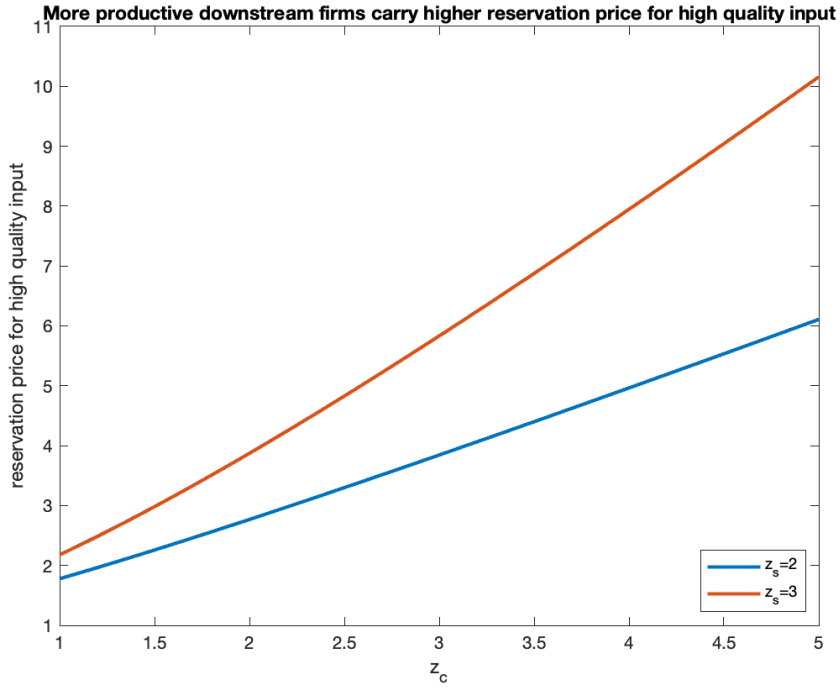


FIGURE 8 – Upstream Profits at Different Productivities

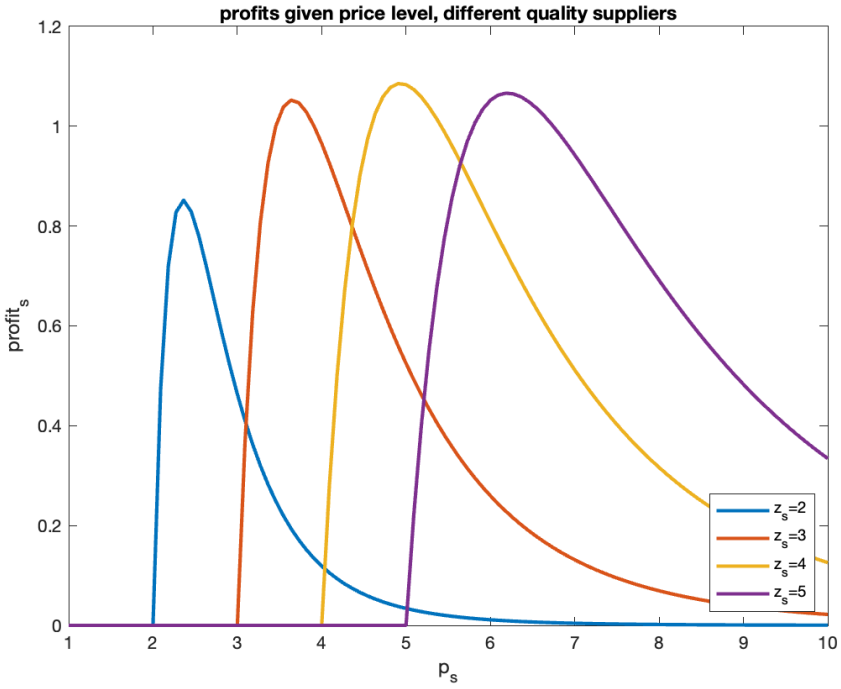


FIGURE 9 – Upstream Profits at Different Productivities

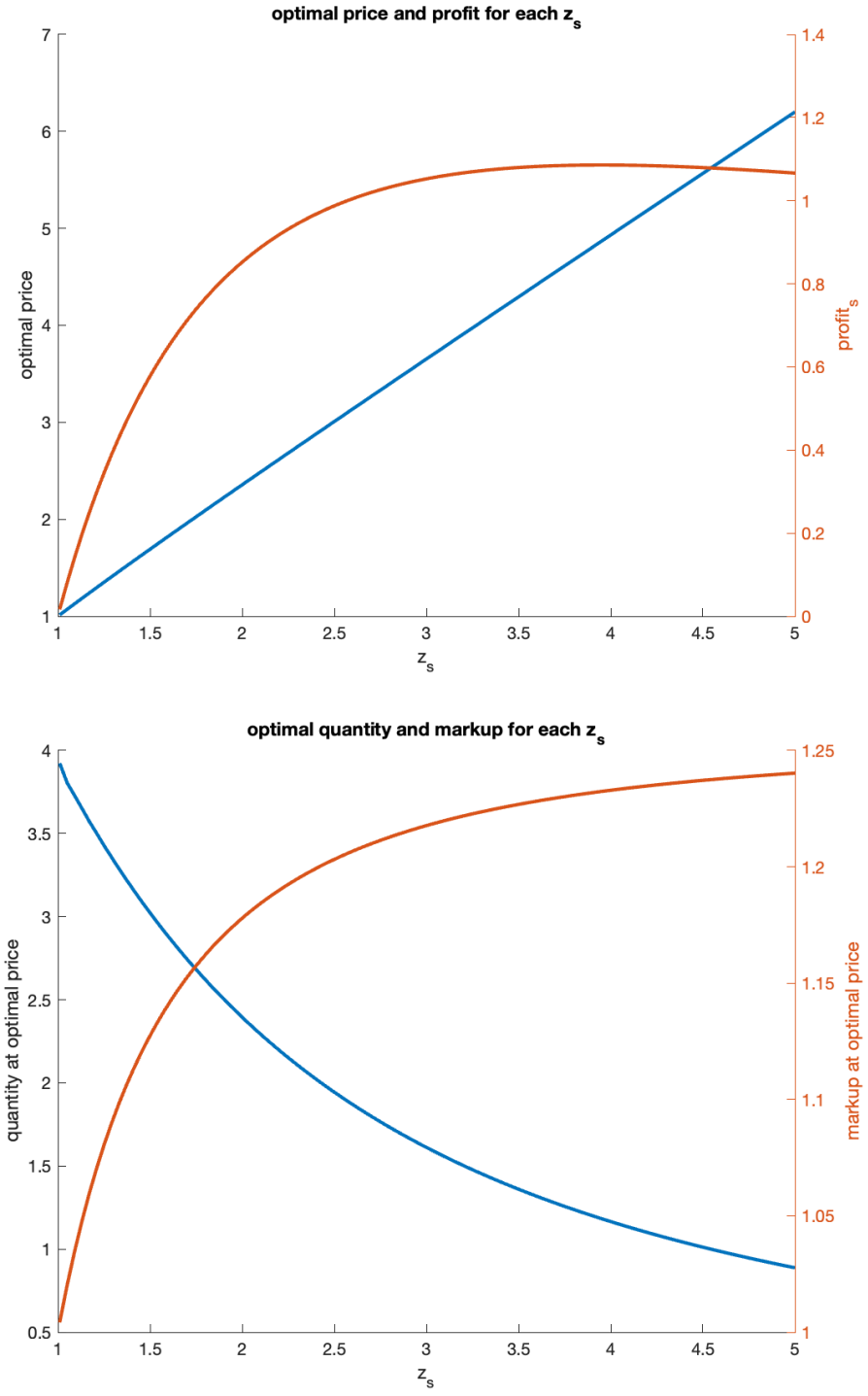


FIGURE 10 – Upstream Profits Vary with Downstream Distribution

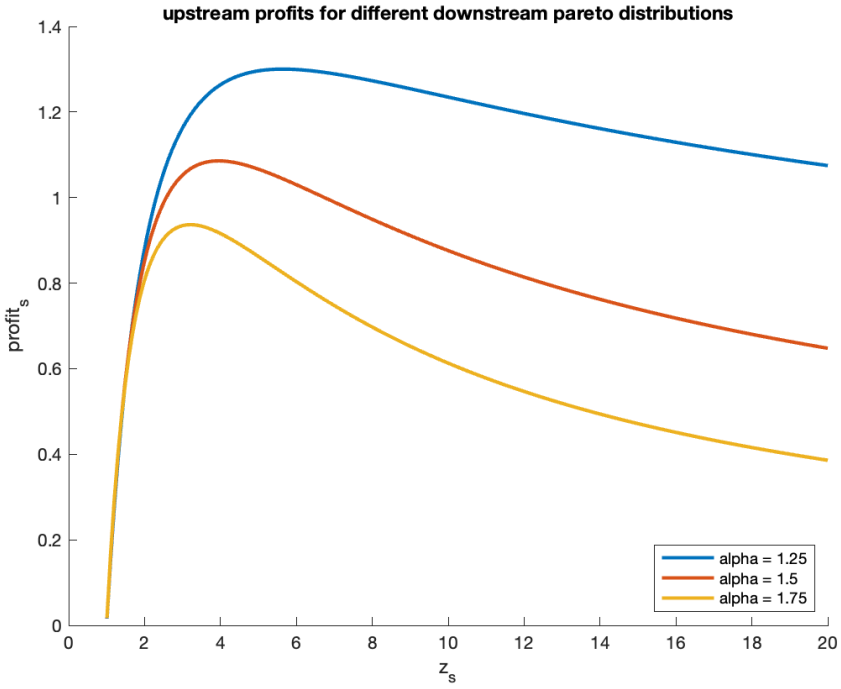


FIGURE 11 – Downstream Profits Vary with Downstream and Upstream Productivity

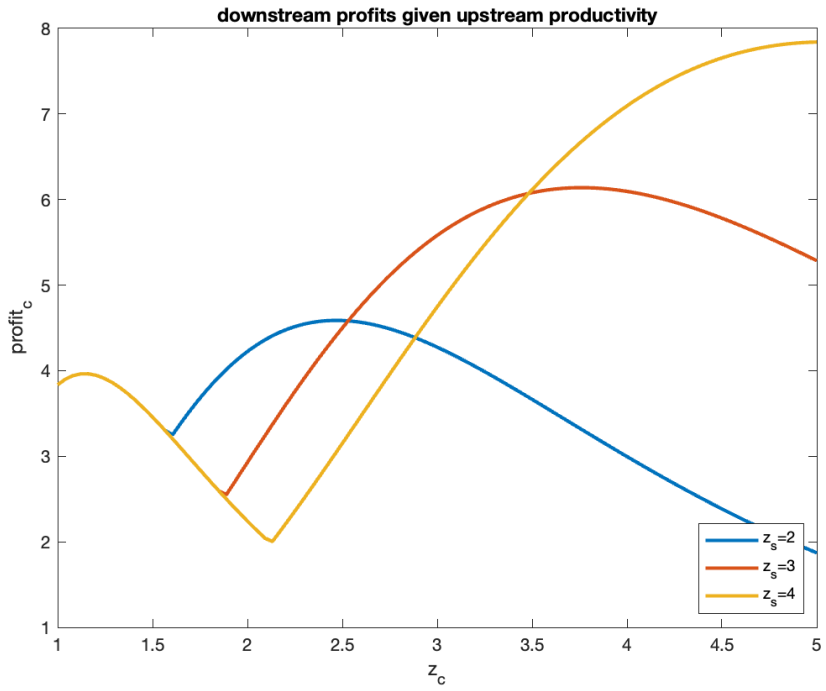


FIGURE 12 – Upstream Profits and Innovation

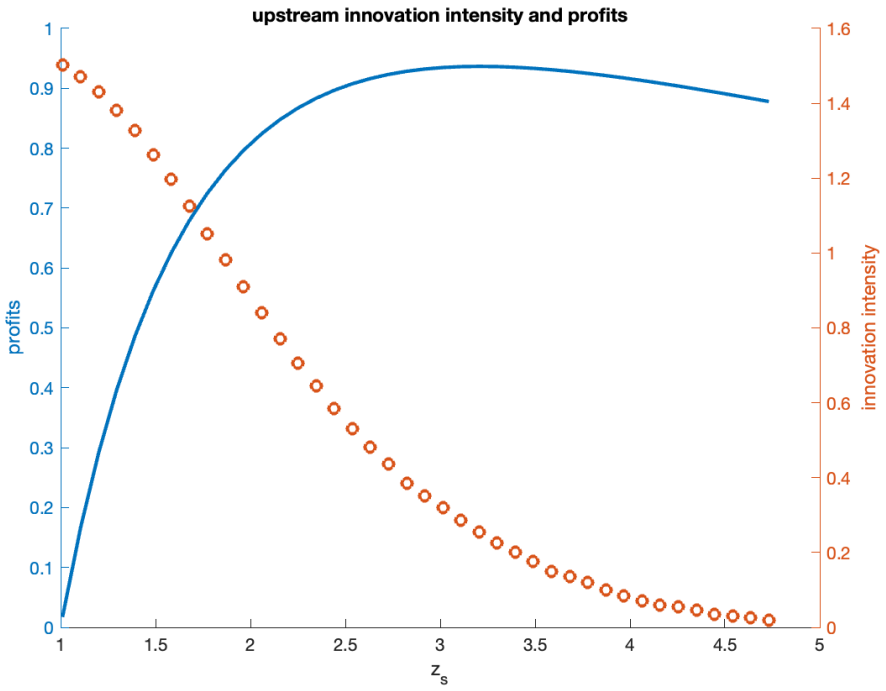
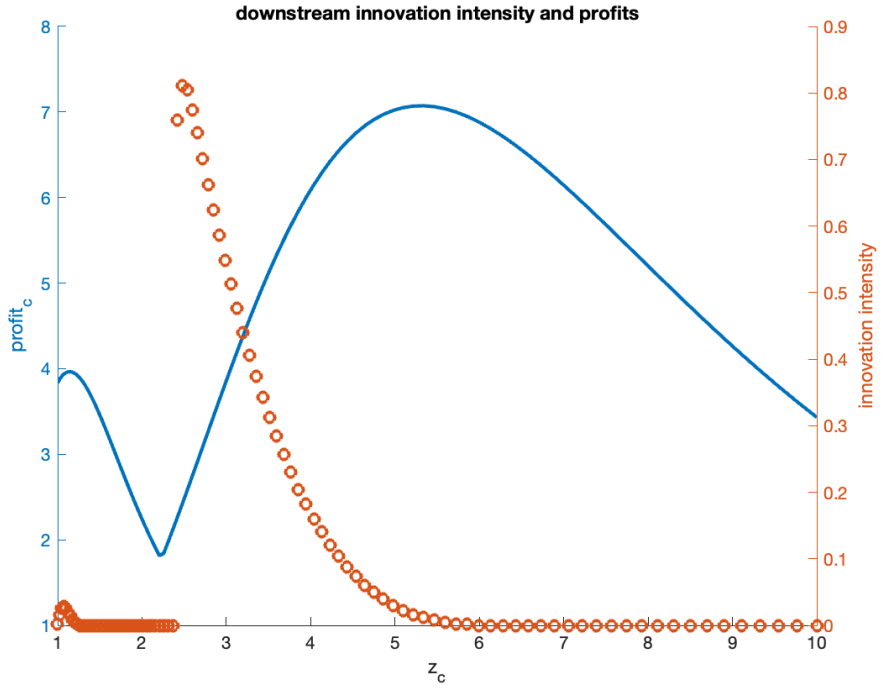


FIGURE 13 – Downstream Profits, Innovation, and Distribution



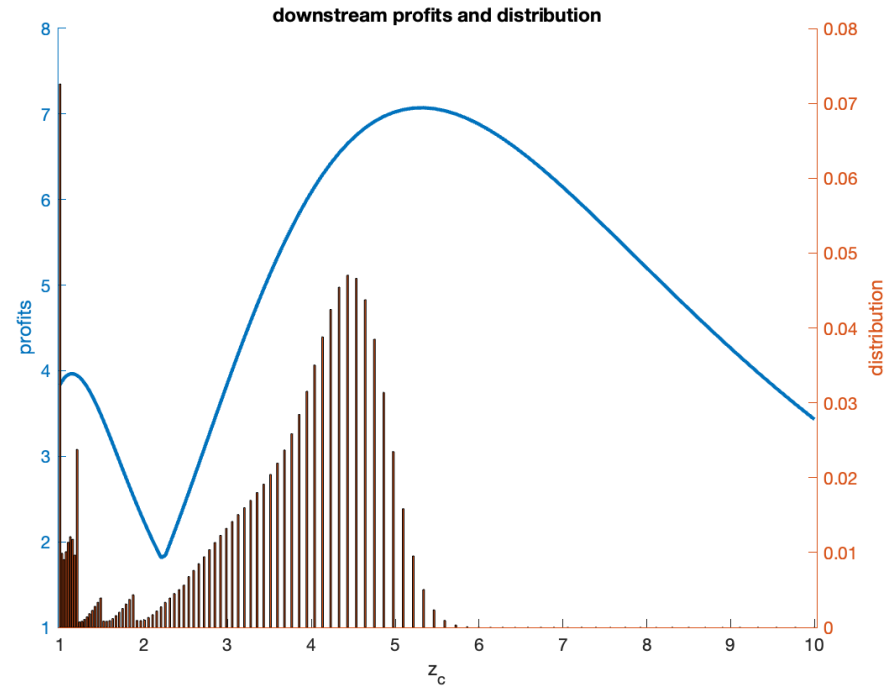


TABLE I – Impact of Customer Innovation Shocks on Monthly Excess Returns

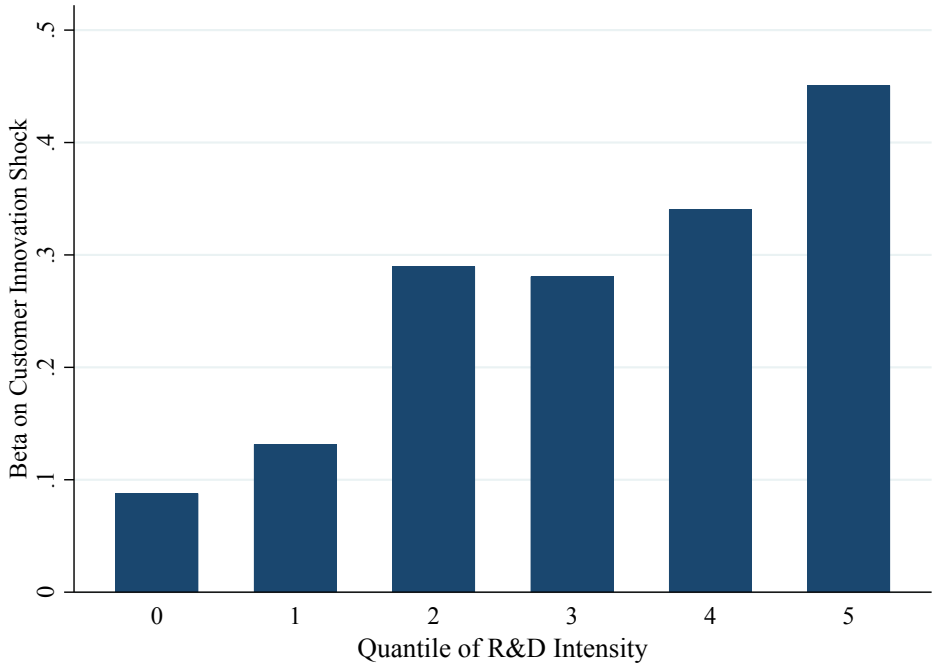
	(1) exret	(2) exret	(3) exret	(4) exret	(5) exret	(6) exret
customer_exret	0.188***	0.882***				
	(56.72)	(9.25)				
customer_innovsk			0.244***	0.0988**	0.251***	-0.245**
			(9.73)	(2.11)	(6.67)	(-2.50)
posrd				-0.00114		
				(-1.54)		
c.customer_innovskc.posrd				0.203***		
				(3.63)		
rdintensity					-0.00420***	
					(-3.74)	
c.customer_innovskc.rdintensity					0.186***	
					(2.62)	
innovsk						1.693***
						(24.21)
c.customer_innovskc.innovsk						9.306***
						(2.98)
r2	0.00786	.	0.000220	0.000252	0.000434	0.0234
n	406399	406399	429360	429360	237927	54735
F	3217.6		94.64	36.05	34.46	438.0

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

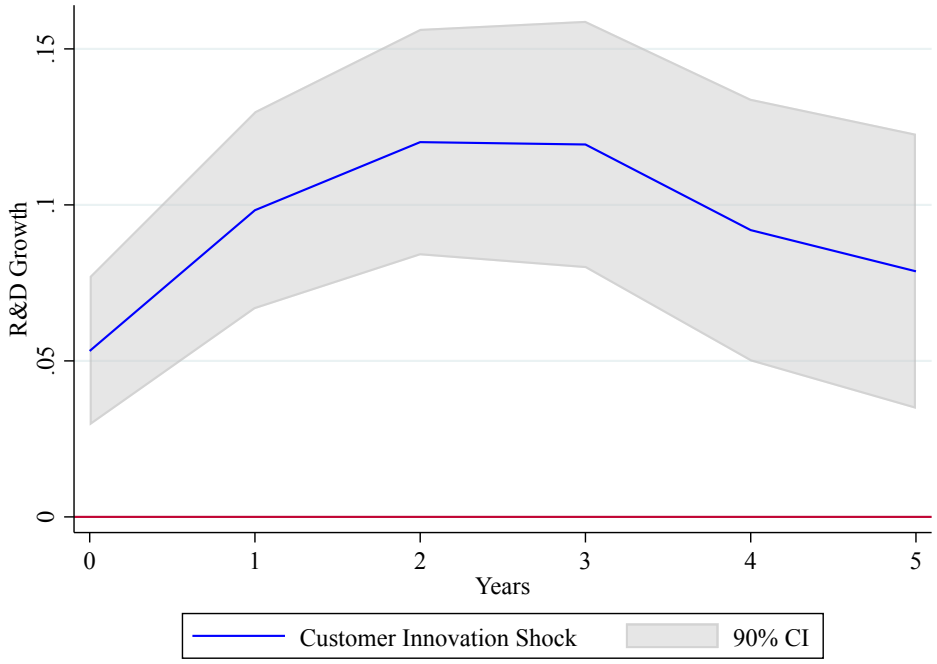
Note: A 1 p.p. innovation shock (defined as the percent change in market value attributed to newly issued patents) of the firm's average customer corresponds to a 25 b.p. increase in excess returns of the firm. However, this mainly accrues to firms that innovate themselves. Indeed, a customer innovation shock alone has 0 or negative impact on excess returns if the firm itself does not experience an innovation shock. Moreover, customer innovation shocks are amplified by a firm's own innovation.

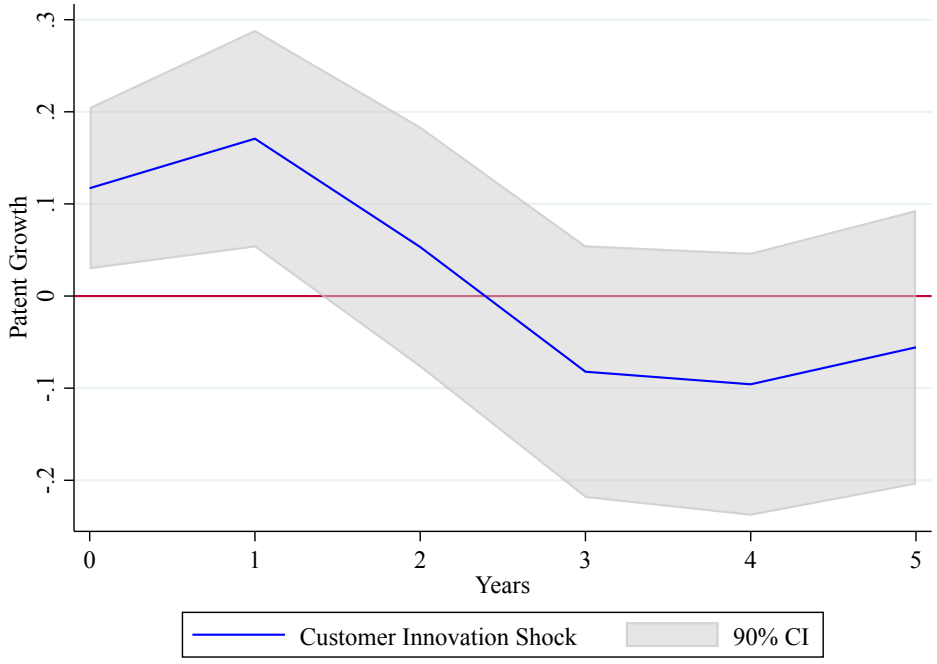
FIGURE 14 – Impact of Monthly Customer Innovation Shocks



Note: Consistent with column 2 of Table I, customer innovation shocks propagate more to firms that themselves innovation. Here I divide firms into quantiles of R&D intensity (with 0 being firms that do not spend on R&D).

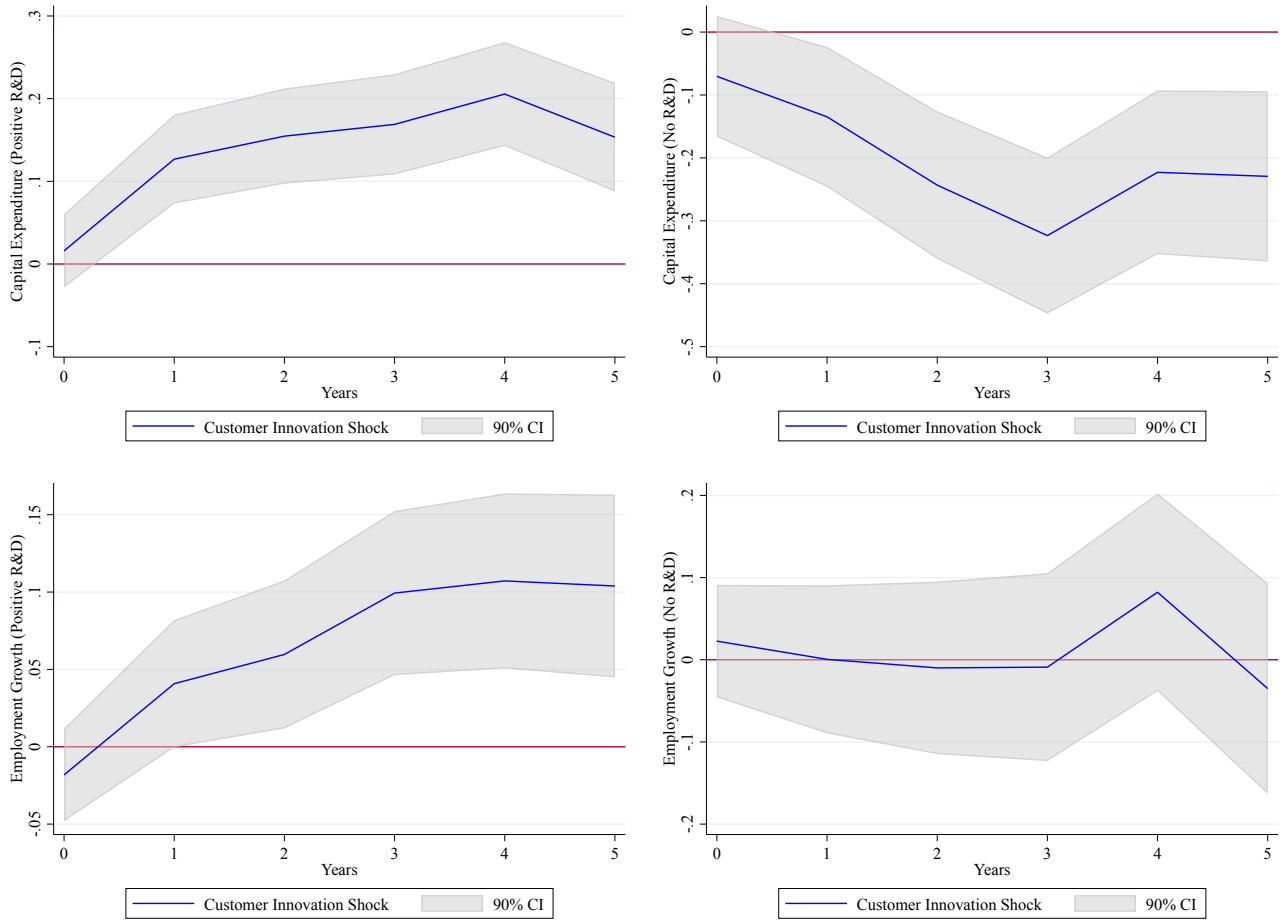
FIGURE 15 – Real Impact of Customer Innovation Shocks on R&D Growth





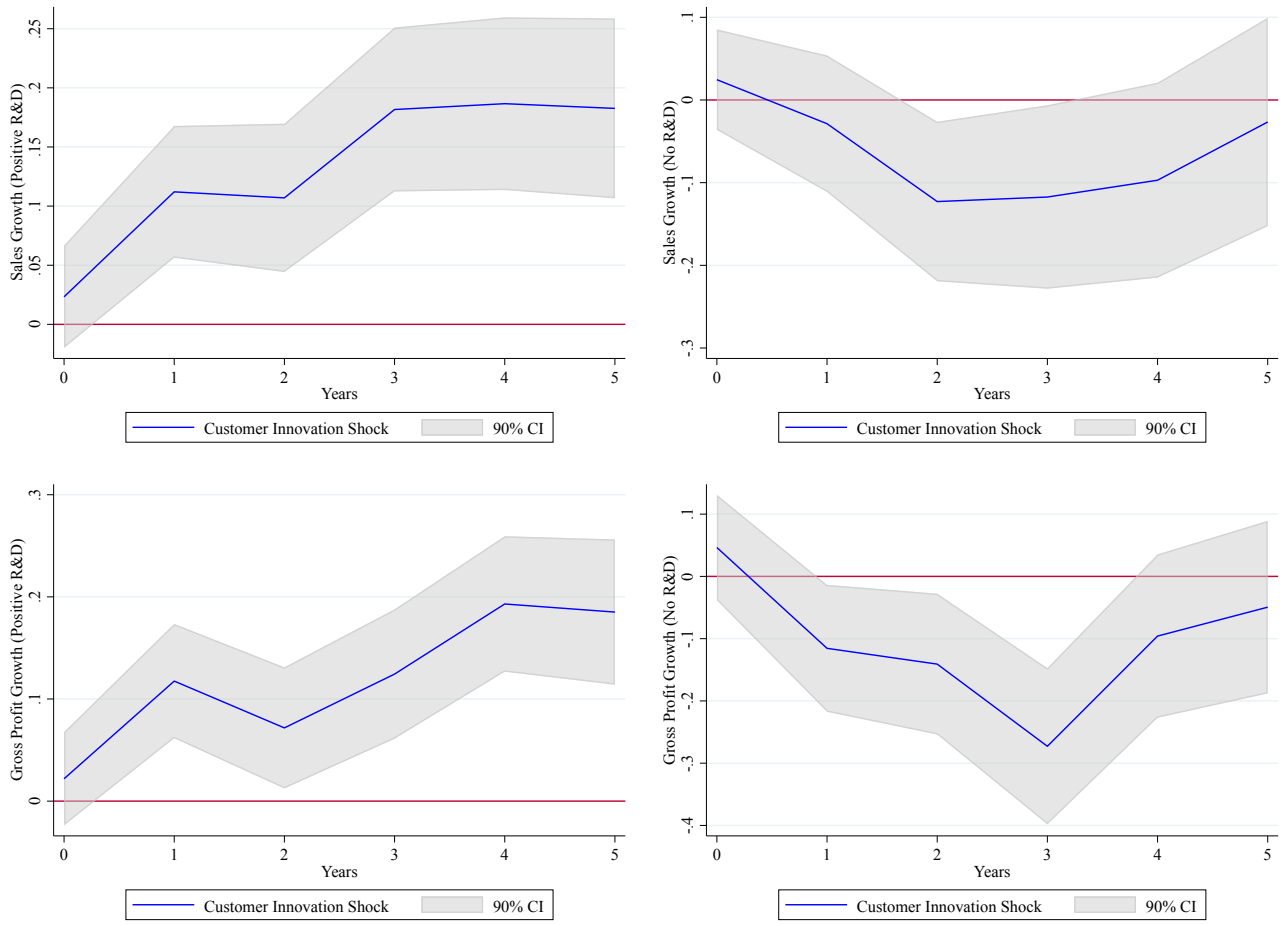
Note: This graph presents the results of the Jorda local projections presented in Section 4. Specifically it shows that firms increase their R&D and patents filed following downstream innovation shocks.

FIGURE 16 – Real Impact of Customer Innovation Shocks on Capital Expenditure and Employment Growth



Note: This graph presents the results of the Jorda local projections presented in Section 4. Specifically it shows that firms that invest in R&D increase their capital expenditure and employment following downstream innovation shocks. In contrast, firms that do not invest in R&D decrease capital expenditure and do not significantly increase employment.

FIGURE 17 – Real Impact of Customer Innovation Shocks on Sales and Gross Profits Growth



Note: This graph presents the results of the Jorda local projections presented in Section 4. Specifically it shows that firms that invest in R&D increase their sales and gross profits following downstream innovation shocks. In contrast, firms that do not invest in R&D experience a decrease to sales and gross profits.

TABLE II – Impact of Supplier Innovation Shocks on Monthly Excess Returns

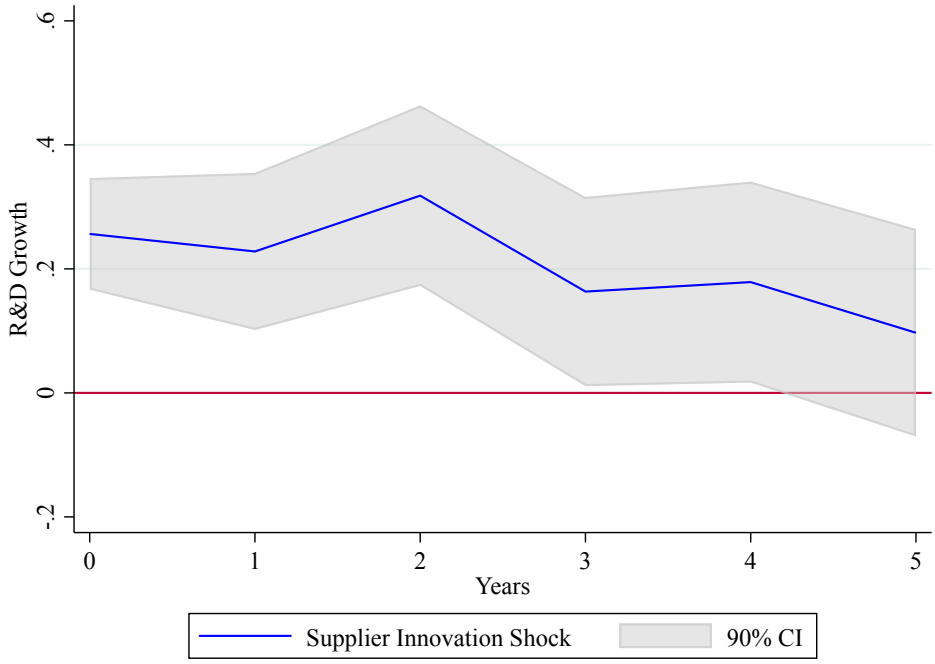
	(1) exret	(2) exret	(3) exret	(4) exret	(5) exret
supplier_exret	0.0891***	0.310***			
	(56.31)	(5.65)			
supplier_innovsk			0.244***	0.0153	-0.390***
			(5.03)	(0.16)	(-2.89)
posrd				0.000568	
				(1.08)	
c.supplier_innovskc.posrd				0.288**	
				(2.55)	
innovsk					0.980***
					(27.84)
c.supplier_innovskc.innovsk					11.64***
					(2.79)
r2	0.0141	.	0.0000975	0.000135	0.0158
n	222113	222113	259759	259759	64718
F	3170.5		25.34	11.66	345.9

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

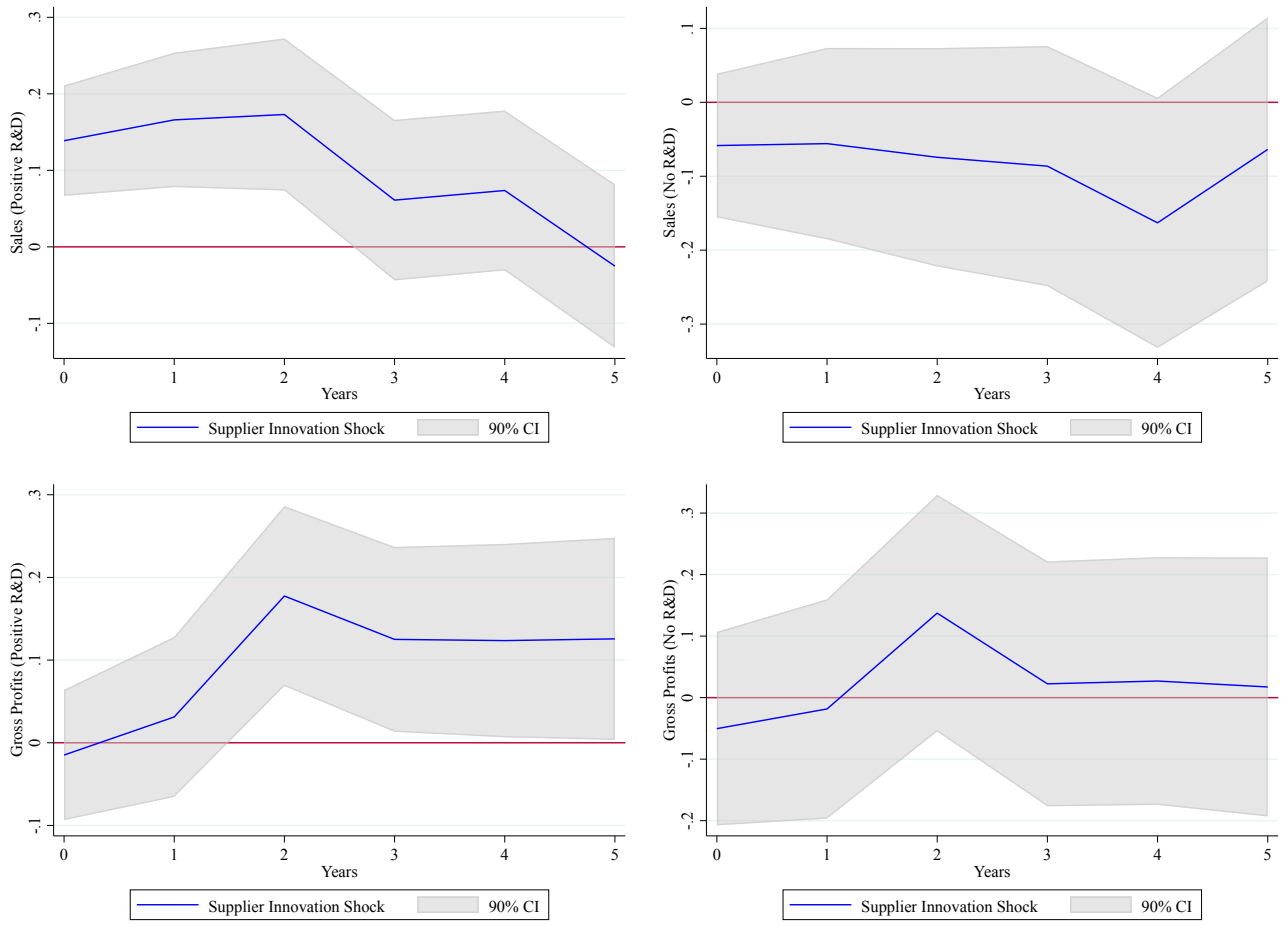
Note: A 1 p.p. innovation shock (defined as the percent change in market value attributed to newly issued patents) of the firm's average supplier corresponds to a 24 b.p. increase in excess returns of the firm. However, this mainly accrues to firms that innovate themselves. Indeed, a supplier innovation shock alone has negative impact on excess returns if the firm itself does not experience an innovation shock. Moreover, supplier innovation shocks are amplified by a firm's own innovation.

FIGURE 18 – Real Impact of Supplier Innovation Shocks on R&D Growth



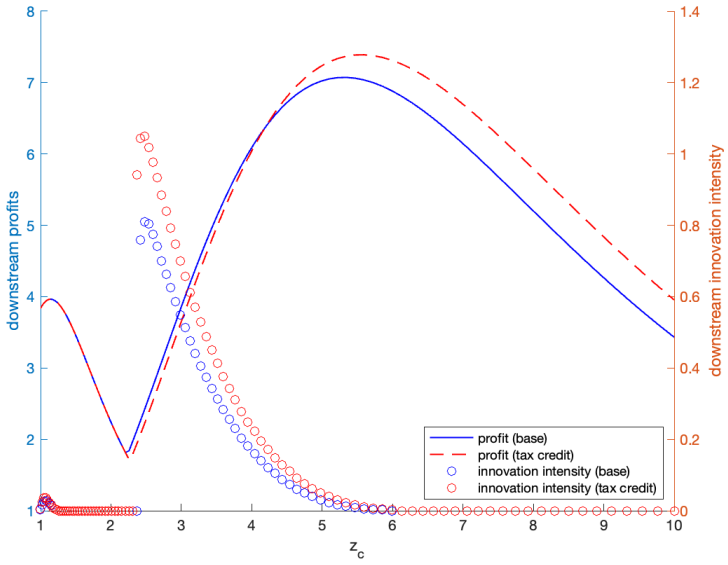
Note: This graph presents the results of the Jorda local projections presented in Section 4. Specifically it shows that firms increase their R&D investment following upstream innovation shocks.

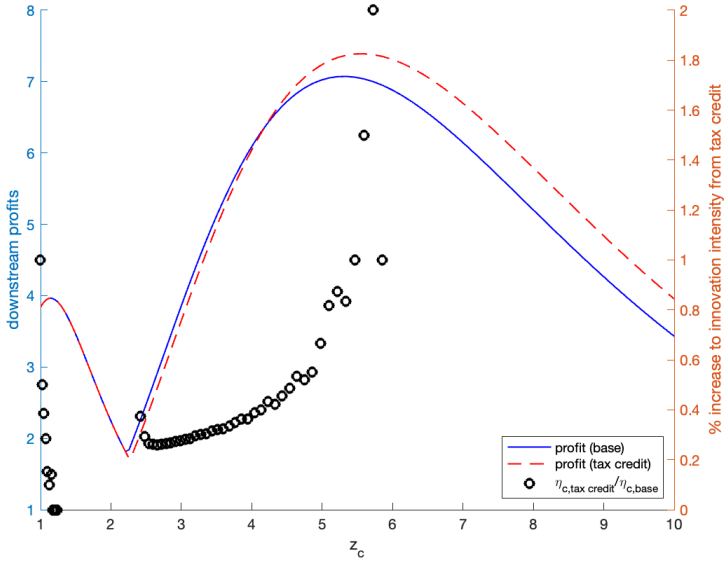
FIGURE 19 – Real Impact of Supplier Innovation Shocks on Sales and Gross Profits Growth



Note: This graph presents the results of the Jorda local projections presented in Section 4. Specifically it shows that firms that invest in R&D increase their sales and gross profits following upstream innovation shocks. In contrast, firms that do not invest in R&D experience no change to sales and gross profits.

FIGURE 20 – Impact of R&D Tax Credits





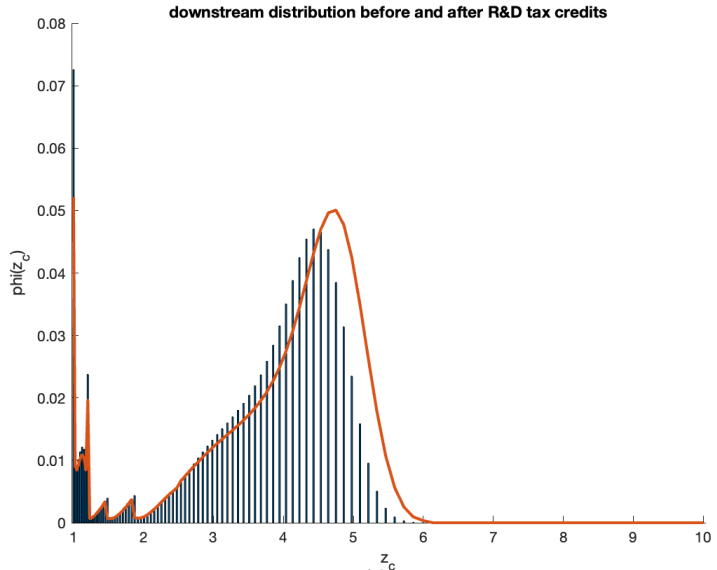
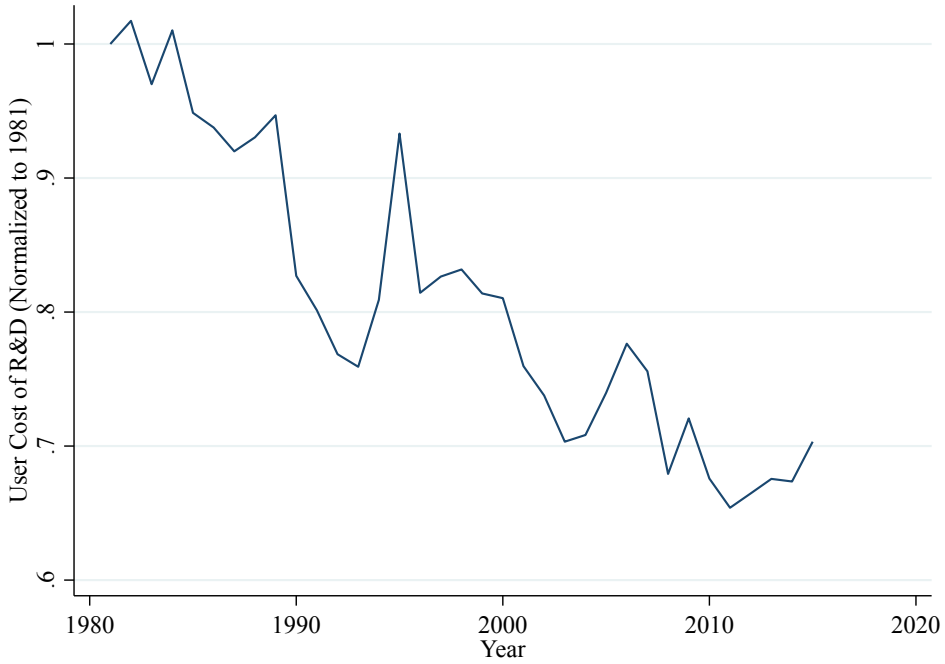


FIGURE 21 – Time Series of R&D User Costs



Note: This graph presents the time series of average R&D user costs across states incorporating both state and federal exposure to R&D tax credits, normalized such that the user cost for 1981 is 1.

TABLE III – Role of Size on the Impact of R&D Tax Credits

	(1) lxrd	(2) lxrd	(3) lxrd	(4) lxrd	(5) lxrd	(6) lxrd
lstate	1.215***			1.912***		
	(6.72)			(11.14)		
L.sale_pctile	0.0507***	0.00440***	0.00329***			
	(29.27)	(17.46)	(10.45)			
c.lstatecL.sale_pctile	-0.0326***					
	(-28.72)					
L.lsale	0.257***	0.239***	0.168***	0.186***	0.171***	0.138***
	(46.65)	(72.95)	(46.65)	(52.12)	(76.15)	(60.07)
lfirm		0.142***			0.232***	
		(4.14)			(7.33)	
c.lfirmcL.sale_pctile		-0.0182***				
		(-34.32)				
lrho_m			0			0
			(.)			(.)
c.lrho_mcL.sale_pctile			-0.0348***			
			(-55.12)			
L.at_pctile				0.0796***	0.0145***	0.0103***
				(51.35)	(85.15)	(46.49)
c.lstatecL.at_pctile				-0.0453***		
				(-42.28)		
c.lfirmcL.at_pctile					-0.0197***	
					(-39.74)	
c.lrho_mcL.at_pctile						-0.0386***
						(-65.94)
r2	0.954	0.949	0.949	0.959	0.954	0.956
n	45964	102297	87233	45964	102297	87233
F	2735.8	7886.3	8409.0	4108.3	10987.4	13334.8

t statistics in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: This figure presents log R&D expenditure on the user cost of R&D interacted with the firm's size percentile, where the size percentile is measured as the percentile of sales or assets within the previous year and SIC3 sector. For all specifications of user cost and size, larger firms respond more strongly to changes to R&D user costs and hence respond more strongly to R&D tax credits.