Is Innovation Always Beneficial? Externalities of Innovation on Product Market Relationships *

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Abstract

This paper investigates the externalities of innovations along supply chains by analyzing the effects of customers' innovations on suppliers' trade credit provision. Suppliers extend more trade credit after customers innovate on both the extensive and intensive margins, consistent with the holdup channel as opposed to the demand or financing channel. Further, the results suggest that (i) acquisitions of innovative targets as well as in-house innovations by customers increase supplier trade credit, (ii) technological overlaps between customers and suppliers attenuate the holdup effects, and (iii) suppliers internalize the externalities by adjusting financial policies and innovating more by learning from customer innovation. Ultimately, customer innovation can lead to the termination of trade relationships. The findings point to the reestablishment effects of corporate innovation on product market relationships.

JEL Classifications: G10, G32, O31, O33
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1 Introduction

Technology innovation has been regarded as an important corporate investment decision and outcome (e.g., Schumpeter, 1911; Solow, 1957; Hall and Lerner, 2010). Previous studies highlight the role of innovation in firm productivity, growth, and survival, yet a firm's innovation also can affect the other stakeholders as well as the firm itself and its security holders. In other words, stakeholders, such as the firm's suppliers, customers, competitors, employees, local communities, and even governments, can be affected through their economic relationship with the innovative firm even if they may not have direct monetary stake in it. The innovation literature mostly focuses on the spillover effect of innovation on the industry competitors but has so far paid little attention to how innovation shapes the dynamics between upstream and downstream firms.[1] This paper helps bridge that gap by investigating how a firm's innovation affects the relationship with a customer or supplier firm as the innovation changes its bargaining power.

The changed dynamics stemming from one party's innovation can show up in various ways; for instance, trade credit (i.e., payment delay), cash before delivery (i.e., advanced payment), product delivery delay, pricing on traded product, length of customer-supplier trade relationship, or long-term supply contract can appear or be affected as the relative bargaining power between the two firms changes.[2] In this paper, we specifically focus on trade credit for the following reasons. To the extent that trade credit proxies for relative bargaining power as documented in the literature, the variation of which can also be a good measure for any dynamic shift in bargaining power (e.g., Wilner, 2000; Giannetti, Burkart, and Ellingsen, 2011; Dass, Kale, and Nanda, 2015; Fabbri and Klapper, 2016). Also, given that contract-level variables (e.g., inter-firm product price or contract terms) are not generally observable, trade credit, which is available from annual filings,

[1]For example, one source of such externality on competitors takes place in the technology space. More specifically, Hsu (2011) finds that firms can save innovation costs by taking advantage of innovation made by their competitors or geographically close firms. Bloom et al. (2013) investigate a positive effect from knowledge spillovers and negative business stealing effects from rival firms. Tambe and Hitt (2014) report that spillovers from innovations of a firm's peers, as well as its own investment, contribute substantially to its productivity growth. Matray (2021) examines local innovation spillovers from listed firms to neighboring private firms. Ma (2021) investigates technological obsolescence that creates winners and losers in the technology space. On the other hand, Li (2018) contends that supplier experience improved performance from its customer innovation and emphasizes the positive externality of innovation. Conversely, this paper identifies the potential adverse externality of innovation, which is understudied in the literature, by focusing on the relationship dynamics in the product market space.

[2]Supporting Information in Internet Appendix provides Apple and Samsung case as an illustration. The case illustrates how the innovativeness of one party is critical to its counterparty in the trade relationship and relative bargaining power.

can be an important proxy of ex post bargaining outcome.[3] Additionally, as the importance of trade credit in the balance sheet of U.S. firms grows, investigating determinants of the trade credit policy is interesting in its own right.[4]

On this ground, we explore how one party's innovation affects the trade credit provision between itself and the counterparty. First, a customer's more active innovation can generate a higher degree of appropriation of quasi-rent and lead to more extension of trade credit from the supplier. We label this mechanism as "holdup channel." The innovation can generate completely new technology and products that enable the innovator to switch to another trade relationship and end up terminating the current relationship.[5] Especially, such actions and outcomes of innovation are generally not contractible or verifiable because innovation investments are uncertain and often irreversible (Holmstrom, 1989); thus, innovation can have a substantive effect on the holdup incentive. Importantly, note that the quasi-rent problem arising from additional innovation is not necessarily identical to the monopoly rent problem (Klein, Crawford, and Alchian, 1978). The holdup problem can arise even when there is no market closure and open competition for entry is allowed.

This paper focuses on how suppliers shape their trade credit policies toward innovative customers because the Compustat Segment file provides important customers of each supplier (i.e., customers comprising 10% or more of each supplier's total sales). Put differently, the data identifies whether a firm is an important customer of another firm, but not whether a firm is an important supplier of another firm. Also, pinpointing that direction has the advantage

[3]Suppliers with weak bargaining power may offer price discounts rather than trade credit to customers. Klapper, Laeven, and Rajan (2012) explains that price discounts can be less useful than trade credit because regulations (e.g., the Clayton Act) prohibit price discrimination across customers. Thus, trade credit can provide better terms to more important buyers. Using a database of trade credit contracts, they also show that price discounts are typically given to small buyers. Given that the customers in my sample are large and established firms, price discounts might not be too common in the sample. Also, Klapper, Laeven, and Rajan (2012) and Singh (2018) show that suppliers extend trade credit even when they provide price discounts to customers. Still, we acknowledge that suppliers can make a concession to customers other than through trade credit or price discount, which may be a substitute (or even complement) for trade credit provision. We plan to assess the simultaneity of such decisions in future research.

[4]Freeman (2020) documents that trade credit constitutes 73% of short-term liabilities among Compustat firms as of 2016. Barrot (2016) observes that trade credit plays a significantly larger role than bank loans or commercial paper in financing the operations of nonfinancial U.S. businesses as of 2012. The importance of trade credit can be further highlighted in economies with less developed financial markets because industries that are heavily reliant on trade credit financing exhibit higher rates of growth in such economies (Fisman and Love, 2003).

[5]However, it is not clear whether it is supplier or customer that induces the decision of increased trade credit; for example, a customer may demand more trade credit with its strengthened bargaining power from innovation, but it is also possible that a supplier may voluntarily offer more trade credit upon observing the greater bargaining power of its customer. Even if it is the decision of the supplier side, the explanation is still consistent with the holdup hypothesis.

that it is less likely to be contaminated by endogeneity; to the extent that the ultimate goal of a customer's innovation is to introduce innovative products, targeting its own customers or competitors rather than its supplier, its effect on the trade credit would be an *unintended* consequence of the innovation.[6]

Customers may require suppliers to make relationship-specific investments. Titman and Wessels (1988) and Allen and Phillips (2000) show that customer-dependent firms tend to procure unique assets. The relationship-specific investments can compound the holdup problem; as Klein, Crawford, and Alchian (1978) claim, specialized assets create more quasi-rents that are appropriable by counterparties due to their low salvage value. To the extent that customer innovation creates a holdup problem, the holdup effect should be more pronounced for suppliers with higher asset specificity (i.e., more relationship-specific investments) compared to those with lower asset specificity (i.e., less relationship-specific investments) vis-à-vis their customers.

On the other hand, it is also plausible that the supplier is able to extend more trade credit with increased demand from the customer ("demand channel"). Customer innovation can lead to more active transactions with a supplier and thus a more solid trade relationship between them if the innovation increases customer demand for input products and/or decreases supplier's average cost of production, especially when the supplier has a high fixed cost. If so, the supplier's provision of trade credit increases *mechanically* after customer innovation, which has nothing to do with any change in relative bargaining power that is predicted by the holdup channel. If the demand channel is in play, then we should expect that supplier sales to the customer or the customer's cost of goods sold (COGS) increases after customer innovation.

Another possibility arises from the financing role of trade credit given to liquidity- or credit-constrained trading partners (e.g., Schwartz, 1974; Petersen and Rajan, 1994; Biais and Gollier, 1997; Wilner, 2000; Cunat, 2007); after innovation, the customer might ask more trade credit to cover its innovation cost. More specifically, if the customer lacks liquidity and cannot pay its supplier in full before it recoups the innovation cost from its final sales, then it might request more trade credit. On the other hand, it is also possible that the supplier may choose to provide the customer with trade credit if the customer's risk decreases after innovation. Specifically, the

[6]However, a holdup issue arises *bilaterally* between any two parties. To examine the bilaterality of holdup, Section 3.9.5 shows how supplier innovation also affects trade credit and the sensitivity of trade credit to customer innovation.

supplier may revise its perception of the customer's financial risk once the customer completes its investment in innovation, resulting in the publication of patents and thereby resolving uncertainty regarding the pending investment outcome. These channels are accounted for by the decrease in liquidity or risk, not any shift in bargaining power, from the innovation ("financing channels"). If these channel hold, then we should observe that the supplier extends even more trade credit to the innovative customer, particularly those that are more financially constrained or have demonstrated lower efficiency in translating innovation input to output.

As for the empirical results, we find that suppliers extend more trade credit 1, 2, and 3 years after their customers increase innovation activity; the effect is statistically and economically significant and occurs both at the extensive and the intensive margins. Since industry-specific market conditions can shape the trade credit, we perform a battery of additional tests using different combinations of fixed effects, such as industry $\times$ year or industry pair fixed effects. Next, because the possible channels (i.e., holdup, demand, and financing channels) predict the same empirical outcome and are not mutually exclusive, we examine which mechanism drives the result, using cross-sectional heterogeneity tests. Given that the impact of customer innovation on a supplier's trade credit is stronger when the supplier's asset specificity is high, it is likely that the holdup problem between customer and supplier drives the main effect. In contrast, we do not observe any systematic evidence that are predicted by the demand and financing channel; supplier sales to the customer or the customer's COGS do not increase after customer innovation, and the sensitivity of trade credit to customer innovation is invariant across different levels of financial constraint or innovation efficiency of the customer.

A potential concern with the main results is that a supplier may motivate its customer to increase innovation activity with its ability to provide a large amount of trade credit. Alternatively, a supplier's capability to extend much trade credit could attract innovative customers in the first place. Another concern is that customer innovation could be correlated with unobservable confounding factors such as product market or technology market conditions that affect a supplier's trade credit decision. To limit the potential effect of endogeneity, we conduct two-stage least squares (2SLS) regressions with plausibly exogenous shifters of the costs that firms bear when making innovations, following Hsu et al. (2015). More specifically, we use average R&D expenditures per patent and average duration from application filing to issue (or grant) of patent

in the customer's industry level as the two instruments. Because these two measures proxy for monetary cost and time cost of innovation at the customer's industry level, respectively, they are not policy variables for suppliers and likely affect the supplier's trade credit policy only through their association with the customer's incentive to innovate. The instrumental variables (IV) estimations confirm the prior that following decreases in the costs of innovation, customers achieve more innovation outcomes. These instrumented shifts, in turn, induce higher trade credit provisions, confirming the observed baseline effects. Furthermore, we enhance the validity of the tests in terms of the exclusion condition, by focusing on the groups of suppliers whose industries are least likely to be systematically affected by the technological or productivity growths in their customer industries and whose customer choices are least likely endogenous. Besides, we use state R&D tax credit as the additional instrument to exploit the variation in the incentives of innovation at the geographical level as well as industry level. On balance, the results establish plausibly causal effects of customer innovation on supplier trade credit provision.

Next, we investigate whether the acquisition of innovation firms as well as in-house innovations by customers can lead to more trade credit. Previous studies establish that firms can acquire innovation and technology by acquiring target firms that have accumulated innovation and technology (Harford, 2005; Higgins and Rodriguez, 2006; Sevilir and Tian, 2012; Phillips and Zhdanov, 2013; Bena and Li, 2014; Bernstein, 2015; Celik, Tian, and Wang, 2022). In the current framework, customers can enhance their innovation capacity by acquiring innovative firms, which, in turn, can increase their bargaining power against the suppliers as their own innovations do. The results show that supplier trade credit increases not only with the customers' own innovations, but also with their innovation outsourcing from targets.

We next address whether the technological class of the customer innovation affects the positive sensitivity of the supplier's trade credit provision to customer innovation. If the customer's innovation is closely related to the supplier's existing product technology and, hence, is likely to be relationship-specific vis-à-vis the supplier, then it should mitigate the holdup problem. Consistent with this prediction, we find that the positive sensitivity of supplier trade credit to customer innovation decreases when the customer's new patent class overlaps with the existing patent classes of the supplier. On the other hand, the sensitivity is invariant when the customer's new patent class overlaps with its own existing patent classes. These results highlight the holdup

effect and suggest that a customer's making supplier-related innovation can be a commitment to the current relationship. Also, the results differentiate product innovation from process innovation as the key factor that affects the trade relationship.

Having established the holdup effect of customer innovation on the supplier, we explore how customer innovation shapes the financial and investment decisions of the supplier. A supplier, when faced with holdup by its customer, might change its financial and investment policy to protect itself from the holdup. The supplier might need to adjust financial policies to internalize its weakened bargaining power and the resulting increase in trade credit provision. At the same time, it can increase its own innovative activity to improve its bargaining power against the customer, to the extent that the increase in the customer's bargaining power has been caused by the change in innovation capacity of the customer. It may also learn from the customer's innovation to provide input products customized for the customer's new product and thus prevent the customer from switching to another supplier. In fact, the results show that suppliers hold higher cash holdings and lessen payout when customers innovate. Suppliers also develop their own innovation activities after their customers innovate. Moreover, their patents cite the patents of their customers more frequently, that is, they learn from their customers' innovation. This analysis implies that customer innovation influences a supplier's internal policy as well as its policy toward interfirm relationship (i.e., trade credit policy).

Lastly, we investigate the ultimate outcome of customer innovation by examining the likelihood of termination of the trade relationship. This investigation complements the former analysis because the variation in the relationship status, as well as trade credit, represents the change in relationship dynamics per se. However, a priori, the prediction on this association is unclear because customers would face a tradeoff between various dimensions of benefits (e.g., switching to new suppliers who have a better technological fit) and costs (e.g., forgoing increased trade credit and accommodation from the current suppliers) upon termination. Thus, it remains an empirical question whether customer innovation ultimately results in the termination of relationships. The results show that while the likelihood is not significantly affected by customer innovation in the short run—possibly because of the internalization effort of the supplier in its financial and innovation decisions—the relationship is more likely to be terminated in the long run. Collectively, the findings indicate the reestablishment effect of innovation on product market relationships.

This research contributes to the literature in three ways. First, our study focuses on the real and financial effects of corporate innovation, which are relatively understudied compared to the determinants of innovation.[7] Previous studies find a positive linkage between innovation (measured widely by R&D, patents, patent originality, patent quality, innovation efficiency, etc.) and firm value (Eberhart, Maxwell, and Siddique, 2004; Lanjouw and Schankerman, 2004; Cohen, Diether, and Malloy, 2013; Hirshleifer, Hsu, and Li, 2013, 2018; Farre-Mensa, Hegde, and Ljungqvist, 2020; Fitzgerald et al., 2021; Cooper, Knott, and Yang, 2022; Shu, Tian, and Zhan, 2022). In addition, Hsu (2009), Papanikolaou (2011), Kogan and Papanikolaou (2014), and Stoffman, Woeppel, and Yavuz (2022) highlight the stock return predictability of technological innovation. Also, Arora, Belenzon, and Sheer (2021) find that firms obtain greater value from scientific research, but the value enhancement is reduced when there are knowledge outflows to rivals. Yet, a recent study by Haddad, Ho, and Loualiche (2022) shows that the market value of innovation (as measured by the change in stock price) reflects its economic impact in general, but not during bubbles. On the other hand, Hsu et al. (2015) document a negative relation between innovation and bond issuance premium (or default probabilities). Relatedly, Bai and Tian (2020) emphasize the importance of innovation-based variables in bankruptcy prediction. Chava, Nanda, and Xiao (2017), Mann (2018), Gao et al. (2023), and Ma et al. (2024) also emphasize the role of patents in debt contracting. Moreover, the literature studies how innovation and technology affect firm policies, such as M&A (Bena and Li, 2014; Wu and Chung, 2019), cash holdings (Qiu and Wan, 2015), manager selection and compensation (Pan, 2017; Bereskin, Byun, and Oh, 2023), entrepreneurial firm success (Gaule, 2018), foreign profitability of U.S. firms (De Simone, Huang, and Krull, 2020), firm disclosure (Huang et al., 2021), and startup exits (Bowen III, Frésard, and Hoberg, 2023).

In particular, our paper emphasizes the real effects of corporate innovation on *other* firms, which has not been much documented in the innovation literature. Previous studies (e.g., Adams and Jaffe, 1996; Keller, 2002; Hall and Lerner, 2010; Lychagin et al., 2016; Matray, 2021; Ma,

[7]The extensive literature on the determinants of innovation suggests a wide range of firm-level or institutional characteristics as the drivers (along with many others, Acharya and Subramanian, 2009; Manso, 2011; Aghion, Van Reenen, and Zingales, 2013; Amore, Schneider, and Žaldokas, 2013; Chava et al., 2013; He and Tian, 2013; Nanda and Rhodes-Kropf, 2013; Fang, Tian, and Tice, 2014; Ferreira, Manso, and Silva, 2014; Hsu, Tian, and Xu, 2014; Tian and Wang, 2014; Cornaggia et al., 2015; Bradley, Kim, and Tian, 2017; Chang et al., 2019; Antón et al., 2024). Chemmanur and Fulghieri (2014), Kerr and Nanda (2015), He and Tian (2018, 2020), and Lo and Thakor (2023) provide a comprehensive survey of the literature.

2021) document that a firm's innovation can affect the productivity of other firms within the same industry, or, even other firms in nearby regions. In the meantime, this paper is not the first to investigate corporate innovation and product market relationship. Frésard, Hoberg, and Phillips (2020) show that firms that have heavily invested in R&D are less likely to be acquired in vertical acquisitions, and firms with patented innovation are more likely to sell to vertically related acquirers. Chu, Tian, and Wang (2019) also highlight corporate innovation along the supply chain and show that a closer relationship between supplier and customer, as identified by their geographic proximity, can promote supplier innovation through the feedback and demand channels. Dasgupta, Zhang, and Zhu (2021) find that supplier innovation increases with greater cooperation between suppliers and customers arising from their social connections. In contrast, we investigate the other side of the interaction; this paper estimates the effect of customer innovation on relationship dynamics, as proxied by supplier trade credit and length of trade relationship. Thereby, this paper complements those related studies in the literature. On the other hand, Li (2018) claims that customer innovation increases the profitability of its supplier through operational improvement and knowledge diffusion. On the contrary, our paper emphasizes that customer innovation can cause potential externalities on the supplier through the holdup effect. Also, importantly, this paper showcases the significant impact of a firm's innovation on the financial and investment policies of another firm, extending beyond their interfirm relationship.

This paper is also related to the product market literature that investigates the externalities along the supply chain. The literature documents that the customer-supplier relationship is influenced by various dimensions of counterparty risk or behavior: downstream merger activities (Fee and Thomas, 2004; Shahrur, 2005; Bhattacharyya and Nain, 2011), cross equity ownership (Fee, Hadlock, and Thomas, 2006), negative news (Cohen and Frazzini, 2008), economic distress (Kolay, Lemmon, and Tashjian, 2016), financial distress or bankruptcy risk (Hertzel et al., 2008; Hertzel and Officer, 2012), or takeover risk (Cen, Dasgupta, and Sen, 2016). This paper adds counterparty innovativeness as a significant determinant of product market relationship, thereby bridging this strand of literature with the corporate innovation literature.

Lastly, this paper explains post-contractual opportunistic behavior, which is emphasized in the transaction cost theory literature (e.g., Klein, Crawford, and Alchian, 1978; Williamson, 1979; Grossman and Hart, 1986; Rhodes-Kropf and Robinson, 2008). This paper focuses on the

post-innovation holdup problem during the trade contract period, as captured by trade credit provision or termination of a relationship.

The remainder of the paper is organized as follows. Section 2 describes the database used and sample construction procedure. In Section 3, I provide empirical results to test the hypotheses given above. Section 4 summarizes the results and provides concluding remarks.

2 Data Description

Customer-supplier relationship data are obtained from the Compustat Segment Customer files, following phonetic string matching to link customer names with their PERMNOs as in Cohen and Frazzini (2008). The patenting activity data are collected by Kogan et al. (2017) and based on Google Patents Data.[8] Its advantage is that it includes more detailed information about patents (e.g., patent class code, citation information, and patent market value) relative to the U.S. Patent Office data. We first define *Principal Customer* as the customer that takes the largest sales portion of each supplier in each year to construct customer-supplier pairs.[9] We then exclude financial (SIC code 6000-6999) or utility (SIC code 4900-4999) suppliers or customers. Next, we merge the customer-supplier data with the patent data at the *Principal Customer* or supplier level. Observations are treated as zero patents when patent information is missing. The customer-supplier database covers the period from 1976, and the patent data of Kogan et al. (2017) comprise the period from 1926 to 2010. Thus, our sample period spans from 1976 to 2010 and our sample consists of 9,602 customer-supplier-year observations (2,919 customer-supplier pairs).

The main dependent variable, *Trade Credit*, is the proportion of the supplier's trade receivable

[8]The patent data is available from Kogan et al. (2017) and downloaded from Professor Noah Stoffman's website (`https://host.kelley.iu.edu/nstoffma`). We are grateful to Professor Noah Stoffman for making this data available.

[9]We focus on *Principal Customers* because they are likely to be most influential in a supplier's corporate policy (e.g., trade credit provision) among all customers with their greatest sales portion. Also, SFAS No. 14 requires that suppliers report customers that take at least 10% of total sales; thus, we exclude customers other than *Principal Customers* to minimize the selection bias. However, large customers often disproportionately influence suppliers as compared to other customers (Fee and Thomas, 2004; Murfin and Njoroge, 2015; Herskovic et al., 2020). It is, therefore, possible that a test using only *Principal Customers* inflates the effect size because other minor customers may not attain such bargaining power even after innovations. We acknowledge that as one caveat with my approach stemming from the tradeoff. To address this, Section 3.9.1 restricts the sample to the suppliers whose *Principal Customer* is the sole customer.

attributable to its *Principal Customer* and is calculated as[10]

$$Trade\ Credit = \frac{Trade\ Receivable \times Sales\ Dependence}{Total\ Assets} \tag{1}$$

where *Sales Dependence* is the portion of sales to *Principal Customer* to the total sales of supplier as below:

$$Sales\ Dependence = \frac{Sales\ to\ Principal\ Customer}{Total\ Sales} \tag{2}$$

The main independent variable, *Customer Innovation*, is measured by the *Principal Customer*'s patenting activities and is calculated as

$$Customer\ Innovation = log(1 + The\ Number\ of\ Patents\ of\ Principal\ Customer) \tag{3}$$

measured at the year of patent issuance dates.[11]

Insert Table 1 here.

Table 1 shows summary statistics of our sample. Customer and supplier firms are different in various dimensions as documented in Panel A. For example, customer firms are larger in size, more profitable, more innovative, more levered, and hold less cash balances, possibly because the sample concentrates on *Principal Customers* that are likely large and established firms. In Panel B, suppliers with positive customer innovation are larger, less levered, less profitable, and hold more cash than those with zero customer innovation. Also, suppliers undertake more R&D and make more innovation when they have customers with positive innovation. On the other hand, the differences in *Trade Credit* do not appear to be significant when suppliers are simply classified by whether their customers have innovation or not. Thus, the following sections analyze the differences in multivariate settings, using the continuous *Customer Innovation* variable.

[10]The results are quantitatively similar when the dollar amount of trade credit is scaled by the total sales, not the total assets, of supplier. In the meantime, the customer's account payable cannot be used for the calculation because the customer's purchase dependence on the supplier is unavailable in the data. On the other hand, the measurement assumes that a supplier provides its *Principal Customer* with trade credit proportionate to its portion of sales. To alleviate concerns regarding this assumption, Section 3.9.1 aggregates patents (of other customers as well as the *Principal Customer*) and total trade credit, finding consistent results.

[11]Section 3.9.2 measures the patenting activities (i) in the year of patent filing dates, (ii) as the citation-weighted patent counts, or (iii) as the market value of patents for robustness.

3 Empirical Results

3.1 Baseline Effects

In this section, we test whether the supplier extends more trade credit after customer innovation. Even though the prediction is uniformly in line with the holdup, demand, and financing channels, it is plausible that a customer's innovation increases its cash flows and profitability, which, in turn, decrease its reliance on trade credit provided by the supplier. Alternatively, a supplier might avoid providing trade credits that are hard to collect from innovative and, thus, arguably risky customers. Therefore, it is an empirical question whether customer innovation positively or negatively affects supplier's trade credit decision. The regression models include *Customer Innovation* (the main independent variable) and several supplier firm characteristics such as size, growth opportunities, profitability, capital structure, and investment at year t. Also, the models contain year fixed effects and supplier's industry fixed effects (3-digit SIC code) to control for time trends and time-invariant industry heterogeneity.[12] The dependent variable, *Trade Credit*, allows time lags of 1 to 3 years, because it might take time for customer innovation to take effect along the supply chain. In addition, all models account for possible within-pair serial correlation by clustering the standard errors at customer-supplier firm pair level.[13]

Insert Table 2 here.

Table 2 Column 1 exhibits that customer innovation induces more trade credit provided by supplier at year $t+1$. The coefficient of *Customer Innovation* are both statistically and economically significant in Column 1. For example, a one standard deviation increase in *Customer Innovation* is associated with a 0.415 percentage point increase in *Trade Credit* after 1 year. Given that the dependent variable *Trade Credit* is scaled by the supplier's total assets, the effect size is economically substantial to the supplier. For a diagnostic, ten more patents of customer (from the

[12] For example, trade credit can be a substitute for bank credit during financial crisis or monetary tightening periods (Love, Preve, and Sarria-Allende, 2007). On the other hand, Ng, Smith, and Smith (1999) and Klapper, Laeven, and Rajan (2012) show that most of the determinants of trade credit are industry-driven.

[13] We also reiterate all the tests in this paper by clustering the standard errors at alternative levels: customer industry-supplier industry pair level, supplier firm level, customer firm level, two-way year and supplier firm levels, or two-way customer and supplier firm levels. These clustering schemes account for unspecified correlations at various levels and produce t-statistics that are approximately the same or stronger.

mean of 19.16 patents) lead to a 0.062 percentage point increase in *Trade Credit*, which translates into a $1.01 million increase in the dollar amount of trade credit for an average-asset supplier. In Columns 2 and 3, the effects of *Customer Innovation* are significant, and the size of which gradually decreases over time. Columns 4, 5, and 6 report the results for logit regressions of trade credit indicators for year $t+1$, $t+2$, and $t+3$, respectively, on *Customer Innovation*, using only the customers that are not granted any trade credit in year t.[14] The results indicate that suppliers extend more trade credit after customer innovation at both the extensive and intensive margins.

Insert Figure 1 here.

Interestingly, the coefficients of $R\&D/TA$ are not significantly different from zero, implying that an innovation output (i.e., patent) is a more dominant determinant of trade credit—and arguably the degree of holdup—than an innovation input (i.e., R&D).[15] Figure 1 further shows that the effect of *Customer Innovation* is monotonic as the number of patents increases.

Insert Table 3 here.

Further, to rule out the possibility that industry-specific market condition, such as market competition, can confound the estimates, we perform a battery of additional tests using different combinations of fixed effects, such as industry-year fixed effects and industry pair-year fixed effects.[16] In all specifications of Table 3 except Column 2, the coefficients of *Customer Innovation* are statistically significant at a 1% level. Therefore, the result implies that the baseline effect is robust after controlling for time-varying customer or supplier industry conditions.

[14]The number of observations in Columns 4 through 6 drops considerably by 95%, reflecting the fact that *Principal Customers* generally receive trade credit.

[15]The outcome of R&D investments may vary significantly across firms. For example, Nokia spent more than three times the amount on R&D than Apple did in the 2000s, but it could not introduce innovative and market-relevant products as compared to Apple (Lerner and Seru, 2017). Accordingly, patenting activities can be a more meaningful innovation factor that draws attention from trade counterparties.

[16]For example, Chod, Lyandres, and Yang (2019) show that industry-level competition among suppliers affects their willingness to extend trade credit to customers.

3.2 Mechanisms

In Section 3.1, the results show that the supplier provides more trade credit after the customer innovates. Because the possible channels (i.e., holdup, demand, and financing channel) predict the same outcome and are not mutually exclusive, this section examines which mechanism drives the results, using cross-sectional heterogeneity tests.

3.2.1 Holdup Channel

According to the holdup channel, a customer's more active innovation can generate a higher degree of appropriation of quasi-rent and lead to more extension of trade credit from the supplier. Customer innovation can generate completely new technology and products, which enable the customer to switch to another supplier and end up terminating the current relationship. Given that complete contracting or monitoring on the counterparty's innovation (or its outcome) is challenging by nature, it can be an important determinant of the ex post holdup incentive.[17]

Klein, Crawford, and Alchian (1978) explain that the holdup problem becomes more severe as the assets of the exploited party are more relationship-specific, since specialized assets create quasi-rents that are appropriable by counterparties due to their low salvage value. Thus, the holdup channel predicts that a supplier with higher asset specificity extends even more trade credit when faced with customer innovation.

To measure the supplier's asset specificity, we introduce four proxies of specificity, because

[17] Previous studies also point out the role of trade credit as an implicit warranty (Lee and Stowe, 1993; Long, Malitz, and Ravid, 1993; Antras and Foley, 2015), price discrimination among customers (Brennan, Maksimovics, and Zechner, 1988; Giannetti, Burkart, and Ellingsen, 2011; Klapper, Laeven, and Rajan, 2012), or commitment device for making more relationship-specific investments (Dass, Kale, and Nanda, 2015). However, it is beyond the scope of this paper to test the existing theories of trade credit. This paper instead exploits trade credit as the ex post bargaining outcome between customer and supplier, and the existing theories are not exclusive to the holdup framework in this paper. More specifically, a supplier's response to the increased bargaining power of its customer from innovation can be to accommodate the customer by providing more warranty, favorable price discrimination, and/or commitment for more relationship-specific investments, all of which can be demonstrated by the increase in trade credit provision. We provide a detailed discussion in Section 3.9.3.

there is no standard measure.[18] [19]

$$
\begin{aligned}
Supplier\ Specificity_1 &= \frac{1}{Asset\ Redeployability} \\
Supplier\ Specificity_2 &= \frac{1}{Asset\ Liquidation\ Value / Going\ Concern\ Value} \\
Supplier\ Specificity_3 &= \frac{1}{Proportion\ of\ Nearby\ Alternative\ Customers} \\
Supplier\ Specificity_4 &= Vertical\ Relatedness\ to\ Principal\ Customer
\end{aligned}
\tag{4}
$$

$Supplier\ Specificity_1$ measures the reciprocal of a supplier's asset redeployability from Kim and Kung (2017). The paper defines a firm's asset redeployability using the number of industries that purchase a certain asset type, sourced from the Bureau of Economic Analysis (BEA) capital flow table. Consequently, a higher redeployability score indicates that more firms or industries in the economy utilize the same asset, while assets specific to a particular use restrict alternative uses and redeployability for the supplier.

$Supplier\ Specificity_2$ is based on the inverse of a supplier's asset liquidation value (scaled by its going-concern value) according to Kermani and Ma (2023). Specifically, the paper calculates the average liquidation recovery rate of major asset categories (e.g., fixed asset, inventory) at the industry level, using disclosures from U.S. Chapter 11 bankruptcy filings. It then estimates a firm's asset specificity using its asset composition and liquidation recovery rate for each asset type. In summary, if a supplier's assets are specialized and have low liquidation values, its $Supplier\ Specificity_2$ value will be higher.

On the other hand, we also exploit geographic distance between a supplier and its customers to proxy for the supplier's dependence on and specificity to its *Principal Customer* as in Giannetti, Serrano-Velarde, and Tarantino (2021). More specifically, we compute the ratio of alternative

[18] It is generally challenging to observe how much firms' assets are relationship-specific individually, but, for example, Fan (2000) focuses on a single industry (petrochemical) and estimates the asset specificity of a firm in the industry using its input material information. However, concentrating on a single industry would limit the data coverage and test power in this paper. An advantage of this paper's approach is that it uses firm pair-level measures of specificity in various industries.

[19] Asset redeployability data is available from Kim and Kung (2017) and obtained from Hyunseob Kim's website (`https://sites.google.com/view/hyunseobkim/asset-redeployability`). Asset liquidation value data is available from Kermani and Ma (2023) and obtained from the website (`https://assetspecificity.com/`). The vertical relatedness score data is available from Frésard, Hoberg, and Phillips (2020) and downloaded from Gerard Hoberg's website (`https://faculty.marshall.usc.edu/Gerard-Hoberg/FresardHobergPhillipsDataSite`). We are grateful to Professors Hyunseob Kim, Howard Kung, Amir Kermani, Yueran Ma, and Gerard Hoberg for making their data available.

customers that are geographically closer to the supplier than the *Principal Customer*, based on their historical ZIP codes as collected from their 10-K filings on EDGAR. To the extent that a supplier has alternative customers nearby, its asset would be less dependent on and specialized to its *Principal Customer*, as compared to another supplier who only has *Principal Customer* nearby, and thus, whose assets are likely more relationship-specific.

The last measure, $Asset\ Specificity_4$, employs the firm pair-level vertical relatedness score measure from Frésard, Hoberg, and Phillips (2020). The score is measured by mapping business descriptions of a firm-pair (from the 10-K filings) to the vertically linked commodity descriptions (from the Bureau of Economic Analysis input-output tables). To wit, the score represents the extent to which a firm is located upstream relative to another firm. Although suppliers and *Principal Customers* in the sample are already identified as linked through their transactions, the vertical relatedness score reflects the variation in the strengths of linkage by utilizing the commodity-level information. The higher the score, the more a supplier's commodities produced from its assets are used by its *Principal Customer*.[20]

Using each measure of asset specificity, we first divide the sample into "High" supplier specificity and "Low" supplier specificity groups with its median value. We then contrast the effects of *Customer Innovation* among the two groups using their interaction terms. Besides, supplier specificities are measured at the time of customer innovation, not when trade credit is measured, because suppliers expecting ex post holdup may have less incentive to make further relationship-specific investments (Khanna and Mathews, 2016; Fang, Lerner, and Wu, 2017) and would thus exhibit reduced specificities after customer innovation is realized.

Insert Table 4 here.

Table 4 Columns 1 shows the statistically significant coefficients of the interaction between

[20]Previous studies (e.g., Allen and Phillips, 2000; Kale and Shahrur, 2007; Raman and Shahrur, 2008; Campello and Gao, 2017; Chen et al., 2022) employ R&D intensity (or intangible capital investment) as a measure of relationship specificity. However, R&D investment of suppliers would not be a useful measure in the current framework because it can be correlated with customer R&D and innovation. Alternatively, sales dependence might be used as a measure of relationship specificity because a supplier's higher dependence on its customer can promote relationship-specific investment (Fee, Hadlock, and Thomas, 2006). The measure, however, would not be useful either in this paper, because the dependent variable (*Trade Credit*) is constructed based on sales dependence. In the meantime, unreported regressions show the results that are consistent with Table 4 even when R&D intensity or sales dependence is used as an alternative measure of asset specificity.

Customer Innovation and *High Specificity* and insignificant coefficients of *Customer Innovation*. This indicates that the positive effects of customer's innovation on supplier trade credit are pronounced among suppliers with high $Supplier\ Specificity_1$. The economic significance of *Customer Innovation* among *High Specificity* suppliers is comparable to that in the baseline results presented in Table 2. Columns 2 and 3 exhibit qualitatively similar results for supplier trade credit in years $t+2$ and $t+3$, respectively.

Furthermore, the remaining columns (except Column 4), which use alternative definitions of supplier specificity, consistently show the significant coefficients of the interaction between *Customer Innovation* and *High Specificity*. This consistency persists despite variations in sample size due to the availability of each proxy in the sample. Collectively, the results in Table 4 support the holdup channel that predicts a higher sensitivity of supplier trade credit to customer innovation among the high asset specificity group.

In the meantime, it is worth noting that the results contradict an alternative explanation that is seemingly related to, but not perfectly in accordance with, the holdup explanation; when a supplier's customer innovates, the supplier may spontaneously extend trade credit as a relationship-specific "investment" expecting some benefits, such as technological spillover, from the customer's innovation.[21] This can occur even when the supplier does not face (potential) threat from the customer arising from its greater bargaining power (i.e., when the holdup problem does not arise). Thus, this explanation is independent from the holdup mechanism. However, the results of Table 4 do not support this explanation, in that the benefits from customer innovation should not be much different among suppliers with different levels of asset specificity according to the reasoning. Rather, it is more plausible from the explanation that the high asset specificity group would make less of such additional investment because those firms have already made relationship-specific investments, which are viewed as risky (Titman, 1984; Rauch, 1999). Put differently, it predicts that the low asset specificity group has a higher marginal value in providing trade credit as investment, which are at odds with the results in Table 4.

[21]This alternative explanation refers to the pure benefit aspect of customer innovation to supplier, which is different from the avoidance of losses from the holdup problem. In the current framework, the benefits do not correspond to, for instance, the continuation of the current trade relationship, which is endangered under the holdup problem.

3.2.2 Demand Channel

The previous section provides evidence that is consistent with the holdup channel, but an alternative mechanism, the demand channel, might be at work. The demand channel predicts that when customer innovation increases input demand, suppliers with a higher fixed cost of production would be able to extend more trade credit because of their greater economies of scale. To test this prediction, we use the (logarithm of) capital-to-labor (K/L) ratio, defined as the ratio of fixed capital stock per employee, as the measure of fixed cost, following MacKay and Phillips (2005) and Haushalter, Klasa, and Maxwell (2007). Firms with labor-intensive technology (i.e., low K/L) have a high labor cost, which is more variable than capital outlay, and thus are likely to extend less trade credit from an increase in customer demand.

In addition, if the demand channel is in play, then we should expect that the supplier's sales to the customer or the customer's COGS increases after the customer's innovation, which mechanically ramps up the supplier's trade credit. For this, we construct two customer-level variables as follows and test whether they are affected by *Customer Innovation*.

$$\begin{aligned} (Customer)\ Sales\ Growth &= \frac{Change\ in\ Sales\ to\ Principal\ Customer}{Current\ Sales\ to\ Principal\ Customer} \\ (Customer)\ COGS/TA &= \frac{Principal\ Customer's\ Cost\ of\ Goods\ Sold}{Principal\ Customer's\ Total\ Assets} \end{aligned} \tag{5}$$

We run regressions with customer-level control variables and customer industry fixed effects because the dependent variables are measured at the customer-level. Also, we allow up to 3 years of time lag because the effect could show up later.

Insert Table 5 here.

Table 5 Panel A shows significantly negative coefficients of the interaction between *Customer Innovation* and K/L, indicating that suppliers with a high fixed cost of production do not extend more trade credit as customers innovate, as compared to suppliers with a low fixed cost. Even though the results may provide evidence that is at odds with the demand channel, there is a concern that the capital-labor ratio can be correlated with the asset tangibility or specificity, which is used in the previous section to test the holdup channel. If so, the results in Table 5 Panel A

would mix the effects from the holdup and demand channels. Therefore, we implement more direct tests for the demand channel, using the actual sales or COGS information of customers in Panel B.

Columns 1 through 3 in Panel B show that suppliers' sales amounts to *Principal Customers* do not grow after customer innovation. Furthermore, the COGS of customers do not increase significantly after innovation, as shown in Columns 4 through 6. In the meantime, *Sales Dependence* does not increase either with innovation in Columns 7 through 9. The results, together with that in Table 2, imply that suppliers extend more trade credit even though they do not have a greater sales dependence on their customers after innovation. Overall, the results in Table 5 do not render support on the demand channel.[22]

3.2.3 Financing Channel

This section explores the possibility of another channel: the financing channel. After innovation, the customer, lacking liquidity or credit availability, might ask for more trade credit to cover its innovation cost, which can be recouped after the final sales of innovative products are realized (i.e., "demand-driven" financing). If this hypothesis holds, then we should observe that the supplier extends even more trade credit to the innovative customer that is more credit- or liquidity-constrained.

However, it is important to note that the supplier may also choose to provide the customer with trade credit if the customer's risk decreases after innovation (i.e., "supply-driven" financing). To wit, the supplier might revise its perception on the customer's financial risk once the customer's investment in innovation is successfully completed and results in the publication of patents, thereby resolving the uncertainty. If this hypothesis holds true, then we should expect that the supplier to extend more trade credit to customers who have demonstrated lower efficiency in translating innovation input to output.[23]

To explore the demand-driven financing channel, we first examine whether customers face any liquidity shortages after innovations. Table 6 Panel A reports the regressions of *Customer Cash/TA*

[22] Li (2018) finds that supplier profitability increases with customer innovation under the assumption that customers increase orders to suppliers after innovation. However, it does not provide direct evidence on the assumption.

[23] Prior studies show that firms with greater investments in innovation have higher overall firm risk (e.g., Bhagat and Welch, 1995; Eberhart, Maxwell, and Siddique, 2004; Coles, Daniel, and Naveen, 2006; Cassell et al., 2012; Kini and Williams, 2012).

on *Customer Innovation* in Columns 1 through 3, indicating that the level of cash holdings is not significantly affected by innovation. Further, we run regressions of customer cash flows on customer innovation because the customers may experience reduced cash flows after innovation while maintaining a certain level of cash reserves. Columns 4 through 6 show the significantly positive coefficients of *Customer Innovation*. While the estimates are not much economically significant, the results show that customers do not face liquidity shortages after innovations.

In the meantime, the increase in customer cash flows after innovation (documented in Columns 4 through 6) can be interpreted as a sign of the supply-driven financing channel, to the extent that the increased cash flows may help alleviate firm risk. Therefore, we also examine the post-innovation change in the customer's overall risk level using the total and idiosyncratic volatility of customer's stock return. More specifically, we compute the post-innovation change in the annualized standard deviation of daily stock returns to measure *Customer Total Risk*. *Customer Idiosyncratic Risk* is measured as the annualized standard deviation of the residuals from the regression of daily returns on the Fama and French three factors.[24] In Table 6 Panel B, Columns 1 through 3 report the insignificant coefficients of *Customer Innovation*, implying that the total volatility does not change significantly from the pre-innovation level. Also, Columns 4 through 6 indicate that the idiosyncratic volatility does not change significantly either.

Insert Table 6 here.

To further test whether the demand-driven financing channel is in play, we use four customer-level financial constraints proxies: *KZ Index* from Kaplan and Zingales (1997), *SA Index* from Hadlock and Pierce (2010), *WW Index* from Whited and Wu (2006), and debt rating unavailability (Denis and Sibilkov, 2010). This channel predicts that the sensitivity of trade credit provision to innovation varies between financially constrained and unconstrained customers.

Also, we use innovation efficiency proxy following Hirshleifer, Hsu, and Li (2013) to further examine the supply-driven financing channel. Innovation efficiency is measured as the ratio of patents granted in year t scaled by its R&D capital (i.e., the 5-year cumulative R&D costs assuming

[24]Even though the supplier's "perceived" risk on the customer is unobservable, prior studies employ the total or idiosyncratic volatility of stock returns as a proxy for overall riskness, where greater volatility implies greater firm risk (e.g., Guay, 1999; Cassell et al., 2012; Kini and Williams, 2012). We repeat the tests using instead monthly returns, log change in volatility, and/or market model, and the results remain consistent across these alternative specifications.

an annual depreciation rate of 20% following Chan, Lakonishok, and Sougiannis (2001) and Lev, Sarath, and Sougiannis (2005)). This metric assesses a firm's ability to produce patents per dollar of R&D investment. The supply-driven financing channel predicts that suppliers extend more trade credit to customers who lack such ability, and thus, have uncertainty resolved only after the successful completion of their patents. To explore both channels, we run regressions with interactions between *Customer Innovation* and each customer-level financial constraint or innovation efficiency measure.

We categorize customers with KZ, SA, or WW indices higher than each median as financially constrained, as these indices increase with the level of financial constraints. Additionally, we classify customers as financially constrained if they have debt outstanding but have never received a long-term debt rating. Firms with no outstanding debt or those that have had a long-term debt rating (excluding default rating of "D" or "SD") are classified as unconstrained (Denis and Sibilkov, 2010). On the other hand, customers with innovation efficiency higher than its median are classified as innovation-efficient.

In Table 6 Panel C, none of the coefficients of interaction between *Customer Innovation* and *Financially Constrained* are significantly different from zero. The results thus imply that suppliers do not significantly differentiate their trade credit provision among financially constrained and unconstrained customers for a given level of customer innovation. Additionally, the insignificant coefficients of *Customer Innovation* $\times$ *Innovation-Efficient* suggest that the sensitivity of supplier trade credit to customer innovation is indifferent among innovation-efficient and innovation-inefficient customers. In unreported tests, the interactions between *Customer Innovation* and other customer-level financial variables (cash ratio, payout ratio, leverage) or R&D dollar expense variable are not significant either.[25] Altogether, the results in Table 6 do not support the financing channel.

[25] In unreported results, the interactions between *Customer Innovation* and the changes (not levels) in those variables after innovation are not significant either. In the meantime, previous studies emphasize the collateral value of patents in debt financing (Mann, 2018), loan contracting (Chava, Nanda, and Xiao, 2017), and venture lending (Hochberg, Serrano, and Ziedonis, 2018). To the extent that the enhanced pledgeability of customers from their new patents influences the *inter-firm* financing as well, we would expect differentiation in trade credit provision among customers with varying levels of pre-existing asset tangibility. However, untabulated results indicate that the interaction between *Customer Innovation* and *Customer Tangibility* is not statistically significant.

3.3 Endogeneity

The previous results would not imply a causal relationship from customer innovation to supplier trade credit because of three potential sources of endogeneity. First, a supplier may motivate its customer to increase innovation activity with its ability to provide a large amount of trade credit. Alternatively, a supplier's capability to extend much trade credit could attract innovative customers in the first place ("reverse causality").[26] Second, it could also be case that customer innovation is correlated with unobservable confounding factors that affect a supplier's trade credit decision. A supplier's ability or willingness to accommodate its customer, for example, might be positively correlated with its trade credit provision, and the partial correlation between the accommodation and the customer's innovation could be positive; this unobservable factor would then bias *upward* the coefficient estimates of *Customer Innovation* ("omitted variable"). Third, SFAS No. 14 reporting requirement does not apply to minor customers (with less than 10% of supplier total sales) and may lead to an overestimation of trade credit provided to *Principal Customers*. The overestimation could be lower for customers that are large and arguably innovative, which induces a *downward* bias on the OLS coefficient estimate of *Customer Innovation* ("measurement error").

To address the potential endogeneity, we conduct 2SLS regressions with two IVs following Hsu et al. (2015). More specifically, we use as the two IVs the (logarithm of one plus) average R&D expenditures per patent and the (logarithm of) average duration from the application filing to the issue or grant of the patent in the customer's industry-year level.[27] The two variables are plausible instruments for the following reasons: (i) a customer faces the monetary and time costs of innovation that are pervasive in its technology peers (i.e., contemporary firms in the same industry), which can impede the innovation of the individual customer. (ii) The monetary costs should be shaped by the nature and complexity of the technology prevailing at that time, and the time costs should be subject to the decision process of the patent granting authorities (i.e., USPTO). The innovation costs in downstream industries, hence, are not policy variables for suppliers. Therefore, there is little reason to believe that the IVs have a direct influence on the supplier's

[26] However, the results in Internet Appendix Table A2 do not show systematic correlations between current trade credit and future customer innovation, implying that the reverse effect seems unlikely in the sample.

[27] When the industry-year level instruments are not available due to a lack of patenting activities, the cost variables, measured in firm level using the past three years of information, are used as the instruments.

trade credit decision other than through their association with the customer's innovation.

One concern is that the costs of innovation might have a direct impact on customers' product market condition, which could, in turn, be affecting suppliers' trade credit decisions. For example, customer industries with high costs of innovation may face more competitive environments, which could lead to less trade credit provision from the suppliers. To assess this, Internet Appendix Table A3 presents the regressions of product market competition, as measured by HHI or NPM at industry (or industry-state) level, on the two IVs within the customer industries. An industry's HHI is the standard Herfindahl-Hirschman index. An industry's NPM is the average net profit margin, which is commonly used as an empirical proxy for the Lerner index—the Lerner index represents firms' market power to set prices above marginal cost and can be proxied by net profit margin under the assumption that the marginal cost is close to the average variable cost. Internet Appendix Table A3 shows insignificant correlations between the IVs and HHI or NPM. While the falsification test cannot provide formal evidence about whether or not the IVs satisfy the exclusion condition, it bolsters confidence that the IVs are uncorrelated to supplier trade credit, other than through their correlations with customer innovation.

Insert Table 7 here.

Table 7 re-estimates the effects of customer innovation in the 2SLS regression framework. Along with the control variables from the previous tables, we include innovation level of customer's industry (excluding the innovation of the focal customer) as the additional control to avoid contagion effects resulting from information spillovers. Column 1 of Table 7 Panel A reports the results of the first-stage regression.[28] Consistent with the prior, $Time\ Cost_{t-1}$ and $Monetary\ Cost_{t-1}$ are inversely related to $Customer\ Innovation_t$. The reported IV F-statistics, Durbin's p-value, and overidentification χ^2-value support that the monetary and time costs of innovation are valid instruments regarding the weak IV problem, exogeneity condition, and overidentification restriction problem, respectively. In Columns 2 through 4, the 2SLS coefficients of *Customer Innovation* are statistically significant and much larger than in the OLS regressions in Tables 2 and

[28] In every Panel of Table 7, Column 1 demonstrates the first-stage regression for the specification in Column 2 where the dependent variable is trade credit in year $t+1$. The first-stage regression results for Columns 3 (for year $t+2$) and 4 (for year $t+3$) are qualitatively identical and are thus omitted for brevity.

3. However, in terms of economic significance, a one standard deviation increase in the predicted *Customer Innovation* is associated with a 0.462 percentage point increase in *Trade Credit* after 1 year (in Column 2), comparable to the economic significance (0.415 percentage point) observed in the OLS regressions.

The magnitude of 2SLS coefficients being larger than that of OLS coefficients can be a threat to the validity of IV model. Jiang (2017) documents in her survey that most studies report IV estimates that are larger than OLS estimates, even when there is no a priori reason to expect such bias.[29] In our case, the uninstrumented OLS coefficients can be downward biased due to measurement error in *Trade Credit*, expected from the lax reporting requirement of SFAS No. 14 on minor customers, as explained above. Alternatively, an omitted variable, which is positively (negatively) correlated with *Trade Credit* but partially negatively (positively) correlated with *Customer Innovation*, can attenuate the OLS coefficients toward zero. For example, strong personal connection between the managers of supplier and customer could bolster trade credit but make the customer less eager to innovate.

It is also possible that the 2SLS regressions are estimating the effects for suppliers, the innovation level of whose customers is affected by the instruments (i.e., local average treatment effects), which are larger than the true population effects for an average supplier (i.e., average treatment effects). In the 2SLS specifications, the estimates represent the effect of *Customer Innovation* among compliers, who innovate more if and only if the costs of innovation decrease. It is plausible that the complier customers have been constrained by the marginal cost of innovation, rather than by the lack of desire to benefit from innovation (in the form of increased trade credit and bargaining power against the suppliers). In turn, the response of the suppliers could be stronger to those customers than to the other customers who have no interest in innovation, despite reduction in cost of innovation. The response of the suppliers to the compliers may also be stronger than that to the other customers who innovate regardless of cost because they can afford it. They are likely to be customers who have been constantly innovating for a long time anyway, and the suppliers may expect less holdup even in the future.

Another possibility is that the IVs are not completely exogenous or valid. However, it is

[29] However, the ratio of the IV estimates to the OLS estimates in this paper is less than 5, which is relatively moderate compared to the papers surveyed in Jiang (2017), where the magnitude of the IV estimates is on average 9.2 times that of the OLS estimates.

reassuring because (i) the innovation costs in downstream industries are not likely policy variables for suppliers, (ii) the large *F*-statistics make an "IV blow-up" problem (Jiang, 2017) unlikely, (iii) the economic significance among the OLS and 2SLS estimates is comparable, and (iv) the IVs still help increase the ability to account for endogeneity bias. Further, we propose the following refinements to the tests to enhance the effectiveness of the IV methods.

Importantly, it is still plausible that some confounding factors correlate with both the costs of innovation and a customer's industry status that possibly affect the supplier's trade credit provision, especially given that the cost measures are constructed in the customer industry level. For example, a supplier might endogenously choose to trade with and provide trade credits to a customer whose industry is facing both technological and productivity growth.[30] Even though *Customer Industry Innovation* and the customer industry fixed effects are controlled and thus serve to limit such endogeneity biases, we also focus on the groups of suppliers whose industries are least likely to be systematically affected by industrial growths in their customer industries and whose customer choices are least likely to be endogenous. Although this process may decrease the variations in the IVs and downsize the sample, it can further help mitigate the issue of endogenous matching.

First, Table 7 Panel B reports the identification outcomes with excluding the supplier-customer relationships that are newly formed. Because the issue of endogenous matching should be most severe for the pairs that have been formed recently, exclusion of such pairs relieves the issue. The exclusion process downsizes the sample by 15% (from 3,612 to 3,093), but the coefficient estimates of *Customer Innovation* remain significant.

Table 7 Panel C shows the results after excluding the customer industries with too high or too low (monetary or time) costs of innovation. More specifically, both extremes in the costs can attract specific types of suppliers. For example, customers with costs of innovation that are too low may be accommodated by suppliers who expect benefits from future innovation of a customer. Alternatively, customer with too high innovation costs could attract suppliers who expect a consolidation on the current production rather than innovation from the customer. In turn, such preferences of suppliers could be reflected in trade credit decisions. For implementation,

[30]However, a supplier's switching to other customers in its current customer's industry would reduce its trade credit to the current customer. If so, it would cause an underestimation in the positive sensitivity of trade credit to customer innovation (i.e., holdup effect), which rather gives more supports to the main findings.

we exclude the observations with the customer whose industry costs of innovation place in the 10% of each tail in each year. The results confirm the previous findings even after decreasing the variations in the instruments.

Table 7 Panel D demonstrates the results after excluding supplier industries that show a volatile turnover rate in their trade relationships. To wit, a supplier industry that can switch to other customer industries flexibly can more endogenously choose a customer when it observes a certain level of expected cost or incentive of innovation of the customer. For implementation, we exclude supplier industries with the industry-level volatility in customer turnover rates greater than its median. Columns 3 and 4 show that the effects are robust to the exclusion process.

Lastly, Table 7 Panel E adds *State R&D Tax Credit* as the additional IV to exploit the variation in the incentives of innovation at the geographical level as well as industry level. Given that firm innovations mostly concentrate on their headquarters, we focus on customers' headquarter locations to exploit the plausibly exogenous variation that is likely to result in a shift in innovation.[31] The state-level R&D tax credit is available for the period from 1990 to 2015 for 33 states from UpJohn Institute's Panel Database on Incentives and Taxes (PDIT) (Bartik, 2017). The database simulates average R&D and investment tax incentives based on the firm balance sheet, local business tax rates, and rules for incentives determination.[32] Importantly, one concern with using the data in my analysis is that a change in the state's R&D tax credit (and other accompanying tax credits) can influence customer earnings as well as the incentives of innovation; hence, it is unclear whether the R&D tax credit affects supplier trade credit only through an increase in customer innovation. We therefore include customer net income as the additional control to alleviate the concern. The customer and supplier (headquarter) state fixed effects are also added to filter out the effect of any geographic preference of suppliers in customers. The first stage in Column 1 shows that *State R&D Tax Credit* is positively associated with the innovation of firms headquartered in the state, as predicted. Also, *Monetary Cost* is negatively correlated with *Customer Innovation* as in the other Panels.[33] Columns 2 and 3 reconfirm the effects of

[31]The majority (70%) of firm inventors work in corporate headquarters (Chu, Tian, and Wang, 2019).

[32]Source: W. E. UpJohn Institute PDIT (https://www.upjohn.org/bied/home.php).

[33]Due to the concern of overidentifying restriction, we use only one cost instrument and one credit instrument. When the three instruments are altogether used in the test, it still presents the relevance of the three instruments to *Customer Innovation* in the first stage and a significantly positive coefficient of *Customer Innovation* in the second stage (0.560 with a p-value of 0.047). However, the Sargan χ^2 is 5.001 with a p-value of 0.082, which rejects the null hypothesis that the overidentifying restrictions are valid.

Customer Innovation on *Trade Credit*. Even though it could be the case that the instruments are not completely exogenous, the various identifications in Table 7 still help lessen the endogeneity biases.

3.4 Innovation through Acquisition

Firms can achieve innovations by outsourcing stock of innovation as well as pursuing in-house innovations. In the current framework, customers can enhance their innovation capacity by acquiring innovative firms, which, in turn, can increase their bargaining power against the suppliers as their own innovations do.

Within the intersection of the sample and the Securities Data Corporation (SDC) M&A database, we collect the customers' acquisition deals that are classified as mergers, acquisitions of majority interest, asset acquisitions, or acquisitions of certain assets. The patenting activities of the targets are obtained from the patent data of Kogan et al. (2017). The patenting activities of the targets are aggregated at the supplier-customer-year level, not the supplier-customer-year-deal level, to incorporate the total increase in innovations acquired by customer in each year. Next, 7-year windows centered on the year of acquisition announcements (-3, +3) are used to construct the main independent variables of the test.

Insert Table 8 here.

In Table 8, *Post Acquisition* is controlled for any change in the bargaining power of customers from business or capacity expansion after acquisitions, which is unrelated to target innovativeness.[34] *Target Innovation*, defined as the logarithm of one plus the number of patents of targets in the announcement year, is included to capture innovativeness and further firm heterogeneity among targets. *Customer Innovation* is also included to control for the effect of the customer's in-house innovation. While the effects of *Customer Innovatio*n remain significant, the variable of interest, *Post Acquisition*$\times$*Target Innovation*, demonstrates significantly positive coefficients, indicating that supplier trade credit provision increases after acquisitions of innovative targets as well as in-house innovations by customers.

[34]See e.g., Fee and Thomas (2004), Bhattacharyya and Nain (2011), Campello and Gao (2017) for the effect of customer concentration from mergers.

3.5 Technological Space of Customer Innovation

In this section, we examine whether the technological class of customer innovation affects the positive sensitivity of supplier trade credit provision to customer innovation. If the customer's innovation is closely related to the supplier's existing product technology and is hence likely to be relationship-specific innovation, then it should mitigate the holdup problem. Put differently, the customer's making supplier-related innovation can be a commitment to maintain the current relationship, especially considering that patents are irreversible innovation outputs. Conversely, if the customer's current innovation is irrelevant to the supplier's existing technology, the supplier may anticipate the customer appropriating quasi-rent and potentially switching to another supplier, which lead to a holdup problem.

To measure the relatedness of customer innovation to supplier technology, we use the technology class information recorded in Kogan et al. (2017)'s data. More specifically, *Class Overlap*$_t$ is the indicator variable that equals 1 if the technology class of a customer's patent (issued newly in year t) overlaps with historical technology classes of its supplier's patents (issued previously as of year t). When a customer does not have a patent record (i.e., *Customer Innovation* equals zero), the observation is discarded from the sample because *Class Overlap* cannot be defined.

Insert Table 9 here.

Table 9 Columns 1 through 3 show that the interaction between *Customer Innovation* and *Class Overlap* has negative associations with *Trade Credit* in all specifications. The interaction effect is also economically significant; the sensitivity of *Trade Credit* to *Customer Innovation* drops by approximately 73% when there is *Class Overlap*. In the meantime, an overlap with a supplier's recent technology is likely more relevant for the customer's commitment than its distant past technology. In Columns 4 through 6, *Class Overlap*$_t$ is replaced by *Class Overlap*$_t^{5yr}$, which gauges the overlap between customer's patent class in year t and supplier's patent class from year $t-4$ to t. Also, Columns 7 through 9 replace *Class Overlap* with *Class Overlap*$_t^{Cos}$, which calculates the cosine similarity between a customer's patent class and the supplier's historical classes. This variable reflects continuous technological proximity instead of an indicator variable (e.g., Lee et al.,

2019). The results remain consistent across these alternative specifications.

In contrast, it is not observed that the sensitivity significantly changes when a customer's patent class overlaps with its own historical patent classes (i.e., $Class\ Overlap_t^{Own}$). In Columns 10 through 12, the interaction between *Customer Innovation* and $Class\ Overlap_t^{Own}$ is not significantly different from zero, implying that overlapping a customer's patent class with its own past classes is not such a credible commitment as that with the supplier's past classes.

It is worth noting that the results in Table 9 may also highlight the difference between "product innovation" and "process innovation." The innovation literature (e.g., Levin and Reiss, 1989; Cohen and Klepper, 1996; Lin and Saggi, 2002; Bena, Ortiz-Molina, and Simintzi, 2022; Bena and Simintzi, 2019) classifies corporate innovation into two types: innovation to generate new products (i.e., product innovation) and innovation to increase the productivity of existing assets (i.e., process innovation). A customer's product innovation can give it the opportunity to switch to another supplier and increase its bargaining power against its original supplier. To the extent that the deviation of the customer's technology space from that of the supplier is interpreted as the customer's product innovation, the result implies that product innovation can cause the holdup problem. In the meantime, it is not clear whether a customer's process innovation increases or decreases its bargaining power. On one hand, the customer, for instance, can start to develop a new product with its extra resources attained from its process innovation. In turn, the customer will be able to hold up its supplier with the new product. On the other hand, it is also possible that the customer's process innovation increases its production efficiency and lowers its production costs where the extra surplus can be appropriated by its supplier. To wit, increased production efficiency can enable the supplier to hold up the customer. To the extent that the overlap between the new technology space and original technology space within a firm translates into process innovation, the result suggests that the impact of a customer's process innovation on its bargaining power is neutral.[35]

[35]Internet Appendix Table A4 further breaks down *Customer Innovation* into *Process Innovation* and *Product Innovation*. While both are highly correlated with each other, the results show that product innovation, as compared to process innovation, is associated with an increase in supplier trade credit. Bena and Simintzi (2019) implement textual analysis to count process claims of each patent. We are grateful to Professors Jan Bena and Elena Simintzi for making this data available on the website (`https://www.janbena.com/en/process-innovation-patent-dataset`).

3.6 Financial and Investment Decisions of Supplier

This section explores how customer innovation shapes the financial and investment decisions of suppliers. A supplier, when faced with holdup by its customer, might change its financial and investment policy to protect itself from the holdup. The supplier might need to adjust its financial policies, for instance, to cover the increased trade credit provision, to cover the cost of searching for new customers, to build a new factory line for self-production of a final product, to prepare the cost of vertical acquisition of the customer, to prepare innovation costs, and so on. At the same time, it can increase its own innovative activity to strengthen bargaining power against its customer. It may also learn from the customer's innovation to provide input products customized for the customer's new product and thus prevent the customer from switching to another supplier.

To examine the internalization effects, we test how the supplier's financial variables (i.e., cash ratio, payout, leverage) and investment variables (i.e., R&D expenditures, supplier innovation, technology spillover) are associated with the customer's innovation. *Supplier Innovation* is (the logarithm of one plus) the number of patents of the supplier. *Tech Spillover* is defined as (the logarithm of) the ratio of the number of the customer's past patents cited by the supplier's patent at year t over the total number of the supplier's patents at year t.

Insert Table 10 here.

Table 10 demonstrates that suppliers hold higher cash holdings and lessen payout when customers innovate, even though the sensitivity of supplier leverage to customer innovation is not significantly different from zero. For a one standard deviation in *Customer Innovation*, a supplier increases $Cash/TA$ by 0.28 percentage points and decreases *Payout* by 0.16 percentage points, which account for 1.4% increase and 8.4% decrease over the averages of $Cash/TA$ and *Payout*, respectively. On the other hand, Column 5 shows that suppliers increase their own innovation activities after their customers innovate, consistent with previous studies (e.g., Li, 2018) that document knowledge spillovers as the positive externalities. Moreover, Column 6 implies that their patents cite their customers' patents more frequently; that is, they learn from customer innovation. However, the impact of customer innovation on supplier R&D expenditures is positive but statistically insignificant. Collectively, this analysis implies that customer innovation influences a supplier's

internal policy as well as its policy toward interfirm relationship.

3.7 Termination of Trade Relationship

This section examines how a customer's innovation affects the likelihood of termination of the trade relationship. A priori, the relation is not obvious; firstly, the customer may want to switch to another supplier that better aligns with its new technology. Despite receiving increased trade credit from current suppliers, it may not be sufficient to accommodate large customers, especially. However, it is also costly for the customer to terminate the current relationship if the supplier is willing to provide more trade credit than before. This would be particularly costly for customers whose costs of capital from other sources are high.[36] Additionally, the supplier seems to cater to the customer's needs through internalization efforts in financial and innovation policies, which the customer may not want to forgo. As a result, the customer would weigh the various benefits and costs of termination. Overall, it is an empirical question whether customer innovation ultimately leads to the termination of relationships.

For this, we define a supplier-customer relationship as ended when the relationship is not identified in the data, or the customer does not serve as the supplier's *Principal Customer* any longer.

Insert Table 11 here.

Columns 1 and 2 in Table 11 show that the likelihood of termination in a relationship is not significantly associated with *Customer Innovation*, indicating that the relationship is not terminated by a high level of customer innovation in two years. In the meantime, Column 3 shows that the likelihood of termination is significantly positively affected by the customer's innovation after three years. To check whether the effect holds in the long term, Columns 4 and 5 show the likelihood of termination from customer innovation as of $t+5$ and $t+10$, respectively.[37] The effects are also economically substantial. For a one standard deviation increase in *Customer*

[36] Data on the contract terms of trade credits would help identify the relative cost of trade credit compared to other sources of capital, but it is unavailable in the current sample.

[37] Even though the termination status is accumulated over time, the size of the coefficients does not necessarily increase over time. A terminated relationship is identified as restored to active status once the supplier and customer resume trades during the sample period.

Innovation, the odds ratio that a relationship ends increases by 26.9% in Column 5's specification. Moreover, given that the unconditional average duration of a supplier switching to a new *Principal Customer* (2.3 years) is longer than that of a *Principal Customer* to a new supplier (2.0 years), a supplier would likely suffer more than its *Principal Customer* from their relationship termination. Together with the results in Table 10, the results in Table 11 imply that the trade relationship is sustained in the short term even after customer innovation, possibly because of the internalization effect of suppliers, but it can be terminated in the long term.

On the other hand, an extensive literature emphasizes within-firm transaction or vertical integration as a preventive measure of holdup problem (e.g., Coase, 1937; Fan, 2000; Lafontaine and Slade, 2007). In the current sample, however, only 5 customer-supplier pairs out of 2,919 pairs execute vertical integrations during the sample period, presumably because the suppliers are much smaller in size than the *Principal Customers*. Thus, an examination of vertical integration from the standpoint of a trade counterparty's innovation, especially using an extended sample of larger suppliers, could be an interesting topic for future research.

3.8 Discussion and Aggregate Implications

Even though trade credit resulting from customer innovation is costly to suppliers given its economic significance (as diagnosed in Section 3.1), it is worth discussing whether increased trade credit always presents adverse implications for suppliers. Specifically, extending more trade credit to an innovative customer might foster a better relationship and eventually be *value-enhancing* for suppliers. For example, while the results in Section 3.7 show that relationships are more likely to be terminated after customer innovation, the results in Section 3.6 indicate that suppliers reconfigure their financial and investment policies by increasing cash holdings and innovation while decreasing payouts. These adjustments can offset the potential adverse effects of increased trade credit and termination likelihood, ultimately increasing firm values *ex post*. Besides, Breza and Liberman (2017) demonstrate that trade credit helps enable trade by guaranteeing product quality among Chilean firms.

However, trade credit decisions can be critical for individual suppliers; the provision of trade credit can constrain a supplier's investment and even force it into distress (Murfin and Njoroge,

2015; Barrot, 2016). Barrot and Nanda (2020), focusing on the federal Quickpay reform that accelerated payments to small business government contractors, show that payment delay and the associated liquidity risk have strong negative impacts on employment growth of suppliers. Additionally, the trade credit disproportionately given to an innovative customer can limit the resources available to other less innovative customers, potentially hurting the supplier's value. Moreover, suppliers not specialized in collecting unpaid trade credit may find it costly to collect or factor it (especially against large customers). To this end, Internet Appendix Table A5 examines the net association between increased trade credit and supplier value or performance by regressing supplier MTB, ROA, or sales growth on the trade credit. The coefficients of *Trade Credit* are statistically indistinguishable from zero. The results imply that the value implications of increased trade credit are neutral *ex post*, possibly because suppliers' financial and innovation responses to customer innovation offset the expected increase in trade credit and termination likelihood. Nevertheless, we acknowledge that an identification exploiting variations in trade credit (exogenously induced by customer innovation) may allow a more meticulous investigation of the value implication of trade credit.

On the other hand, another main result (in Section 3.7) should also be interpreted with caution because it concentrates on ex-post termination outcomes. More specifically, it can be the supplier, not the customer, who terminates the relationship due to the burden of consistently providing increased trade credit or any other accommodations. Also, it is possible that the supplier may switch to another customer upon achieving its own innovation. A dynamic matching model between customers and suppliers may shed light on this problem. While incorporating this into the current framework is beyond the scope of this paper, the sample statistics provide suggestive evidence that it might be the customer's decision; first, given that the unconditional average duration of a supplier switching to a new *Principal Customer* (2.3 years) is longer than that of a *Principal Customer* to a new supplier (2.0 years), a supplier would likely suffer more than its *Principal Customer* from their relationship termination. Furthermore, the customers in the sample are an order of magnitude larger than the suppliers, implying greater negotiating leverage for customers, which weighs the customer-induced termination more heavily than supplier-induced termination.

3.9 Robustness & Additional Tests

3.9.1 Measurement of Trade Credit

The previous results show that suppliers extend more trade credit to their customers when the trade credit is measured as the proportion of a supplier's trade receivable attributable to its *Principal Customer*. This measurement relies on the assumption that a supplier provides its customers with trade credit proportionate to their portions of sales. Meanwhile, Freeman (2020) finds that a supplier extends less trade credit to its customer with higher sales dependence to avoid credit concentration. Thus, this section loosens the assumption and examines whether the main results are robust to it.

First, we use a supplier's aggregated trade credit (i.e., total trade receivables) as the dependent variable and aggregated patenting activities of all other customers as well as the *Principal Customer* as the independent variable. In this way, the concern of the measurement error in trade credit received by the *Principal Customer* can be mitigated by measuring trade credit and patents in the aggregated level. Panel A of Internet Appendix Table A6 aggregates the patenting activities by counting the number of patents of all customers, and Panel B uses the number of patents of all customers averaged using sales portion as the weights. The results are robust to the aggregation of trade credit and patenting activities.

Also, we focus on the suppliers whose *Principal Customers* are most influential customers in order to minimize any confounding effects of the other customers and their relationship with the suppliers. More specifically, the sample is restricted to the suppliers whose *Principal Customer* is the sole customer in the data, or the suppliers whose *Principal Customer*, as the sole customer, takes more than 80% of the suppliers' sales.[38] Panels C and D of Internet Appendix Table A6 report the regression results with the restricted samples. The estimated coefficients of *Customer Innovation* are larger than in Table 2, reflecting that the innovations of the influential *Principal Customers* affect the trade credit decisions more significantly.

[38]Given that the median sales portion of the *Principal Customer* is about 25%, the requirement of 80% is a conservative threshold. Even though this strict requirement downsizes the sample to only 240 observations, the restricted sample would serve better to minimize any confounding effects of the other customers.

3.9.2 Measurement of Innovation

Throughout the paper, we use the number of patents as the proxy for innovation. We also repeat the analysis, replacing the patent count measure with the citation-weighted patent counts and the market value of patents as constructed in Kogan et al. (2017). Patent citations may contain quality aspects of patent values (e.g., Hall, Jaffe, and Trajtenberg, 2000; Aghion, Van Reenen, and Zingales, 2013). Kogan et al. (2017) estimate the market value of a patent using the product of the stock return at the announcement of the patent issuance and market capitalization of the patenting firm. Panel A and B of Internet Appendix Table A7 exhibit the regression results, confirming that the alternative measures of innovation also have significantly positive impacts on trade credit.

Also, the firm-year level innovation is measured throughout the paper as the number of patents *issued* by the firm in the year, but we also compute an alternative level of innovation as the number of patents *filed* by the firm in the year because filing date is closer to the actual time of inventions (Hall, Jaffe, and Trajtenberg, 2001). Panel C of Internet Appendix Table A7 shows the similar coefficient estimates for *Customer Innovation* with that of Table 2, suggesting that the baseline effects arise for both actual invention and innovation disclosure.

3.9.3 Other Factors

Even though the effects of *Customer Innovation* are robust to controlling for a battery of fixed effects (e.g., supplier industry $\times$ customer industry $\times$ year), the fixed effects may not capture firm-level status changes, which potentially affect a customer's bargaining power with which the customer can demand more trade credit. We thus use the symmetric set of firm characteristics at the customer level as the additional controls. Besides, as innovation is a long-term process, customers' patent stock from the past may also be relevant for suppliers' trade credit policies, which could be an important omitted variable. We therefore include past patent stock as an additional control.

On the other hand, previous literature on trade credit explores its existence and roles. The first strand of literature emphasizes information advantage and superior access to the capital market of suppliers over customers, which leads to trade credit as an alternative form of financing (e.g., Schwartz, 1974; Smith, 1987; Brennan, Maksimovics, and Zechner, 1988; Petersen and Rajan, 1994;

Burkart and Ellingsen, 2004; Cunat, 2007; Ivashina and Iverson, 2018). The second strand views trade credit as an implicit warranty for product quality given to the customers as they need more time to inspect the product quality before paying in full (e.g., Lee and Stowe, 1993; Long, Malitz, and Ravid, 1993; Antras and Foley, 2015). The other strand focuses on product market position and concludes that customers with market power receive more favorable trade contract terms (e.g., Giannetti, Burkart, and Ellingsen, 2011; Klapper, Laeven, and Rajan, 2012; Dass, Kale, and Nanda, 2015; Fabbri and Klapper, 2016). Also, the literature identifies product type (Giannetti, Burkart, and Ellingsen, 2011), arbitraging tax differences among counterparties (Brick and Fung, 1984), risk management (Frank and Maksimovic, 1998), and liquidity management (Ferris, 1981) as the determinants of trade credit. Importantly, this paper does not aim to test the existing theories but instead uses trade credit as the ex post bargaining outcome. Put differently, this paper concentrates on how one party's innovation affects its relative bargaining power against the counterparty, captured by the trade credit which is jointly determined by the changes in such factors.

Those factors, however, could also be influenced by other unobserved variables than innovation. To isolate the time-invariable supplier characteristics (e.g., product type or the tendency to use trade credit as an implicit warranty), we include supplier firm fixed effects (with supplier industry fixed effects subsumed) in Columns 1 through 3 of Internet Appendix Table A8. The effects of *Customer Innovation* persist even after including the supplier fixed effects. Also, to isolate the time-invariable customer characteristics, we further add customer firm fixed effects (with customer industry fixed effects subsumed) in Columns 4 through 6, and the results remain consistent. Still, unobserved characteristics of customer-supplier pairs could confound the effects. One way to control for the factors is to include customer-supplier pair fixed effects. This allows us to capture the effect on trade credit when customer innovates compared to when customer does not innovate *within* the same customer-supplier pair. In addition, the firm-pair fixed effects can control for other pair-level characteristics that can be correlated with innovation, such as social connection (Dasgupta, Zhang, and Zhu, 2021) and geographic proximity (Chu, Tian, and Wang, 2019) between customers and suppliers. Columns 7 through 9 show that the effect of *Customer Innovation* remains significant and is not entirely subsumed by the customer-level variables and firm-pair fixed effects, although it is less significant than in Table 2.

3.9.4 Innovation Jump vs. Innovation Drop

This section compares supplier trade credit granted to customers with an abrupt change in the innovation level (i.e., jump or drop) and that to customers with a persistent level of innovation. Although a high level of customer innovation can lead to a holdup problem, it may not be much effective if it is weaker relative to the customer's past innovation record. In the same vein, customer innovation may be more effective if it is stronger than the customer's past record. Another purpose of this section is to relieve a concern that the regressions in Table 2 may be estimating only cross-sectional effects from the cross-sectional variations in firm innovation, given that innovation policies are sticky for many firms (e.g., Hall, Jaffe, and Trajtenberg, 2000). By exploiting abrupt changes in the innovation level, this section explores whether the differences in supplier trade credit can be explained by the time-series variations as well as the cross-sectional variations in customer innovation. For these, we construct:

$$Customer\ Innovation_t^{Jump} = \begin{cases} Customer\ Innovation_t & \text{if } Innovation\ Jump \text{ in } t \\ 0 & \text{otherwise} \end{cases}$$

$$Customer\ Innovation_t^{Drop} = \begin{cases} Customer\ Innovation_t & \text{if } Innovation\ Drop \text{ in } t \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$Customer\ Innovation_t^{Pers} = \begin{cases} Customer\ Innovation_t & \text{if no } Innovation\ Jump \text{ or } Drop \text{ in } t \\ 0 & \text{otherwise} \end{cases}$$

where *Innovation Jump* is an indicator for the number of patents of the customer being greater than 1.5 times (or 2 times or 5 times) the average (or median) number of patents in the past three consecutive years. Similarly, *Innovation Drop* is an indicator equal to one if the past 3-year average (or median) is 1.5 times (or 2 times or 5 times) greater than the current number of patents. $Customer\ Innovation_t^{Pers}$ is the historically persistent level of customer innovation without *Innovation Jump* or *Innovation Drop*. Overall, $Customer\ Innovation_t$ is decomposed into the three

variables.

Column 1 in Internet Appendix Table A9 Panel A shows that the coefficients of the three variables are comparable to each other when jump (drop) is defined from whether current patents (past 3-year average of patents) are 1.5 times greater than its past 3-year average of patents (current patents). However, with more progressive multipliers (i.e., 2 and 5) in Columns 2 and 3, $Customer\ Innovation_t^{Jump}$ shows coefficient estimates that are more statistically and economically significant than that of $Customer\ Innovation_t^{Pers}$ and $Customer\ Innovation_t^{Drop}$. Especially, the coefficients of $Customer\ Innovation_t^{Drop}$ are not significantly different from zero. The similar results are observed in Columns 4 through 6 when the 3-year median of past patent records is used as the reference value. Collectively, the results show that customer innovation brings a stronger holdup effect when its level is substantially higher than the past level.

In addition, Internet Appendix Table A9 Panel B exploits customer switching that creates variations in customer innovation at the extensive margin for the same supplier. For each customer switch of a supplier, we compare innovation levels of the original and new customers to define $Customer\ Switch^{Jump}$ and $Customer\ Switch^{Drop}$. The inclusion of supplier firm fixed effects allows me to capture the changes in the trade credit outcome after switching to a new customer with a different level of innovation *within* the same supplier. Also, we include *New Customer* to control for any accommodation effect of supplier for a newly matched customer. Column 1 (2) shows that suppliers provide more (less) trade credit when they switch to more (less) innovative customers. To control for the heterogeneity between original and new customers, Columns 3 and 4 include customer characteristics as the additional controls and find similar effects.

3.9.5 Customer Innovation vs. Supplier Innovation

A supplier's innovation may increase its bargaining power against the customer just as the customer's innovation does to the supplier; holdup problems arise *bilaterally*. Internet Appendix Table A10 shows that supplier's innovation is negatively associated with its trade credit provision. Also, the negative coefficient of the interaction between *Supplier Innovation* and *Customer Innovation* in Column 4 indicates that the holdup from customer innovation can be attenuated by supplier innovation. Overall, the results indicate the countervailing force of supplier

innovation against customer innovation and the resulting bargaining power.

3.9.6 Net Trade Credit

It is possible that an increase in a supplier's trade credit to its customer is attributable to an increase in its upstream supplier's trade credit to itself (i.e., an increase in the focal supplier's trade payables), which unwittingly coincides with customer innovation. Alternatively, the supplier may demand more trade credit from its upstream supplier to finance its trade credit provision to the customer. However, Columns 1 through 3 in Internet Appendix Table A11 demonstrate that a supplier's total trade payables do not increase after customer innovation. In the meantime, Columns 4 through 6 employ supplier *Net Trade Credit*, defined as

$$Net\ Trade\ Credit = \frac{(Trade\ Receivable\ -\ Trade\ Payable) \times Sales\ Dependence}{Total\ Assets} \tag{7}$$

that adjusts any change in supplier trade payables. The lower statistical and economic significances of *Customer Innovation*, when *Net Trade Credit* is used instead of *Trade Credit*, suggest that an increase in supplier trade credit due to customer innovation can be partially financed by an increase in supplier trade payable. That being said, the results show that a significant amount of increment in trade credit is paid by the supplier out of its own pocket.

3.9.7 Placebo Test: Innovation of Customers Other than Principal Customer

To the extent that a holdup effect arises in a bilateral relationship, a supplier's trade credit provision to its *Principal Customer* should not be influenced by the innovation of the other customers. Otherwise, one could argue that an unobservable product market consideration of the supplier on its overall customers would confound the trade credit outcomes. For example, the supplier may attempt to draw innovation from its entire customers by consistently granting them more trade credit. If this is the case, we should observe a positive correlation between the trade credit given to the *Principal Customer* and the innovation level of the other customers. However, the results in Internet Appendix Table A12 show that *Trade Credit* (granted to *Principal Customer*) is not significantly associated with *Other Customer Innovation*.

4 Conclusion

This paper investigates externalities of innovation along the supply chain by analyzing the effect of customer innovation on supplier trade credit. The main finding of this paper is that a supplier extends more trade credit after a customer creates an innovation, and the effect is robust after controlling for various firm characteristics and industry-specific market conditions and correcting for potential endogeneity biases.

We also analyze three possible channels (i.e., holdup, demand, and financing channels) which can uniformly derive the main effect. Our results are consistent with only the holdup channel, which predicts the stronger effect size in the high asset specificity group than the low asset specificity group. Also, the results show that acquisitions of innovative targets, as well as in-house innovations of customers, contribute to the holdup effects.

Next, we suggest that the technological relatedness of customer innovation to supplier innovation downsizes the positive sensitivity of supplier trade credit provision to customer innovation. Further, this result highlights that product innovation rather than process innovation causes holdup problems.

Lastly, we find that a supplier adjusts financial policy (i.e., higher cash holdings and lower payouts) and produces more innovation by learning from customer innovation. Thereby, we conclude that customer innovation impacts a supplier's internal policy as well as its policy in the dimension of interfirm relationship (i.e., trade credit policy). In addition, the results show that the trade relationship is sustained in the short term even after customer innovation, possibly because of the internalization effect of suppliers, but can be terminated in the long term.

However, we acknowledge several limitations of this study. For instance, this paper relies on trade credit or length of relationship as the major proxies for relative bargaining powers between suppliers and customers. Even though contract-level data (e.g., inter-firm product pricing or contract terms) is not generally available, such data source would shed light on more complete dynamics. For example, suppliers can make a concession to customers other than through trade credit when customers innovate, which may be a substitute (or even complement) for trade credit provision. On the other hand, the implications of a firm's innovation (and the resulting change in its trade relationship) on the entire product market are limited in this study. The termination of

its existing relationship may lead to a more efficient match with another supplier. Such efficient matches, in turn, may increase the efficiency of the product market.

While this paper emphasizes the externalities of innovation along the supply chain, a firm's innovation can have other types of externalities on its other stakeholders, such as employees, unions, and government, which is not deeply studied in the literature. For instance, a firm's innovation might endow its management with increased bargaining power against its (non-inventor) employees in the wage negotiation process by making their skills obsolete. Or, it is possible that certain types of corporate innovation may harm the interest of local communities, such as the local environment. These could be interesting topics for future research.

Overall, our findings propose a unique channel through which corporate innovation can influence upstream or downstream firms, which has been understudied in the literature. Also, this topic becomes pressing as supply chains span across different countries and thus are susceptible to global-level risk or disruption, as we observed in the recent global supply chain crisis.

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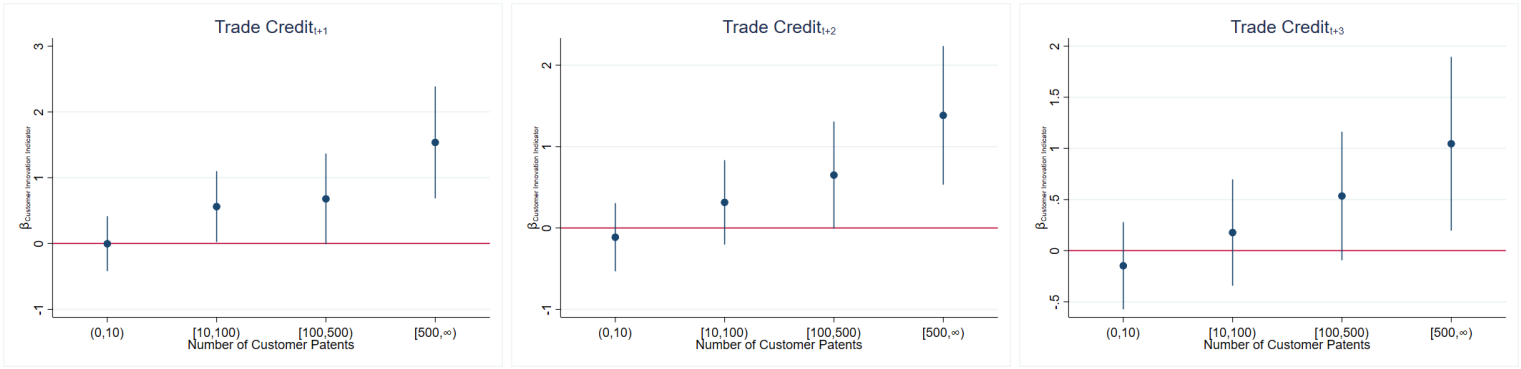
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Figure 1: Average Effects of Customer Innovation on Supplier Trade Credit

This figure demonstrates the differences in *Trade Credit* across different groups of suppliers, which are classified by the number of patents of *Principal Customers*. More specifically, the coefficient estimates and 95% confidence intervals are obtained from:

$$Trade\ Credit_{t+k} = \beta_0 + \beta_1 \cdot 1(0 < \#\ Patents < 10)_t + \beta_2 \cdot 1(10 \leq \#\ Patents < 100)_t + \beta_3 \cdot 1(100 \leq \#\ Patents < 500)_t + \beta_4 \cdot 1(500 \leq \#\ Patents)_t + Firm\ Controls + Supplier\ Industry\ FE + Customer\ Industry\ FE + Year\ FE$$

The suppliers whose *Principal Customer* has zero patent are the base group in the regression. The figures report β_1 through β_4 with their 95% confidence intervals.



(a) Year $t+1$ **(b)** Year $t+2$ **(c)** Year $t+3$

Table 1: Summary Statistics

Summary statistics are reported for the sample of 9,602 supplier-*Principal Customer*-year observations (2,919 supplier-*Principal Customer* pairs) for the period of 1980-2010. Firms in the Compustat Segment Customer files are excluded if they are financials (SIC code 6000-6999) and utilities (SIC code 4900-4999). After the screening procedure, the firm patent information is obtained from Kogan et al. (2017). Panel A reports the firm characteristics of *Principal Customers* and suppliers. The last column demonstrates the difference between *Principal Customers* and suppliers. Panel B reports the firm characteristics of two groups: (i) suppliers whose *Principal Customer* reports zero *Customer Innovation* and (ii) suppliers whose *Principal Customer* reports positive *Customer Innovation*. The symbol ***, **, and * denote statistical significance for two-tailed *t*-tests at the 1%, 5%, and 10% levels, respectively.

Panel A					
	Customer		Supplier		
Firm Variables	*Mean*	*Std.Dev*	*Mean*	*Std.Dev*	$Diff(t)$
$Size(\$bil)$	33.680	54.207	1.613	9.076	32.07*** (56.88)
MTB	1.762	1.707	1.956	2.130	-0.19*** (-6.96)
ROA	0.149	0.139	0.091	0.220	0.06*** (22.06)
Leverage	0.253	0.185	0.230	0.255	0.02*** (7.36)
$Cash/TA$	0.092	0.108	0.173	0.207	-0.08*** (-33.78)
$CAPEX/TA$	0.075	0.051	0.068	0.073	0.01*** (7.63)
$R\&D/TA$	0.036	0.044	0.056	0.129	-0.02*** (-14.34)
Innovation	3.003	2.675	0.662	1.191	2.34*** (77.99)
Observations	9,602		9,602		
Panel B					
	Customer Innovation$= 0$		*Customer Innovation*> 0		
Supplier Variables	*Mean*	*Std.Dev*	*Mean*	*Std.Dev*	$Diff(t)$
$Size(\$bil)$	1.237	5.680	1.851	10.675	-0.61*** (-3.67)
MTB	1.953	1.825	1.959	2.302	-0.01 (-0.14)
ROA	0.097	0.205	0.087	0.230	0.01* (2.18)
Leverage	0.244	0.295	0.221	0.225	0.02*** (4.15)
$Cash/TA$	0.156	0.191	0.183	0.216	-0.03*** (-6.47)
$CAPEX/TA$	0.066	0.077	0.070	0.071	-0.00* (-2.46)
$R\&D/TA$	0.043	0.098	0.063	0.145	-0.02*** (-7.97)
Innovation	0.532	1.053	0.744	1.264	-0.21*** (-8.87)
$Trade\ Credit_{t+1}(\%)$	4.667	5.118	4.743	4.936	-0.08 (-0.72)
$Trade\ Credit_{t+2}(\%)$	4.545	5.020	4.506	4.816	0.04 (0.37)
$Trade\ Credit_{t+3}(\%)$	4.395	5.014	4.235	4.756	0.16 (1.56)
Observations	3,720		5,882		

Table 2: Baseline Effects

This table shows the results of OLS and logit regressions examining the effect of customer's innovation on supplier's trade credit provision. The dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. The dependent variables are indicator variables equal to one if a supplier provides its *Principal Customer* with trade credit at year $t+1$, $t+2$, and $t+3$ in Columns 4, 5, and 6, respectively. Columns 4, 5, and 6 use only the *Principal Customers* that are not granted any trade credit in year t. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Trade Credit$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit Initiation*$_{t+1}$	*Trade Credit Initiation*$_{t+2}$	*Trade Credit Initiation*$_{t+3}$
Customer Innovation$_t$	0.155***	0.142***	0.112***	0.117**	0.127*	0.132
	(0.044)	(0.043)	(0.042)	(0.053)	(0.073)	(0.093)
Size$_t$	-0.033***	-0.028***	-0.025***	-0.207	-0.366*	-0.126
	(0.007)	(0.006)	(0.005)	(0.139)	(0.193)	(0.171)
MTB_t	0.081	0.022	0.002	-0.049***	-0.067***	-0.080**
	(0.055)	(0.048)	(0.055)	(0.019)	(0.026)	(0.031)
ROA_t	-0.635	-1.542**	-1.912***	-0.001	-0.127	-0.178
	(0.653)	(0.635)	(0.670)	(0.222)	(0.239)	(0.339)
Leverage$_t$	-0.647	-0.259	-0.303	0.168*	0.181	0.182
	(0.442)	(0.448)	(0.391)	(0.097)	(0.171)	(0.334)
$Cash/TA_t$	-3.434***	-2.949***	-2.781***	0.041	-0.460	-0.229
	(0.588)	(0.555)	(0.517)	(0.480)	(0.730)	(0.931)
$CAPEX/TA_t$	-3.053**	-3.360***	-4.002***	-2.690	-0.284	-3.054
	(1.221)	(1.161)	(1.148)	(2.317)	(2.039)	(2.213)
$R\&D/TA_t$	-0.071	-1.114	-1.385	0.226	-0.037	0.409
	(2.201)	(1.727)	(1.498)	(0.279)	(0.231)	(0.462)
Observations	9,602	9,602	9,602	499	446	424
(Pseudo) R-squared	0.211	0.207	0.197	0.131	0.131	0.131
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 3: Multiple Fixed Effects

This table shows the results of OLS regressions examining the effect of customer's innovation on supplier's trade credit provision with different combination of fixed effects. The dependent variable is the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Trade Credit$_{t+1}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+1}$
Customer Innovation$_t$	0.155***	0.114*	0.150***	0.171***	0.182***	0.160***	0.153***
	(0.044)	(0.063)	(0.054)	(0.066)	(0.067)	(0.056)	(0.055)
Observations	9,602	9,602	9,602	9,602	9,602	9,602	9,602
R-squared	0.211	0.118	0.255	0.468	0.353	0.471	0.473
Firm Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N	Y	N
Supplier Industry FE	Y	N	Y	N	Y	N	N
Customer Industry FE	N	Y	Y	Y	N	N	N
Supplier Industry × Year FE	N	N	N	Y	N	N	N
Customer Industry × Year FE	N	N	N	N	Y	N	N
Supplier Industry × Customer Industry	N	N	N	N	N	Y	N
Supplier Industry × Customer Industry × Year	N	N	N	N	N	N	Y

Table 4: Holdup Channel

This table shows the results of OLS regressions examining the holdup channel. The dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Panels A, B, and C, respectively. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. $Asset\ Specificity_1$ is the reciprocal of the logarithm of one plus the number of *Alternative Customers*. $Asset\ Specificity_2$ equals one minus the ratio of *Tangible Assets* over *Total Assets*. $Asset\ Specificity_3$ is the logarithm of one plus the number of years of trade relationship with *Principal Customer*. $Asset\ Specificity_4$ is the vertical relatedness score from Frésard, Hoberg, and Phillips (2020). Each low (high) *Asset Specificity* group is defined as suppliers with *Asset Specificity* lower (higher) than the median. In each odd (even) column, only low (high) *Asset Specificity* group is used in the regression. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$Supplier\ Specificity_1$			$Supplier\ Specificity_2$			$Supplier\ Specificity_3$			$Supplier\ Specificity_4$		
	Trade $Credit_{t+1}$	*Trade* $Credit_{t+2}$	*Trade* $Credit_{t+3}$	*Trade* $Credit_{t+1}$	*Trade* $Credit_{t+2}$	*Trade* $Credit_{t+3}$	*Trade* $Credit_{t+1}$	*Trade* $Credit_{t+2}$	*Trade* $Credit_{t+3}$	*Trade* $Credit_{t+1}$	*Trade* $Credit_{t+2}$	*Trade* $Credit_{t+3}$
Customer Innovation$_t$	0.057	0.029	-0.005	0.106	0.086	0.058	0.056	0.044	0.024	0.026	0.035	0.029
	(0.074)	(0.072)	(0.069)	(0.066)	(0.063)	(0.062)	(0.086)	(0.082)	(0.078)	(0.063)	(0.058)	(0.055)
Customer Innovation$_t$	0.164*	0.206**	0.201**	0.091	0.125*	0.114*	0.280***	0.252**	0.210**	0.238***	0.214***	0.162***
$\times$ *High Specificity*$_t$	(0.085)	(0.082)	(0.078)	(0.068)	(0.067)	(0.063)	(0.099)	(0.098)	(0.096)	(0.067)	(0.063)	(0.061)
High Specificity$_t$	0.244	0.032	0.002	-0.807***	-0.911***	-1.016***	-0.261	-0.207	-0.143	-0.634**	-0.623**	-0.494*
	(0.406)	(0.395)	(0.386)	(0.242)	(0.236)	(0.238)	(0.323)	(0.320)	(0.332)	(0.297)	(0.281)	(0.269)
Observations	8,010	8,010	8,010	9,140	9,140	9,140	4,645	4,645	4,645	9,559	9,559	9,559
R-squared	0.277	0.266	0.251	0.248	0.242	0.232	0.328	0.317	0.303	0.256	0.249	0.237
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 5: Demand Channel

This table shows the results of OLS regressions examining the demand channel. In Panel A, the dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. K/L is the (logarithm of) capital-to-labor ratio and is interacted with *Principal Customer*. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. In Panel B, the dependent variables are (*Customer*) *Sales Growth*, defined as the change in the sales to *Principal Customer* scaled by the lagged sales to *Principal Customer*, in Columns 1, 2, and 3. The dependent variables are $COGS/TA$, defined as the cost of goods sold divided by the total assets of *Principal Customer*, in Columns 4, 5, and 6. The dependent variables are *Sales Dependence* in Columns 7, 8, and 9. All other independent variables are measured in year t at customer's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Supplier's Fixed Cost of Production			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ innovation_t$	0.368***	0.339***	0.278**
	(0.133)	(0.128)	(0.125)
$Customer\ innovation_t \times K/L$	-0.055*	-0.049*	-0.040
	(0.030)	(0.029)	(0.029)
K/L	-1.179***	-1.033***	-0.965***
	(0.119)	(0.116)	(0.119)
Observations	9,358	9,358	9,358
R-squared	0.299	0.284	0.269
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

Panel B: Sales to Customer and Customer COGS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sales $Growth_{t,t+1}$	*Sales* $Growth_{t,t+2}$	*Sales* $Growth_{t,t+3}$	$\frac{COGS}{TA}_{t+1}$	$\frac{COGS}{TA}_{t+2}$	$\frac{COGS}{TA}_{t+3}$	*Sales* $Dependence_{t+1}$	*Sales* $Dependence_{t+2}$	*Sales* $Dependence_{t+3}$
Customer Innovation$_t$	-0.112*	-0.102*	-0.103**	-0.005	-0.004	-0.007	0.002	0.002	0.002
	(0.059)	(0.060)	(0.052)	(0.011)	(0.012)	(0.013)	(0.002)	(0.002)	(0.002)
Observations	10,414	10,414	10,414	27,846	27,846	27,846	10,408	10,408	10,408
R-squared	0.005	0.007	0.009	0.666	0.704	0.701	0.128	0.112	0.098
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 6: Financing Channel

This table shows the results of OLS regressions examining the financing channel. In Panel A, the dependent variables are *Customer Cash/TA* (*Customer Cash Flows/TA*) at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3 (4, 5, and 6), respectively. In Panel B, the dependent variables are post-innovation change in the total (idiosyncratic) volatility of *Principal Customer*'s daily stock returns at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3 (4, 5, and 6), respectively. The main independent variable in Panel A and B is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at customer's level and as defined in Internet Appendix Table A1. Standard errors are clustered at customer level, and are reported in parentheses. In Panel C, the dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$ in Columns 1, 4, 7, and 10. The dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+2$ in Columns 2, 5, 8, and 11. The dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+3$ in Columns 3, 6, 9, and 12. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t and is interacted with *Financially Constrained* or *Innovation-Efficient*. *Principal Customer* is classified as *Financially Constrained* based on KZ Index, SA Index, WW Index, or debt rating unavailability at year t. *Principal Customer* is classified as *Innovation-Efficient* based on innovation efficiency at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Customer Cash Holdings and Cash Flows

	(1)	(2)	(3)	(4)	(5)	(6)
	$\frac{Cash}{TA}_{t+1}$	$\frac{Cash}{TA}_{t+2}$	$\frac{Cash}{TA}_{t+3}$	$\frac{Cash\ Flows}{TA}_{t+1}$	$\frac{Cash\ Flows}{TA}_{t+2}$	$\frac{Cash\ Flows}{TA}_{t+3}$
Customer Innovation$_t$	-0.000	-0.001	-0.001	0.008***	0.011***	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
Observations	27,837	27,837	27,837	27,710	27,710	27,710
R-squared	0.793	0.685	0.623	0.081	0.030	0.091
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Panel B: Customer Stock Return Volatility

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Risk$_{t,t+1}$	*Total Risk*$_{t,t+2}$	*Total Risk*$_{t,t+3}$	*Idiosyncratic Risk*$_{t,t+1}$	*Idiosyncratic Risk*$_{t,t+2}$	*Idiosyncratic Risk*$_{t,t+3}$
Customer Innovation$_t$	-0.001	-0.001	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	27,387	27,387	27,387	27,387	27,387	27,387
R-squared	0.430	0.463	0.445	0.252	0.308	0.322
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Panel C: Customer Financial Constraints and Innovation Efficiency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		KZ			*SA*			*WW*			*Debt Rating*	
	Trade Credit$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$	0.223***	0.250***	0.209***	0.187**	0.146*	0.094	0.256***	0.209***	0.159**	0.235***	0.214***	0.173**
	(0.073)	(0.069)	(0.066)	(0.088)	(0.086)	(0.080)	(0.085)	(0.080)	(0.073)	(0.081)	(0.077)	(0.071)
Customer Innovation$_t$	0.003	-0.013	-0.009	0.045	0.105	0.135	-0.028	0.082	0.107	-0.071	0.076	0.073
$\times$ *Financially Constrained*$_t$	(0.086)	(0.079)	(0.078)	(0.109)	(0.105)	(0.098)	(0.090)	(0.090)	(0.090)	(0.144)	(0.126)	(0.124)
Financially Constrained$_t$	0.216	0.171	0.099	-0.339	-0.471	-0.498	0.363	-0.195	-0.224	0.293	-0.001	0.142
	(0.383)	(0.359)	(0.357)	(0.426)	(0.422)	(0.407)	(0.426)	(0.405)	(0.413)	(0.419)	(0.409)	(0.441)
Customer Innovation$_t$	-0.034	-0.018	0.028	0.019	0.065	0.104	0.038	0.058	0.107	0.023	0.041	0.072
$\times$ *Innovation-Efficient*$_t$	(0.126)	(0.123)	(0.119)	(0.118)	(0.117)	(0.112)	(0.126)	(0.122)	(0.115)	(0.124)	(0.122)	(0.117)
Innovation-Efficient$_t$	0.138	0.007	-0.154	-0.139	-0.416	-0.568	-0.268	-0.424	-0.637	-0.162	-0.361	-0.442
	(0.637)	(0.644)	(0.635)	(0.580)	(0.589)	(0.577)	(0.609)	(0.611)	(0.582)	(0.602)	(0.611)	(0.602)
Observations	4,904	4,904	4,904	5,339	5,339	5,339	5,131	5,131	5,131	5,346	5,346	5,346
R-squared	0.321	0.305	0.285	0.307	0.291	0.273	0.303	0.280	0.262	0.307	0.291	0.273
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 7: 2SLS Regression

This table shows the results of 2SLS regressions correcting for potential endogenous bias. In each Panel, the first stage regression is reported in Column 1. The second stage regressions use as the dependent variables the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 2, 3, and 4, respectively, in each Panel. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Panels A, B, C, and D use $Time\ Cost_{t-1}$ and $Monetary\ Cost_{t-1}$ as the instruments. Panel E uses $Monetary\ Cost_{t-1}$ and $State\ R\&D\ Tax\ Credit_{t-1}$ as the instruments. Panel A and E use the full sample. Panels B, C, and D use the sample excluding new trade relationships, customer industries with too high or too low costs, and supplier industries with high customer-turnover, respectively. Robust standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Two IVs in the Full Sample

	(1)	(2)	(3)	(4)
		Second Stage		
	First Stage	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$		0.587**	0.626**	0.636***
		(0.255)	(0.247)	(0.245)
Time Cost$_{t-1}$	-1.813***			
	(0.221)			
Monetary Cost$_{t-1}$	-0.298***			
	(0.036)			
Customer Industry Innovation$_t$	-0.113***	0.062	0.036	0.023
	(0.021)	(0.073)	(0.070)	(0.070)
Size$_t$	-0.000	-0.030***	-0.024***	-0.020***
	(0.002)	(0.007)	(0.007)	(0.007)
MTB_t	-0.023*	0.050	0.013	0.003
	(0.012)	(0.036)	(0.035)	(0.035)
ROA_t	0.188	0.391	-1.510***	-2.462***
	(0.155)	(0.474)	(0.459)	(0.455)
Leverage$_t$	-0.173	-0.399	-0.276	-0.388
	(0.124)	(0.382)	(0.370)	(0.367)
$Cash/TA_t$	-0.320**	-2.551***	-2.288***	-1.830***
	(0.152)	(0.473)	(0.459)	(0.454)
$CAPEX/TA_t$	-0.787*	-0.505	-1.336	-2.375*
	(0.454)	(1.396)	(1.353)	(1.341)
$R\&D/TA_t$	0.285	1.919**	-0.099	-1.298*
	(0.264)	(0.808)	(0.783)	(0.775)
Observations	3,612	3,612	3,612	3,612
R-squared	0.619	0.260	0.241	0.215
IV F-stat	72.30			
Durbin p-value	0.0803			
Sargan χ^2	2.111			
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y

Panel B: Two IVs with Excluding Newly Formed Trade Relationships				
	(1)	(2)	(3)	(4)
		Second Stage		
	First Stage	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$		0.477*	0.585**	0.612**
		(0.268)	(0.261)	(0.256)
Time Cost$_{t-1}$	-2.031***			
	(0.236)			
Monetary Cost$_{t-1}$	-0.296***			
	(0.039)			
Customer Industry Innovation$_t$	-0.100***	0.063	0.037	0.028
	(0.021)	(0.073)	(0.072)	(0.070)
Observations	3,093	3,093	3,093	3,093
R-squared	0.644	0.288	0.259	0.229
IV F-stat	69.81			
Durbin p-value	0.237			
Sargan χ^2	1.319			
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y
Panel C: Two IVs with Excluding Too High or Too Low Costs				
	(1)	(2)	(3)	(4)
		Second Stage		
	First Stage	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$		0.751***	0.643**	0.679**
		(0.271)	(0.273)	(0.275)
Time Cost$_{t-1}$	-0.044			
	(0.343)			
Monetary Cost$_{t-1}$	-0.614***			
	(0.063)			
Customer Industry Innovation$_t$	-0.293***	0.331*	0.365*	0.180
	(0.065)	(0.201)	(0.202)	(0.204)
Observations	1,765	1,765	1,765	1,765
R-squared	0.656	0.262	0.258	0.235
IV F-stat	50.75			
Durbin p-value	0.0281			
Sargan χ^2	0.718			
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y

Panel D: Two IVs with Excluding High Customer-Turnover Suppliers				
	(1)	(2)	(3)	(4)
		Second Stage		
	First Stage	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$		0.493	0.726*	0.794**
		(0.384)	(0.383)	(0.387)
Time Cost$_{t-1}$	-1.987***			
	(0.267)			
Monetary Cost$_{t-1}$	-0.190***			
	(0.046)			
Customer Industry Innovation$_t$	-0.091***	0.038	0.026	0.022
	(0.022)	(0.082)	(0.081)	(0.082)
Observations	2,521	2,521	2,521	2,521
R-squared	0.641	0.271	0.225	0.186
IV F-stat	37.25			
Durbin p-value	0.320			
Sargan χ^2	3.268			
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y

Panel E: State R&D Tax Credit as an additional IV in the Full Sample				
	(1)	(2)	(3)	(4)
		Second Stage		
	First Stage	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$		1.072**	0.883**	0.612
		(0.450)	(0.416)	(0.395)
Monetary Cost$_{t-1}$	-0.265***			
	(0.042)			
State R&D Tax Credit$_{t-1}$	357.466***			
	(61.454)			
Customer Industry Innovation$_t$	-0.084***	0.125	0.085	0.041
	(0.018)	(0.081)	(0.075)	(0.071)
Customer Net Income$_t$	1.620***	-0.093	0.714	1.027
	(0.278)	(1.284)	(1.189)	(1.128)
Observations	2,427	2,427	2,427	2,427
R-squared	0.720	0.300	0.302	0.318
IV F-stat	36.09			
Durbin p-value	0.0289			
Sargan χ^2	0.308			
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y
Supplier State FE	Y	Y	Y	Y
Customer State FE	Y	Y	Y	Y

Table 8: Innovation through Acquisition

This table shows the results of OLS regressions examining the effect of customer's innovation acquired from acquisitions as well as customer's own innovation. The dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. Customers' acquisition deals (mergers, acquisitions of majority interest, asset acquisitions, or acquisitions of certain assets) are obtained from the SDC M&A database. Next, 7-year windows (-3,+3) centered on the year of acquisition announcement are used to construct the main independent variables. *Post Acquisition* is the indicator for the years (+1,+3) after acquisition. *Target Innovation* is the natural logarithm of one plus the number of patents of target firms. The other main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.207***	0.190***	0.146**
	(0.066)	(0.065)	(0.061)
$Post\ Acquisition_t \times Target\ Innovation_t$	0.182**	0.210**	0.174*
	(0.092)	(0.086)	(0.094)
$Target\ Innovation_t$	-0.053	-0.060	-0.062
	(0.069)	(0.067)	(0.070)
$Post\ Acquisition_t$	-0.028	0.031	0.048
	(0.228)	(0.216)	(0.202)
Observations	3,082	3,082	3,082
R-squared	0.310	0.309	0.288
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

Table 9: Overlap of Technology Space

This table shows the OLS estimates of customer's innovation and its interaction with technological relatedness between customer and supplier. The dependent variable is the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3 (4, 5, and 6), respectively. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. In Columns 1, 2, and 3, the main independent variable is interacted with an indicator variable (*Class Overlap*) which equals 1 if technology class of customer's patent (issued in year t) overlaps with historical technology classes of supplier's patents (issued previously as of year t). In Columns 4, 5, and 6, the main independent variable is interacted with an indicator variable ($Class\ Overlap^{Own}$) which equals 1 if technology class of customer's patent (issued in year t) overlaps with its historical technology classes of patents (issued previously as of year t). All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$	(4) $Trade\ Credit_{t+1}$	(5) $Trade\ Credit_{t+2}$	(6) $Trade\ Credit_{t+3}$	(7) $Trade\ Credit_{t+1}$	(8) $Trade\ Credit_{t+2}$	(9) $Trade\ Credit_{t+3}$	(10) $Trade\ Credit_{t+1}$	(11) $Trade\ Credit_{t+2}$	(12) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.395***	0.387***	0.322***	0.438***	0.435***	0.373***	0.371***	0.371***	0.330***	0.210**	0.234***	0.155**
	(0.099)	(0.098)	(0.092)	(0.095)	(0.093)	(0.088)	(0.082)	(0.080)	(0.077)	(0.082)	(0.084)	(0.078)
$Customer\ Innovation_t$	-0.288**	-0.284**	-0.232**									
$\times Class\ Overlap_t$	(0.112)	(0.112)	(0.109)									
$Class\ Overlap_t$	0.343	0.650	0.712									
	(0.441)	(0.458)	(0.470)									
$Customer\ Innovation_t$				-0.403***	-0.408***	-0.339***						
$\times Class\ Overlap_t^{5yr}$				(0.114)	(0.113)	(0.108)						
$Class\ Overlap_t^{5yr}$				0.526	0.857*	0.768						
				(0.503)	(0.514)	(0.503)						
$Customer\ Innovation_t$							-1.459***	-1.311***	-1.173***			
$\times Class\ Overlap_t^{Cos}$							(0.307)	(0.299)	(0.283)			
$Class\ Overlap_t^{Cos}$							1.413	1.412	1.417			
							(1.138)	(1.169)	(1.143)			
$Customer\ Innovation_t$										0.029	0.015	0.075
$\times Class\ Overlap_t^{Own}$										(0.064)	(0.066)	(0.062)
$Class\ Overlap_t^{Own}$										-0.125	-0.061	-0.047
										(0.236)	(0.244)	(0.231)
Observations	5,882	5,882	5,882	5,882	5,882	5,882	5,882	5,882	5,882	5,882	5,882	5,882
R-squared	0.274	0.261	0.247	0.282	0.269	0.252	0.288	0.274	0.258	0.266	0.256	0.245
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 10: Financial and Investment Decisions of Supplier

This table reports the results of OLS regressions examining the effect of customer's innovation on financial and investment decisions of supplier. In Columns 1, 2, and 3, the dependent variables are financial variables of supplier (cash to asset ratio, payout ratio, and leverage) in year $t+1$. In Columns 4, 5, and 6, the dependent variables are investment variables of supplier (R&D to asset ratio, logarithm of one plus the number of supplier's patents, and logarithm of the ratio of the number of *Principal Customer*'s past patents cited by supplier's patents over the number of supplier's patents) in year $t+1$. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at supplier level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Cash/TA_{t+1}$	$Payout_{t+1}$	$Leverage_{t+1}$	$R\&D/TA_{t+1}$	*Supplier* $Innovation_{t+1}$	*Tech* $Spillover_{t+1}$
Customer Innovation$_t$	0.001***	-0.001**	-0.001	0.000	0.023***	0.018***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)	(0.005)
$Size_t$	-0.000***	0.001***	0.000	-0.000***	0.034***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.004)
MTB_t	0.000	0.000**	-0.004**	0.003***	-0.000	-0.000
	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.001)
ROA_t	-0.006	0.011***	-0.083*	0.021	0.177***	-0.141***
	(0.008)	(0.003)	(0.050)	(0.019)	(0.037)	(0.029)
$Leverage_t$	-0.001	-0.004*	1.060***	0.021*	-0.041*	0.026
	(0.005)	(0.002)	(0.207)	(0.012)	(0.022)	(0.017)
$Cash/TA_t$	0.761***	0.025***	0.052	0.122***	0.327***	-0.325***
	(0.007)	(0.005)	(0.103)	(0.014)	(0.056)	(0.050)
$CAPEX/TA_t$	-0.049***	-0.009*	0.139***	-0.041***	0.305***	-0.210***
	(0.016)	(0.005)	(0.041)	(0.016)	(0.106)	(0.081)
$R\&D/TA_t$	0.032	0.009	-0.144	0.379***	0.341***	-0.264***
	(0.021)	(0.006)	(0.153)	(0.068)	(0.080)	(0.065)
Observations	26,116	26,122	26,084	27,980	27,980	27,980
R-squared	0.750	0.052	0.417	0.219	0.247	0.189
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 11: Termination of Trade Relationship

This table reports the results of logit regressions examining the effect of customer's innovation on the likelihood of termination in current trade relationship. In Columns 1 through 5, the dependent variables are indicators for a trade relationship having been terminated as of year $t+1$, $t+2$, $t+3$, $t+5$, and $t+10$, respectively. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Relationship	*Relationship*	*Relationship*	*Relationship*	*Relationship*
	End_{t+1}	End_{t+2}	End_{t+3}	End_{t+5}	End_{t+10}
$Customer\ Innovation_t$	-0.001	0.002	0.034***	0.062***	0.089***
	(0.008)	(0.007)	(0.008)	(0.011)	(0.021)
Observations	27,718	27,737	27,524	27,036	24,229
Pseudo R-squared	0.0628	0.0349	0.0291	0.0335	0.0991
Firm Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y

Internet Appendix to "Is Innovation Always Beneficial? Externalities of Innovation on Product Market Relationships"

August 14, 2024

Abstract

This Internet Appendix provides supporting information and additional tests. Internet Appendix Tables A1 through A12 are reported.

Supporting Information: Apple and Samsung Case

The relationship between Apple and Samsung illustrates how the innovativeness of one party is critical to its counterparty in the trade relationship. With its advanced screen technology, Samsung had been the major supplier of Apple, and Apple relied heavily on the OLED screens supplied by Samsung because the company had technological merit as the only supplier that could mass-produce OLED screens.[1] The growing dependence of Apple on Samsung has translated into its weak bargaining power against Samsung, for instance, over its pricing on OLED screens—in fact, the high price charged by Samsung was said to be one reason why Apple had to put a steep price tag on the iPhone X. Samsung could price its OLED at least as high as the price of OLED from alternative suppliers. Also, we would expect Apple to be granted less trade credit or allowed a shorter payment delay by Samsung due to its increasing dependence on Samsung.

More specifically, Apple could not give up OLED-screen iPhones since the next best use of the iPhone devices (before installing screens) was only through equipping the devices with LCD screens, which could not satisfy iPhone consumers, as seen in the poor sales record of the iPhone XR. Thus, we can contend that Apple's assets (i.e., iPhone devices) were specialized to Samsung's product (i.e., OLED screen). Also, there was no market closure or restriction on other screen makers in the OLED screen market. Even if free and open competition for entry had been possible, the other screen suppliers could not catch up with Samsung's technology, only because the development of OLED screen was challenging and too costly for them.[2] In other words, their lack of innovation capacity enabled Samsung to be the major supplier of Apple.

[1] The market demand for the iPhone XR (a more budget friendly version in the iPhone X lineup) fell short of expectations, which is allegedly due to the lower quality of the display (LCD screen) and camera compared to the previous iPhone X lineup (X and XS). As a result, Apple was looking to drop LCD screens from its future iPhone lineup (starting with the 2020 iPhone) and switch to OLED screens.

[2] In fact, Apple was collaborating with LG Display as another potential supplier to break its reliance on Samsung, but this strategy did not go as planned due to technological limitations, not because the entry was blocked. Apple needed smaller, power-efficient displays, which require a different manufacturing process from the one LG used to create its larger OLED panels. As a result, Samsung again took the major share of iPhone OLED supply orders.

Table A1: Variable definition

This table describes the variables for firm characteristics and industry characteristics used in the analyses.

Variable	Description
Alternative Customers	A supplier's potential customers in the *Principal Customer*'s industry whose suppliers are in the same industry as the supplier
$Supplier\ Specificity_1$	Reciprocal of *Asset Redeployability* from Kim and Kung (2017)
$Supplier\ Specificity_2$	Reciprocal of *Asset Liquidation Value/Going Concern Value* from Kermani and Ma (2023)
$Supplier\ Specificity_3$	Reciprocal of the proportion of alternative customers located closer to *Supplier* than *Pricipal Customer*
$Supplier\ Specificity_4$	Vertical relatedness score from Frésard, Hoberg, and Phillips (2020)
$CAPEX/TA$	Capital Expenditures (CAPX) / Total Assets (AT)
$Cash/TA$	Cash and Short-Term Investments (CHE) / Total Assets (AT)
Class Overlap	1 if technology class of *Principal Customer*'s patent overlaps with historical technology classes of a supplier's existing patents and 0 otherwise
$Class\ Overlap^{Cos}$	Cosine similarity between technology class of *Principal Customer*'s patent and historical technology classes of a supplier's existing patents
$Class\ Overlap^{5yr}$	1 if technology class of *Principal Customer*'s patent (at year t) overlaps with technology classes of a supplier's existing patents (in year $t-4$ to t) and 0 otherwise
$Class\ Overlap^{Own}$	1 if technology class of *Principal Customer*'s patent overlaps with historical technology classes of its existing patents and 0 otherwise
$COGS/TA$	Cost of Goods Sold (COGS) / Total Assets (AT)
Innovation	Logarithm of 1 plus the number of patents
Innovation Efficiency	The number of patents$_t$/(R&D$_{t-1}$+0.8*R&D$_{t-2}$+0.6*R&D$_{t-3}$+0.4*R&D$_{t-4}$+0.2*R&D$_{t-5}$)
K/L	Logarithm of Net Property Plant and Equipment (PPENT) / Employees (EMP); use Gross Property Plant and Equipment (PPEGT) if Net Property Plant and Equipment (PPENT) is missing
Leverage	[Long-Term Debt (DLTT) + Debt in Current Liabilities (DLC)] / Total Assets (AT)
Monetary Cost (of Innovation)	Average R&D expenditures (XRD) per patent
MTB	[Total Liabilities (LT) – Deferred Taxes and Investment Tax Credit (TXDITC) + Preferred Stock (defined below) + Common Shares Outstanding (CSHO) * Price Close (PRCC$_F$)] / Total Assets (AT)
Net Income	Net Income (NI)
Net Profit Margin	Operating Income Before Depreciation and Amortization (OIBDP) / Total Sales (SALE)
Net Trade Credit	[Trade Accounts Receivables (RECTR) - Trade Accounts Payables (AP)] * Sales Dependence / Total Assets (AT)
Other Customers	A supplier's customers that are not *Principal Customer*
Payout	[Common Dividends (DVC) + Purchase of Common and Preferred Stock (PRSTKC)] / Total Assets (AT)
Principal Customer	A supplier's customer that takes the largest sales portion
Process Innovation	Logarithm of 1 plus the number of process innovation patents. A patent is classified as process innovation if its proportion of process claims over all claims is greater than 50%. The number of (process) claims of patents are available from Bena and Simintzi (2019)
Product Innovation	Logarithm of 1 plus the number of product innovation patents. A patent is classified as product innovation if it is not classified as process innovation.
$R\&D/TA$	Research and Development Expense (XRD) / Total Assets (AT); replace it with 0 if Research and Development Expense (XRD) is missing
ROA	Operating Income Before Depreciation (OIBDP) / Total Assets (AT)
Sales Dependence	Sales to *Principal Customer* / Total Sales (SALE)
Sales Growth	Sales minus lagged sales divided lagged sales (of supplier to *Principal Customer*)
Size	Common Shares Outstanding (CSHO) / 1000 * Price Close (PRCC$_F$)
State R&D Tax Credit	State-level tax incentives on R&D as calculated in Bartik (2017)
Tangible Assets	Net Property Plant and Equipment (PPENT)
Tech Spillover	Logarithm of 1 plus the number of *Principal Customer*'s past patents cited by a supplier's patent minus the supplier's Innovation
Time Cost (of Innovation)	Average number of months from application filing to issue or grant of patent
Trade Credit	Trade Accounts Receivables (RECTR) * Sales Dependence / Total Assets (AT); use Total Receivables (RECT) if Trade Receivables (RECTR) is missing
Trade Payables	Trade Accounts Payables (AP) / Total Assets (AT)

Table A2: Current Trade Credit and Future Customer Innovation

This table shows results of OLS regressions examining the effect of supplier trade credit on customer innovation. The dependent variables are the natural logarithm of one plus the number of patents of *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. The main independent variable is the proportion of supplier's trade receivable attributable to its *Principal Customer* at year t. All other independent variables are measured in year t at customer's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
	Customer $Innovation_{t+1}$	*Customer* $Innovation_{t+2}$	*Customer* $Innovation_{t+3}$
$Trade\ credit_t$	0.082	0.018	-0.030
	(0.420)	(0.422)	(0.432)
Observations	16,539	16,539	16,539
R-squared	0.544	0.539	0.525
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Table A3: IV Falsification Test

This table shows the results of OLS regressions of product market competition on the instrumental variables. The dependent variables are Herfindahl-Hirschman index and average net profit margin at industry level in Columns 1 and 2, respectively. The dependent variables are Herfindahl-Hirschman index and average net profit margin at industry-state pair level in Columns 3 and 4, respectively. The main independent variables are *Time Cost*, *Monetary Cost*, and *State R&D Tax Credit* used as IVs in 2SLS regressions of Table 7. Standard errors are clustered at industry level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	HHI_{Ind}	NPM_{Ind}	$HHI_{Ind,State}$	$NPM_{Ind,State}$
Time Cost	-0.001	-4.355	0.118	-7.196
	(0.012)	(5.869)	(0.073)	(6.745)
Monetary Cost	-0.000	-1.510	-0.025	0.096
	(0.002)	(1.024)	(0.027)	(0.445)
State R&D Tax Credit			9.755	-2,025.414
			(26.742)	(1,704.294)
Observations	14,324	14,324	4,706	4,664
R-squared	0.928	0.301	0.660	0.170
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
State FE	N	N	Y	Y

Table A4: Process Innovation

This table shows the results of OLS regressions examining the effect of customer's (process) innovation on supplier's trade credit provision. The dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. A patent is classified as process innovation if its proportion of process claims over all claims exceeds 50%, as obtained from Bena and Simintzi (2019); otherwise, it is classified as product innovation. The main independent variables are the natural logarithm of one plus the number of process innovation patents and the natural logarithm of one plus the number of product innovation patents at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Process\ Innovation_t$	0.031	0.064	0.048
	(0.090)	(0.086)	(0.081)
$Product\ Innovation_t$	0.143*	0.119*	0.093
	(0.075)	(0.070)	(0.065)
Observations	9,559	9,559	9,559
R-squared	0.253	0.246	0.236
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

Table A5: Trade Credit and Supplier Firm Value

This table shows the results of OLS regressions examining the effect of supplier's trade credit on firm value and performance. The dependent variables are supplier *MTB* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. The dependent variables are supplier *ROA* at year $t+1$, $t+2$, and $t+3$ in Columns 4, 5, and 6, respectively. The dependent variables are supplier *Sales Growth* at year $t+1$, $t+2$, and $t+3$ in Columns 7, 8, and 9, respectively. The main independent variable is the proportion of supplier's trade receivable attributable to its *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level and are as defined in Internet Appendix Table A1. Standard errors are clustered at supplier level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	MTB_{t+1}	MTB_{t+2}	MTB_{t+3}	ROA_{t+1}	ROA_{t+2}	ROA_{t+3}	*Sales* $Growth_{t+1}$	*Sales* $Growth_{t+2}$	*Sales* $Growth_{t+3}$
Trade Credit$_t$	0.788	2.865	-45.801	-0.319	-0.582	4.204	-40.617	-0.439	0.108
	(1.167)	(2.044)	(60.418)	(0.293)	(0.446)	(4.358)	(28.672)	(0.383)	(0.811)
Observations	23,222	23,222	23,222	24,144	24,144	24,144	24,106	24,106	24,106
R-squared	0.054	0.056	0.007	0.089	0.034	0.002	0.005	0.012	0.010
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A6: Alternative Measurement of Trade Credit

This table replicates the regressions in Table 2 using different measurements of *Trade Credit* or a different sample. In Panels A and B, the dependent variables are supplier's total trade receivables at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. In Panel A (B), The main independent variable aggregates the number (sales portion-weighted average) of patents of *Principal Customer* and *Other Customers* at year t. In Panels C and D, the dependent variables are the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$, $t+2$, and $t+3$ in Columns 1, 2, and 3, respectively. In Panels C and D, the main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. Panel C (D) uses only suppliers whose *Principal Customer* is the sole customer (with sales portion greater than 80%) as the sample. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Aggregated Trade Credit and Patent			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.069	0.100*	0.134**
	(0.053)	(0.054)	(0.055)
Observations	24,223	24,223	24,223
R-squared	0.396	0.368	0.348
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Panel B: Aggregated Trade Credit and Patent (Weight-Averaged)			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.082	0.128*	0.168**
	(0.074)	(0.076)	(0.075)
Observations	24,223	24,223	24,223
R-squared	0.396	0.368	0.348
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y

Panel C: Sole *Principal Customer*			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.164**	0.189***	0.157**
	(0.069)	(0.069)	(0.069)
Observations	5,685	5,685	5,685
R-squared	0.299	0.296	0.291
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y
Panel D: Sole *Principal Customer* with Sales Portion above 80%			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.929**	0.709**	0.710*
	(0.377)	(0.341)	(0.418)
Observations	240	240	240
R-squared	0.851	0.838	0.795
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

Table A7: Alternative Measurement of Innovation

This table replicates the regressions in Table 2 using different measurements of *Customer Innovation*. Panels A and B use the (logarithm of one plus) citation-weighted patent counts and (logarithm of one plus) market value of patents (constructed in Kogan et al. (2017)) as the main independent variables, respectively. Panel C uses the patent count measure but using the patent filing dates. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Innovation Measure using Citation Information			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t^{Citation}$	0.132***	0.127***	0.099**
	(0.047)	(0.046)	(0.044)
Observations	9,602	9,602	9,602
R-squared	0.255	0.248	0.238
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y
Panel B: Innovation Measure using Market Value Information			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t^{MktVal}$	0.088***	0.083***	0.065**
	(0.033)	(0.032)	(0.031)
Observations	9,602	9,602	9,602
R-squared	0.255	0.248	0.238
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y
Panel C: Innovation Measure using Filing Dates of Patents			
	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t^{Filing}$	0.145***	0.138***	0.109**
	(0.051)	(0.049)	(0.047)
Observations	9,602	9,602	9,602
R-squared	0.255	0.248	0.238
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

Table A8: Customer Bargaining Power

This table replicates the regressions in Table 2 using customer characteristics as the additional control variables. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at both supplier's and customer's level. Standard errors are clustered at year level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Trade Credit$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$	0.316***	0.184**	0.021	0.281***	0.128*	-0.041	0.298***	0.142**	-0.043
	(0.096)	(0.069)	(0.071)	(0.096)	(0.072)	(0.075)	(0.101)	(0.067)	(0.074)
$Size_t^{Supplier}$	0.010	0.026***	0.030***	0.009	0.033**	0.033**	0.005	0.022*	0.021*
	(0.007)	(0.006)	(0.006)	(0.013)	(0.014)	(0.015)	(0.007)	(0.011)	(0.011)
$MTB_t^{Supplier}$	0.032	-0.181*	-0.052	0.051	-0.163	-0.034	0.094	-0.098	0.020
	(0.065)	(0.098)	(0.075)	(0.065)	(0.099)	(0.075)	(0.072)	(0.099)	(0.076)
$ROA_t^{Supplier}$	2.437**	-1.131	-3.237**	2.341**	-1.070	-3.162**	2.322*	-1.289	-3.394**
	(1.131)	(1.327)	(1.234)	(1.126)	(1.342)	(1.233)	(1.232)	(1.464)	(1.272)
$Leverage_t^{Supplier}$	0.258	0.573	0.563	0.428	0.815	0.838	0.238	0.550	0.552
	(0.438)	(0.600)	(0.651)	(0.408)	(0.546)	(0.588)	(0.500)	(0.588)	(0.643)
$Cash/TA_t^{Supplier}$	-2.915***	-1.416	-0.924	-2.690***	-1.178	-0.707	-2.972***	-1.612*	-1.014
	(0.896)	(0.902)	(1.031)	(0.856)	(0.869)	(0.991)	(0.869)	(0.898)	(1.056)
$CAPEX/TA_t^{Supplier}$	-1.315	-1.335	-0.786	-1.190	-1.169	-0.642	-2.599**	-2.388*	-1.473
	(1.129)	(1.279)	(1.111)	(1.106)	(1.212)	(1.079)	(1.140)	(1.249)	(0.987)
$R\&D/TA_t^{Supplier}$	12.903***	2.477	-1.681	12.927***	2.700	-1.405	13.034***	2.421	-1.698
	(3.856)	(3.138)	(6.232)	(3.760)	(3.081)	(6.095)	(4.036)	(3.243)	(6.468)
$Size_t^{Customer}$	-0.005	0.000	0.000	-0.006**	-0.003	-0.001	0.000	0.005*	0.005*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$MTB_t^{Customer}$	0.078	0.043	-0.032	0.071	0.046	-0.054	-0.040	-0.094	-0.177**
	(0.091)	(0.084)	(0.076)	(0.085)	(0.073)	(0.061)	(0.099)	(0.085)	(0.071)
$ROA_t^{Customer}$	1.007	0.323	-0.513	0.554	-0.285	-1.216	1.893	0.839	-0.280
	(1.529)	(1.368)	(1.139)	(1.548)	(1.369)	(1.166)	(1.516)	(1.477)	(1.209)
$Leverage_t^{Customer}$	1.440**	1.318	1.344**	0.545	0.319	0.495	1.699**	1.230	1.049
	(0.625)	(0.814)	(0.637)	(0.641)	(0.707)	(0.571)	(0.745)	(0.850)	(0.846)
$Cash/TA_t^{Customer}$	-0.575	-1.417	-1.000	-1.095	-1.757*	-1.157	-0.173	-0.736	-0.370
	(1.396)	(0.875)	(1.197)	(1.393)	(0.896)	(1.184)	(1.534)	(0.931)	(1.252)
$CAPEX/TA_t^{Customer}$	-0.901	0.884	3.922***	-3.152**	-2.032	0.712	-1.441	-0.121	2.172
	(1.569)	(2.041)	(1.288)	(1.454)	(1.987)	(1.130)	(1.824)	(1.878)	(1.297)
$R\&D/TA_t^{Customer}$	-11.767**	-9.076**	-4.541	-10.004**	-7.242*	-2.950	-10.239**	-5.639	-1.919
	(4.939)	(4.079)	(4.380)	(4.539)	(3.790)	(4.123)	(4.682)	(4.483)	(4.222)
$Patent\ Stock_t^{Customer}$	-0.172**	-0.088*	-0.003	-0.149**	-0.055	0.034	-0.157**	-0.060	0.044
	(0.068)	(0.052)	(0.059)	(0.066)	(0.051)	(0.062)	(0.067)	(0.048)	(0.062)
Observations	4,193	4,193	4,193	4,198	4,198	4,198	4,187	4,187	4,187
R-squared	0.779	0.769	0.762	0.778	0.769	0.763	0.801	0.795	0.784
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier FE	Y	Y	Y	Y	Y	Y	N	N	N
Customer FE	N	N	N	Y	Y	Y	N	N	N
Supplier-Customer FE	N	N	N	N	N	N	Y	Y	Y
Supplier Industry FE	N	N	N	N	N	N	Y	Y	Y
Customer Industry FE	Y	Y	Y	N	N	N	Y	Y	Y

Table A9: Innovation Jump vs. Innovation Drop

This table reports the results of the OLS regressions examining the effect of customer innovation on trade credit when there is an innovation jump, innovation drop, or neither. The dependent variable is the proportion of supplier's trade receivable attributable to its *Principal Customer* at year $t+1$. In Panel A, Columns 1 through 3 (4 through 6) use the past three year average (median) of customer patents as the standard when defining *Innovation Jump* and *Innovation Drop*. Columns 1 and 4 employ the multiplier of 1.5 to the reference value. Columns 2 and 5 (3 and 6) employ the multiplier of 2 (5). In Panel B, observations one year before and after customer switching are only used. $Customer\ Switch^{Jump}$ ($Customer\ Switch^{Drop}$) is an indicator that equals 1 if a supplier switches to a more (less) innovative customer. All other independent variables are measured in year t at supplier or customer level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Innovation Change within the Same Customer-Supplier Pair

	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. = $Trade\ Credit_{t+1}$					
	Multiplier x to 3-Year Average			Multiplier x to 3-Year Median		
	x=1.5	x=2	x=5	x=1.5	x=2	x=5
$Customer\ Innovation_t^{Jump}$	0.289***	0.312**	0.408*	0.280***	0.306**	0.428*
	(0.098)	(0.156)	(0.217)	(0.095)	(0.134)	(0.238)
$Customer\ Innovation_t^{Pers}$	0.235***	0.224***	0.234***	0.235***	0.229***	0.236***
	(0.070)	(0.070)	(0.071)	(0.070)	(0.070)	(0.071)
$Customer\ Innovation_t^{Drop}$	0.242***	0.138	0.173	0.233***	0.180*	0.277
	(0.093)	(0.110)	(0.203)	(0.089)	(0.109)	(0.214)
Observations	5,361	5,361	5,361	5,361	5,361	5,361
R-squared	0.273	0.273	0.273	0.273	0.273	0.273
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y

Panel B: Customer Switch within the Same Supplier

	(1)	(2)	(3)	(4)
	Dep. = $Trade\ Credit_{t+1}$			
$Customer\ Switch_t^{Jump}$	0.539***		0.499***	
	(0.150)		(0.159)	
$Customer\ Switch_t^{Drop}$		-0.247*		-0.351**
		(0.143)		(0.154)
$New\ Customer_t$	1.193***	1.508***	1.126***	1.483***
	(0.118)	(0.128)	(0.131)	(0.139)
Observations	3,607	3,607	2,852	2,852
R-squared	0.683	0.681	0.708	0.707
Supplier Controls	Y	Y	Y	Y
Customer Controls	N	N	Y	Y
Supplier FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y

Table A10: Customer Innovation vs. Supplier Innovation

This table replicates the regressions in Table 2 using *Supplier Innovation* as the additional independent variable. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t and is interacted with *Supplier Innovation* at year t. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Trade Credit$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$	0.172***	0.165***	0.129***	0.209***	0.190***	0.146**
	(0.053)	(0.051)	(0.049)	(0.061)	(0.059)	(0.057)
Supplier Innovation$_t$	-0.725***	-0.652***	-0.584***	-0.556***	-0.534***	-0.503***
	(0.074)	(0.070)	(0.068)	(0.091)	(0.090)	(0.094)
Customer Innovation$_t$				-0.049**	-0.034	-0.024
$\times$*Supplier Innovation*$_t$				(0.024)	(0.024)	(0.024)
Observations	9,602	9,602	9,602	9,602	9,602	9,602
R-squared	0.274	0.265	0.252	0.275	0.265	0.252
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y

Table A11: Supplier Trade Payables and Net Trade Credit

This table reports the results of the OLS regressions examining the effect of customer's innovation on supplier trade payables and net trade credit. In Columns 1, 2, and 3, the dependent variables are supplier trade payables (scaled by supplier total assets) in year $t+1$, $t+2$, and $t+3$, respectively. In Columns 4, 5, and 6, the dependent variables are *Net Trade Credit* in year $t+1$, $t+2$, and $t+3$, respectively. The main independent variable is the natural logarithm of one plus the number of patents of *Principal Customer* at year t. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Trade	*Trade*	*Trade*	*Net*	*Net*	*Net*
	Payables$_{t+1}$	*Payables*$_{t+2}$	*Payables*$_{t+3}$	*Trade Credit*$_{t+1}$	*Trade Credit*$_{t+2}$	*Trade Credit*$_{t+3}$
Customer Innovation$_t$	-0.000	-0.000	-0.000	0.090*	0.087*	0.068
	(0.001)	(0.001)	(0.001)	(0.047)	(0.045)	(0.049)
Observations	9,601	9,601	9,601	9,601	9,601	9,601
R-squared	0.325	0.255	0.170	0.228	0.138	0.094
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y

Table A12: Placebo Test - Innovation of Customers Other than Principal Customer

This table replicates the regressions in Table 2 using innovation of *Other Customers*. The main independent variable is the natural logarithm of one plus the total number of patents of *Other Customers* at year t. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level, and are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Other\ Customer\ Innovation_t$	-0.010	-0.009	-0.002
	(0.037)	(0.039)	(0.039)
Observations	9,602	9,602	9,602
R-squared	0.252	0.246	0.237
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

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