JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 56, No. 5, Aug. 2021, pp. 1679–1712 © THE AUTHOR(S), 2020. PUBLISHED BY CAMBRIDGE UNIVERSITY PRESS ON BEHALF OF THE MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON doi:10.1017/S00221090200068X

Do Social Connections Mitigate Hold-up and Facilitate Cooperation? Evidence from Supply Chain Relationships

Sudipto Dasgupta D Chinese University of Hong Kong Business School, ABFER, and CEPR s.dasgupta@cuhk.edu.hk

Kuo Zhang Shanghai Jiao Tong University Antai College of Economics and Management kuozhang@sjtu.edu.cn (corresponding author)

Chenqi Zhu University of California Irvine Paul Merage School of Business chenqiz1@uci.edu

Abstract

We show that prior social connections can mitigate hold-up in bilateral relationships and encourage relation-specific investment and cooperation when contracts are incomplete. We examine vertical relationships and show that relation-specific innovative activities by suppliers increase with the existence and strength of prior social connections between the suppliers' managers and board members and those of their customers. To establish causality, we exploit connection breaches due to manager/director retirements or deaths and find that innovation drops for affected suppliers after the departure of socially connected individuals relative to unaffected suppliers. Our work sheds light on how social connections can shape firm boundaries.

Establishing a collaborative environment is very important, and innovation is key. I'm sure many of the great ideas about how to improve P&G's sustainability will come from our suppliers.

—Len Sauers, P&G VP of Global Sustainability

We thank an anonymous referee, Utpal Bhattacharya, Xin Chang, DuckKi Cho, Yongqiang Chu, David De Angelis, Philip Dybvig, Janet Gao, Vidhan Goyal, Po-Hsuan Hsu, Chen Lin, Paul Malatesta (the editor), Roni Michaely, Abhiroop Mukherjee, Vik Nanda, Bin Qiu, Tao Shu, Dragon Tang, Shawn Thomas, Cong Wang, Wenyu Wang, Michael Weber, Alminas Zaldokas, Xueyong Zhang, and seminar participants at the Chinese University of Hong Kong, Erasmus University, Hong Kong University of Science and Technology, University of Cambridge, University of Hong Kong, University of Oxford, University of Reading, University of Strathclyde, Vienna Graduate School of Finance, and the 2015 Annual Corporate Finance Conference, 2015 Annual Entrepreneurial Finance and Innovation Conference, 2016 Centre for Economic Policy Research (CEPR) First Annual Spring Symposium in Financial Economics, 2016 China International Conference, and 2018 Sun Yat-sen University Finance International Conference, 2018 Greater China Area Finance Conference, and 2018 Asian Finance Association Annual Meeting for helpful comments. Zhang acknowledges financial support from the National Natural Science Foundation of China (No. 71902115).

I. Introduction

Technological innovation is vital for a firm's competitiveness and long-term growth. In addition to innovation undertaken in-house, innovation developed by upstream suppliers is becoming increasingly important (Huston and Sakkab (2006)). Henke and Zhang (2010) conduct an in-depth field study and find that many firms in manufacturing industries rely on their parts or materials suppliers for relation-specific innovations that are customized to improve their products or production processes.

These suppliers often remain as standalone firms presumably because of the costs of complete (vertical) integration. For example, market-based incentives for innovators in the supplier firm could become less effective when the upstream firm is integrated with the downstream firm (Holmström (1989)). Moreover, post-integration, the corporate "headquarters" might expropriate the innovation done by a division, since the resulting patent would legally belong to the firm rather than the innovator. As a result, the supplier's incentives to innovate would be dampened if it is merged with the downstream firm.¹

The lack of integration, however, has some well-known costs of its own. When the relationship is arm's length, the exchange relationship between the upstream and downstream firms has to be governed by a contract. However, technological innovation is a long-term and risky process. The very nature of innovation makes it difficult to specify the exact deliverables and timing of the realized innovation outcome ex ante, rendering the contract in question incomplete. Because supplier innovation is likely to be customized for its major customer and not easily marketable elsewhere, the possibility of customer opportunism and holdup under contractual incompleteness could lead to underinvestment in relationspecific innovation by the supplier (Klein, Crawford, and Alchian (1978), Dyer and Singh (1998)). Moreover, knowledge and know-how of the customer's products, processes, and people could foster supplier innovation. Contractual incompleteness and lack of trust, however, is likely to discourage such information sharing and hinder cooperation between the customer and supplier. Since supplier innovation benefits both the upstream and downstream firms, the inability of both parties to commit not to behaving opportunistically is a nontrivial cost of nonintegration.

A question that naturally arises is whether there exist mechanisms that mitigate hold-up and enhance cooperation when contracts are incomplete. In this paper, we document a previously unexplored mechanism that can sustain implicit agreements, mitigate opportunism, and facilitate cooperation, thereby prolonging business relationships and encouraging relation-specific innovation by the upstream firm. This mechanism is prior social connections between senior managers and board members of the upstream and downstream firms.

Social connections are helpful in this setting for several reasons. First, socially connected individuals are likely to interact repeatedly in many different spheres,

¹Seru (2014) empirically shows that conglomerate organizational forms have a negative and causal impact on the scale and novelty of corporate research and development (R&D) activities.

even outside the current business relationship.² Moreover, they also tend to have more common third parties in their respective social circles than unconnected individuals. The interactions outside the business relationship make honoring implicit contracts more valuable than if these same individuals were to interact only during the course of the current business relationship. The common third-party friends associated with social connections further help to sustain implicit agreements as individuals who breach implicit contracts with connected individuals are more likely to suffer reputational damage in their own social networks and face ostracism than if such breaches were to occur vis-à-vis unconnected individuals.³ Second, social connections could mitigate the possibility of another type of hold-up, namely the leakage or exploitation of sensitive information revealed by the other party, thereby facilitating information sharing and cooperation in R&D activity that are vital for relation-specific innovation to succeed (Dyer and Singh (1998)).⁴ Both channels reduce the possibility of either party in a vertical relationship engaging in opportunistic behavior when prior social connections exist. Third, as Dyer and Singh note, effective cooperation between two trading partners requires that the customer knows "what knowledge will be useful to the supplier, whom to contact at the supplier, and where the absorptive capacity resides at the supplier." Social connections can facilitate this process and foster deeper cooperation. Finally, social connections could prolong the business relationship between the supplier and customer, perhaps because a connected supplier is more likely to be treated favorably or "protected" from the vagaries of customer procurement practices⁵ when contracts are allocated or renewed. Since the timing of innovation success is uncertain, a relationship that is expected to last longer could encourage customerspecific innovation (Dyer and Singh). All these channels predict that social connections between the supplier and customer are helpful in prolonging the business relationship and encouraging customer-specific innovation by the supplier.

Following prior literature, we identify pairwise social connections between two individuals (senior executives or board directors) at the supplier and customer if they have attended the same educational institution or worked at the same company for an overlapping period of time. To mitigate the reverse causality concern that

²Untabulated statistics show that socially connected individuals as per our definition (studied at the same university or worked at the same firm for an overlapping period of time prior to the start of the trading relationship) are much more likely to share memberships in clubs, social organizations, or charities than unconnected ones based on the BoardEx data, confirming that other interactions are much more likely for socially connected individuals than unconnected ones. Note that we do not include these social memberships when constructing our social connection measures because the starting date of many memberships is missing in BoardEx.

³In 2-person experimental trust games played by Harvard undergraduates, Glaeser, Laibson, Scheinkman, and Soutter (2000) find that the degree of social connections between players - the number of common friends and the duration of acquaintance - predicts trust and trustworthiness. See also Allen and Babus (2009), who point out the monitoring effect of social networks.

⁴Throughout the paper, we use the term "hold-up" broadly to include any type of opportunism that could arise in a bilateral relationship from either party, including ex post bargaining over terms of exchange and the use of sensitive and proprietary information revealed by the other party. Thus, greater cooperation in R&D effort can be partially attributed to hold-up mitigation.

⁵For example, procurement officer rotations at the customer firm could cause relationships to be abruptly terminated or contracts not renewed for arbitrary reasons.

productive business relationships lead to the formation of social connections, we focus on pre-existing social connections that are formed at third-party organizations (that is, other than the supplier and customer firms in question) prior to the start of the business relationship. It is worth emphasizing that since our arguments depend on the reputational consequences of breaching implicit contracts, the social connectivity between two individuals as per our measures does not necessarily require familiarity between the two. All we require is that these individuals have common friends in their respective networks, the likelihood of which is extremely high for connected individuals as opposed to unconnected ones as per our measurement of social connectedness.⁶

To empirically test our hypotheses, we extract a large sample of suppliercustomer pairs from the Compustat Segment Files and obtain biographic data on these firms' executive and director experiences from BoardEx. We first show a robust association between the pairwise social connections and the duration of trading relationships. This observation is broadly consistent with our hypothesis that social connections help maintain supply chain relationships - either because they enable these relationships to be more productive (e.g., via mitigating hold-up and fostering cooperation), or because they protect suppliers from arbitrary changes in customer procurement practices (i.e., reflecting favorable treatment of connected suppliers).

To uncover the underlying mechanisms, we investigate the impact of social connections on innovative investment made by the supplier. We find that suppliers do more R&D when their managers and board members are socially connected with their major customers. Moreover, the positive effect of social connections on supplier R&D investment extends to the quantity of innovation output produced by these upstream firms. Specifically, we find that socially connected suppliers are more innovative (measured by the number of patents filed and eventually granted) than unconnected suppliers. All the above results hold whether we use a connection indicator variable or the number of pairwise connections. Furthermore, these results are robust to controlling for the supplier's and customer's overall social network outside the business relationship, and other firm- and pair-level characteristics as well as a variety of fixed effects.

If pairwise social connections promote supplier innovation through the channel of mitigating hold-up and fostering cooperation in R&D efforts, then we should observe that connected suppliers' innovation activities are more likely to be tailored for their major customers. The granularity of the data on innovation allows us to design relation-specific measures to test this conjecture. Specifically, we find that the patents produced by the supplier are more likely to cite their customer's patent portfolio when the pairs are socially connected, and these patents tend to overlap more with the technology classes to which the customer's innovations belong.

⁶Some back-of-the-envelope calculations are useful to illustrate the case hypothetically. Suppose that a school has 2,000 students every year (that is, 8,000 students over a 4-year period), and a given student knows another 100 (150) students in this group. Then an application of Sterling's formula tells us that there is a 71% (94%) chance that any 2 individuals from this 4-year cohort have at least one common friend that they both know.

Moreover, the presence and strength of pre-existing social connections have a more pronounced effect on supplier patents that are less likely to be traded and thus associated with a higher degree of specificity. These results lend further support to the hypothesized economic channel that pre-existing social connections mitigate hold-up and foster R&D cooperation, thereby leading to more customized innovation by supplier firms. Further, we find that the effects of pre-existing social connections are also stronger when the individuals in the connected firms have more common third-party connections (mutual friends). These results speak to the role of network reputational effects in mitigating opportunism. Finally, we find that the effect of social connections on supplier innovation is stronger when the supplier and customer are found to have a spell of trading relationship for the first time in our data. Repeated (or longer term) spells are likely to be associated with trust or relationships that emerge from previous trades, and thus our pre-existing social connection measures are less likely to be important. This is what we find.

Clearly, social connections between supplier and customer firms need not be random, and this nonrandomness essentially presents three types of identification challenges that we need to deal with in designing our empirical tests. First, the presence and strength of social connections could be correlated with unobserved and time-invariant characteristics of either firm that determine the innovation potential of the projects. For example, innovative customer and supplier firms could be drawing their managers or board members from the same talent pool and hence they are more likely to be socially connected. The fact that our results from the aforementioned pooled regressions hold when we include firm or suppliercustomer pair fixed effects rules out this alternative explanation. Essentially, these results imply that when the connection dummy switches from "on" to "off" (or conversely) or the strength of prior social connections becomes "weaker" (or "stronger") during the course of a relationship, R&D and innovation go down (up).

Second, there could be concern that our results are driven by unobserved industry shocks that are correlated with both innovation activities and director/ executive turnovers. For example, technology shocks could increase the scope for innovation and at the same time lead to the hiring of executives which in turn increases the connectivity between trading partners. We address this concern in two ways. First, we include supplier-industry \times customer-industry \times year fixed effects in our regressions and find similar results. Furthermore, we construct a sample of "fake" supplier-customer relationships by randomly selecting a same-industry placebo supplier firm that does not have any disclosed trading relationship with the customer throughout the entire Compustat Segment File. The fact that the significantly positive effect of social connections on supplier innovation disappears in this placebo sample suggests that our results are not driven by unobserved industry-level shocks.

Third, there could also be concern that the pairwise social connections could be endogenous and in anticipation of future changes in the strength of the business relationship. For example, the customer might have offered a new contract to the supplier, and the latter's R&D and innovation then go up in response. At the same time, the supplier might recruit a manager to manage the relationship, and prefer to recruit one who has social connections to the customer. If this is the case, the pair fixed effects are not very helpful, since both supplier innovation and social connections are responding to the growing business relationship and are not causally related to each other. In order to mitigate this endogeneity concern, we first exploit connection changes due to the retirements⁷ or deaths of senior managers or board members at the customer. Presumably, retirements and deaths are unlikely to be caused by anticipated changes in innovation potential and more likely to be exogenous to suppliers' innovation activities. Customer firms, in particular, are much larger than the supplier firms (the median size ratio is almost 60) and it is therefore unlikely that any departures of high-level customer members are in response to declining importance of the relationship or the innovation potential of the supplier. Specifically, we examine the R&D and innovation of suppliers whose connectedness with customers are affected by the departures, relative to suppliers whose connections are unaffected. Consistent with social connections fostering supplier innovation, we find that after such retirements or deaths of customer members, supplier R&D, the number of supplier-produced patents, the number of crosscitations, and the supplier-customer technological proximity all drop for suppliers connected to these leaving members at the customer side, but not for those unconnected to the same members. The results also hold on a subsample where we only focus on more exogenous departures caused by executive or director deaths. We also examine how retirements and deaths of supplier senior managers/directors, and the consequent loss of connectivity to customers, affect the supplier's innovation activity and find similar results. These results provide strong causal evidence that hold-up mitigation and greater R&D cooperation are the most likely reason that connected suppliers innovate more.

Our paper is related to several strands of literature. While there has been a recent surge of interest in factors that spur corporate innovation, with a few exceptions, the important issue of supplier innovation in vertical relationships has remained largely unaddressed. Liang, Williams, and Xiao (2020) find that suppliers increase R&D and investments in customer-related patents after positive market reactions to customers' new product announcements. Chu, Tian, and Wang (2019) demonstrate that knowledge spillover from customers to suppliers is key to supplier innovation. Focusing on customer relocations, they show that the quality and quantity of supplier innovation drop (increase) after customers relocate their headquarters further from (nearer to) their suppliers. Different from Chu et al. who focus on knowledge spillovers and interactions among employees (especially researchers) of suppliers and customers, we are interested in hold-up mitigation and R&D cooperation via prior social connections among high-rank executives and directors of the trading partners.

Our paper also adds to the literature on the economics and finance of the supply chain by demonstrating the influence of the pairwise social connections between the supplier and customer on relationship-specific investment.⁸ Relatedly, we also

⁷We define retirements as managers or directors leaving the firm at the age of 65 or above. To ensure that such departures are "mandatory" and are not caused by shocks to the firms, we further require the leaving members to have no positions in other firms afterward.

⁸Papers studying the economics and finance of the supply chain include Fee and Thomas (2004), Fee, Hadlock, and Thomas (2006), Banerjee, Dasgupta, and Kim (2008), Kale and Shahrur (2007),

show that these connections mitigate contractual incompleteness and shape firm boundaries, thereby adding to the growing empirical literature on the boundary of the firm based on transaction cost economics (e.g., Seru (2014), Frésard, Hoberg, and Phillips (2020)).

Lastly, we also contribute to the literature on social connections, mostly in other contexts such as commercial loans (Engelberg, Gao, and Parsons (2012)), internal capital markets (Duchin and Sosyura (2013)), and mergers and acquisitions (Cai and Sevilir (2012), Ishii and Xuan (2014)). To the best of our knowledge, we are the first to show that social connections mitigate hold-up and promote cooperation in bilateral relationships. Particularly relevant to our study, Faleye, Kovacs, and Venkateswaran (2014) find that a CEO's overall social connections facilitate innovation by providing the CEO with access to relevant information to identify innovative ideas and with implicit labor market insurance to increase reemployment probability in case of innovation failure. Our contribution is in the context of bilateral relationships where tailored investment and the need for knowledge sharing and R&D cooperation are likely to be important. We argue that social connections encourage relation-specific innovation by mitigating hold-up, facilitating cooperation, and enhancing relation durability. Controlling for the supplier's and customer's overall social connectedness, we find that the pairwise social connections between the upstream and downstream firms have an incremental and positive impact on supplier innovation, especially on relationship-specific innovation, in addition to general innovation in Faleye et al.

The rest of the paper is organized as follows: Section II describes the sample and variable construction and reports the summary statistics. Section III discusses the empirical strategy and results. We conclude in Section IV.

II. Sample Construction and Summary Statistics

A. Sample Construction

Our sample construction starts from Compustat Segment files and covers firmyears from 2000 to 2012.⁹ According to Statement of Financial Accounting Standards (SFAS) No. 131, firms are required to disclose the names of customers that account for more than 10% of their total sales, though some firms voluntarily report customers below this threshold. We treat all disclosed customers as principal customers but exclude government buyers or generic customers such as "Foreign Sales," "Major Customer," "Vendor," or "Not Reported."

We then match the disclosed customer names or name abbreviations to CRSP header files following the procedure in Fee and Thomas (2004) and Fee et al. (2006). Specifically, we first use phonetic matching algorithms based on the spelling distances to identify several CRSP companies as potential matches for each

Hertzel, Li, Officer, and Rodgers (2008), Brown, Fee, and Thomas (2009), Ellis, Fee, and Thomas (2012), and Barrot and Sauvagnat (2016).

⁹We start our sample periods from 2000 because the social network information in BoardEx is incomplete before 2000. However, when we calculate the measures of pre-existing social connections and the duration of business relationship, we do use the entire Compustat Segment File (1979–2012) to identify the start date of each trading relationship. Please see Section II.C for more details.

disclosed customer. Then we manually check and confirm each match based on corporate names, industry classification, additional information from the Corporate Library database, and news releases from Factiva. In the whole matching process, we tend to be conservative to ensure that our matched CRSP firms are in fact the customers disclosed by the suppliers. The above matching procedures result in a total of 5,212 unique supplier-customer pairs (1,984 unique suppliers and 1,098 unique customers) and 17,261 pair-year observations.

The social network information is obtained from BoardEx, which provides detailed biographic information (work experience, educational background, and social activities such as club memberships and charity participation) about directors and senior managers. We match each firm in our supplier-customer sample to BoardEx mainly based on CUSIP and Central Index Key (CIK), largely following the procedures used by Engelberg et al. (2013).¹⁰ When the two identifiers are not available from BoardEx, we match the two databases based on company names using a string matching scheme similar to the one used when we match Segment Files to the CRSP universe. To maintain accuracy, we also visually investigate each match and ensure that the two names are referring to the same firm.

Finally, we require both supplier and customer firms to have relevant financial information to be included in our sample. Firm-level characteristics are obtained from the Compustat/CRSP merged database. Following the previous literature, we further exclude firms in any 4-digit Standard Industrial Classification (SIC) industries that have produced no patents during the sample period and firms that are in utility (SIC codes 4900–4999) and financial (SIC codes 6000–6999) industries. The final sample consists of 12,568 pair-year observations with 1,460 unique suppliers, 646 unique customers, and 3,477 unique supplier-customer pairs.

B. Innovation Measures

R&D expenses have been widely used in the literature as a proxy for innovation input and relationship-specific investment (Allen and Phillips (2000), Griffith, Redding, and Van Reenen (2004)). Specifically, we scale R&D expenses by the book value of total assets and replace it with zero if R&D is missing. A limitation of this measure is that it is only measured at the firm level and thus may not capture the level of innovation input for a specific business relationship. To overcome this limitation, we look at the sensitivity of R&D investments between the supplier and customer. The larger the comovement between the R&D invested by the two, the more likely the innovation inputs are relationship-specific.

We utilize patent data to measure firms' innovation output. We obtain the data from Kogan, Papanikolaou, Seru, and Stoffman (2017), which contain the universe of U.S. patents from 1926 to 2010 (the data are downloaded from https://iu.app. box.com/patents). To measure the scale of innovation output, we count the number of patents that are eventually granted to suppliers in each application year. We count by application year instead of grant year because application year is closer to the time when the new technology is developed (Hall, Jaffe, and Trajtenberg (2001)).

¹⁰Among U.S. firms covered by BoardEx between 2000–2012, about 86% of them have CIK and 64% have CUSIP.

Since our data only include patents that are finally granted, toward the end of our sample period, those pending patents do not show up in the data set. We follow Hall et al. and use the empirical application-grant time gap distribution to adjust the truncation bias in patent counts.

In addition to the aggregate patent counts where we treat all patents homogenously, we also distinguish between generalized and specific innovations based on their tradability in the technology market. Specifically, we extract the patent reassignment record from the U.S. Patent and Trademark Office (USPTO) Patent Assignment Database (Marco, Myers, Graham, D'Agostino, and Apple (2015)) and calculate the percentage of patents that are reassigned among all the patents in each technology-class-year (reassignment rate). We then classify a patent as (non) tradable if the reassignment rate of its primary technology class is (below) above the sample median and count the patents in each category separately. The intuition is simple: if patents can be reassigned and utilized by other companies, their applications are more likely to be more generalized and less specific.

The richness of the patent data also allows us to construct pair-level measures that likely capture the supplier innovation that is tailored for the customer. First, we identify whether the supplier produces any patent that cites its customer's patent portfolio as well as the number of cross-citations. The presence and intensity of cross-citations indicate that the supplier tailors its R&D to its customer's technology (Jaffe, Trajtenberg, and Fogarty (2000)). Second, following Jaffe (1986) and Bena and Li (2014), we calculate the overlap of the supplier's and customer's innovation based on their patents' technology class distribution. When the two parties' patents are closer in the technology space, their innovation is likely to be relationship-specific and the bilateral cooperation goes deeper, all else equal.

C. Social Connection Measures

We identify two types of social connections: i) school ties, where two persons study in similar types of programs at the same institution for an overlapping time;¹¹ and ii) third-party employment connections, where two persons work at the same firm outside the current trading relationship for an overlapping period. We further require the social connections to be formed at least 1 year prior to the start of the trading relationship based on the full Compustat Segment Files. All these requirements ensure that the identified social connections are formed at a distant place and time and thus are independent of the business relationship in question.

Based on the criteria above, we construct two proxies to measure the existence and strength of the pairwise social connections between the supplier and customer. The first is a dummy indicator, denoted as CONNECTED, which equals 1 if at least one pre-existing school tie or employment connection exists between senior managers and board directors in the supplier and those in the customer, and 0 otherwise.¹² The second measures the strength of the pairwise social connections.

¹¹We classify all education programs into undergraduate, master, MBA, law degree, and others.

¹²We consider both independent directors and executive directors in the calculation of social connectedness. The coverage of senior managers in BoardEx is also larger than that in ExecuComp. We exclude regional managers, group managers, and other less significant positions based on the job title in BoardEx. The names of positions that cumulatively account for 50% of executives include: CEO;

To construct this variable, we first count the number of social connections each senior manager and board director in the supplier has with the members in the customer. Then we aggregate the number of connections across all members in the supplier to obtain the total number of pairwise social connections. To account for the impact of the overall social connectivity (Faleye et al. (2014)), we construct the supplier's and the customer's aggregate social connections with individuals outside the business relationship, respectively. We assume two individuals stay connected after the establishment of the social connection, which may impose an increasing trend in the network measures. To remove this time trend, we regress the raw network counts (pairwise connections between the supplier and customer, and the aggregated connections for the supplier and customer, respectively) on year dummies and take the residual from the regression, following Faleye et al.¹³ We then take the natural logarithm of a constant (1 plus the absolute value of the minimum sample residual) plus the residual to deal with the skewness in the data. These detrended social connection measures in the log form are denoted as ln(PAIRWISE CONNECTIONS), ln(SUPP CONNECTIONS), and ln(CUST CONNECTIONS), respectively.

D. Control Variables

Following the prior literature (e.g., Fee et al. (2006), Banerjee et al. (2008), and Dass, Kale, and Nanda (2014)), we construct and control for an array of supplier-, customer-, and pair-level characteristics in the analysis. The supplier-level control variables include firm size (natural logarithm of its book value of total assets), market leverage (total debt divided by market value of total assets), market to book ratio (market value of total assets divided by book value of total assets), proportion of tangible assets (net Property, Plant, and Equipment (PPE) divided by book value of total assets), operating performance (return on assets (ROA) measured as the income before extraordinary items divided by book value of total assets), capital expenditure investment (capital expenditure divided by total assets), and the industry competitiveness (Herfindahl-Hirschman Index measured as the sum of squared market shares in each 2-digit SIC industry). The customer-level control variables include R&D intensity, and its market leverage ratio, following Kale and Shahrur (2007). Moreover, to take into consideration the strength of business relationships, we control for the pair-level sales ratio (supplier's sales to each customer divided by its book value of total assets).¹⁴ To account for knowledge spillovers due to geographical proximity (Chu et al. (2019)), we control for the geographic distances between the headquarters of suppliers and their customers. We also control for

CFO; COO; Chairman; Chairman/CEO; Chairman/President/CEO; Executive VP; Executive VP/CFO; Executive VP/COO; General Manager; Managing Director (MD); Manager; Managing Partner; Partner; President; President/CEO; President/COO; Senior VP; Senior VP - Ops; Senior VP/CFO; Vice President; Vice President - HR; Vice President - Marketing; Vice President - Ops; and Vice President - Sales.

¹³We detrend all the continuous connection measures used throughout this study. We choose not to detrend the dummy pairwise network variable (CONNECTED) to preserve its intuitive interpretation. All our results hold if we detrend the dummy connection measure or do not detrend the continuous network variables.

¹⁴The results are robust to using supplier's aggregate sales as the scaling variable.

https://doi.org/10.1017/S002210902000068X Published online by Cambridge University Press

suppliers' and customers' aggregated social connections with individuals outside the trading relationships to account for the impact of overall connectedness on innovation (Faleye et al. (2014)). Detailed definitions of variables can be found in the Appendix.

E. Summary Statistics

We report the summary statistics of the key variables used in our empirical analysis in Table 1. An average supplier in our sample invests 8.7% of their total assets in R&D and these innovation inputs translate into 15.4 granted patents per year. About 10.8% of suppliers have produced at least one patent that cites the customer's patent portfolio and the average number of supplier cross-citations is 2.6 per year. The average technological proximity between the supplier's and customer's produced patents is 0.118. Among the supplier-customer pairs in our sample, about 4.6% of them have established a joint venture or strategic alliance with each other for R&D-intensive projects.

The pairwise social connectedness and other pair-level characteristics of the trading relationships are summarized in Panel B of Table 1. About 47.1% of supplier-customer pairs have at least one school or employment tie and the average

		TABLE 1					
Summary Statistics							
Table 1 reports the summary statistics for value the dependent variables, social connection customer characteristics, respectively. Va	n and other s	supplier-custo	mer pair-level me				
	N	Mean	Std. Dev.	Q1	Median	Q3	
Panel A. Dependent Variables							
SUPP_R&D NUM_OF_PATENTS In(PATENTS) CROSS_CITATION_DUMMY NUM_OF_CROSS_CITATIONS In(CROSS_CITATIONS) TECH_PROXIMITY JV_ALLIANCE_DUMMY	12568 8748 8748 8748 8748 8748 8748 8748 12568	0.087 15.428 0.920 0.108 2.648 0.225 0.118 0.046	0.147 99.531 1.401 0.310 21.509 0.780 0.259 0.210	0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000	0.038 0.000 0.000 0.000 0.000 0.000 0.000 0.000	0.115 3.635 1.534 0.000 0.000 0.000 0.010 0.000	
Panel B. Social Connection and Pair-Level	l Characteris	tics					
CONNECTED NUM_OF_PAIRWISE_CONNECTIONS In(PAIRWISE_CONNECTIONS) SALES_TO_CUSTOMER DISTANCE (miles) SUPP_CUST_SIZE_RATIO	12568 12568 12568 12568 12568 12568 12568	0.471 1.294 0.655 0.166 993 0.102	0.499 2.989 0.624 0.167 806 0.220	0.000 0.000 0.152 0.067 338 0.004	0.000 0.000 0.531 0.116 782 0.015	1.000 2.000 1.099 0.201 1550 0.073	
Panel C. Supplier Characteristics							
In(SUPP_CONNECTIONS) SUPP_SIZE (\$millions) SUPP_LEVERAGE SUPP_MB SUPP_TANGIBILITY SUPP_ROA SUPP_CAPEX HHI	12568 12568 12568 12568 12568 12568 12568 12568 12568	4.018 2741 0.187 2.031 0.206 -0.045 0.047 0.051	0.558 13345 0.206 1.477 0.204 0.238 0.057 0.040	3.707 104 0.002 1.142 0.062 -0.069 0.015 0.029	4.083 351 0.132 1.546 0.138 0.029 0.028 0.038	4.407 1415 0.300 2.330 0.268 0.073 0.052 0.059	
Panel D. Customer Characteristics							
In(CUST_CONNECTIONS) CUST_R&D CUST_LEVERAGE	12568 12568 12568	4.434 0.029 0.225	0.370 0.041 0.160	4.275 0.000 0.101	4.468 0.005 0.202	4.642 0.045 0.291	

pairwise social connections is 1.3.¹⁵ Sales to each customer account for 16.6% of the supplier's book value of assets, indicating that the suppliers in our sample are dependent on their major customers. The mean (median) geographic distance between the headquarters of supplier and customer is 993 (782) miles,¹⁶ which is similar to that of 912 (536) miles reported in Chu et al. (2019). Consistent with previous studies using the Segment Files (e.g., Fee and Thomas (2004), Fee et al. (2006)), customers are typically much larger than their suppliers. For example, the average (median) ratio of the supplier size to its customer's is 0.102 (0.015) in our sample, indicating that the average (median) customer is almost 9.8 (66.7) times as large as the supplier.

We report the summary statistics of supplier and customer firm characteristics in Panels C and D of Table 1, respectively. The average (median) supplier in our sample has a detrended aggregate social network of 4.018 (4.083) with natural logarithm transformation, a book value of total assets of \$2,741 (\$351) million, a market-to-book ratio of 2.031 (1.546), a tangible-to-total asset ratio of 0.206 (0.138), and a return on assets (ROA) of -0.045 (0.029). Regarding firms' investment and financial policies, the average (median) supplier has a leverage ratio of 0.187 (0.132) and invests 4.7% (2.8%) of total assets in capital expenditures. Customers are generally large and mature companies, with a detrended aggregate social network of 4.434, 2.9% of total assets spent on R&D, and a mean leverage ratio of 0.225.

III. Empirical Strategy and Results

In this section, we empirically examine if social connections mitigate hold-up and facility cooperation in the vertical relationship. We start the analysis by investigating the association between the pairwise social connectivity and relationship durability at the relationship level. We continue the analysis with micro-level examinations of supplier innovation, including both innovation inputs (R&D) and outputs (patent counts and patent tradability). To provide further evidence on relationship-specific innovation, we examine the cross-citations and technological relatedness between the supplier and customer. We then study the mediating role of third-party common connections (common friends of a supplier member and a customer member) on the association between the pairwise direct connections and supplier innovation. To mitigate endogeneity concerns and help establish the causal effect of social connections, we implement a placebo test as well as an identification strategy that exploits (relatively exogenous) connection changes due to the retirements or deaths of senior managers and board directors in the supplier and the customer, respectively. Finally, we conduct additional analysis related to the boundary of the firm (the formation of R&D-intensive joint venture or strategic alliance) to enrich the scope of our empirical analysis.

¹⁵In contrast, as we discuss later, if we replace the supplier with another randomly chosen sameindustry firm that has never disclosed a business relationship with the customer, we find that only 30% of the fake business relationships are socially connected. This suggests that some social connections exist for mechanical reasons.

¹⁶We obtain the information on firms' historical headquarters from the SEC Analytics Suite Database.

A. Duration of Supplier-Customer Relationships

We begin by investigating whether social connections are related to the trading relationship duration. If social connections ease contractual frictions and enhance cooperation, implicit contracts governing the trading relationship are more likely to be sustained. It is also possible that social connections help protect suppliers from vagaries of contract renewal/award decisions in the hands of lower-tier customer employees, or that customers favor suppliers to whom they are socially connected. Both channels predict that socially connected business relationships, all else equal, would last longer on average.

To empirically test this prediction, we first follow Fee et al. (2006) and employ duration analysis to explain the length of trading relationships. The main explanatory variables of interest are the two social connection measures: i) a dummy indicator, CONNECTED, which equals 1 if at least one pre-existing education or employment connection exists between the supplier and customer, and 0 otherwise; and ii) a continuous measure, ln(PAIRWISE_CONNECTIONS), which is the natural logarithm of 1 plus the detrended number of pairwise social connections. In selecting the control variables, we follow the literature and control for an array of supplier-, customer-, and supplier-customer-level characteristics that might affect relationship duration.¹⁷ These control variables are introduced in Section II.D and defined in the Appendix.

The results of the Cox proportional hazard model are reported in columns 1 and 2 of Table 2 while those of the Weibull model are reported in columns 3 and 4. The unit of observation is one business relationship and all the explanatory variables are measured in the first year that we observe the relationship within our sample period. We treat relationships that last until the last year of the sample period as right-censored and adjust for the fact that some relationships have existed before they enter our sample. Since we report hazard ratios, an estimate above (below) 1 implies that the explanatory variable shifts the hazard function upward (downward) thus increasing (decreasing) the hazard rate (probability of relationship termination). Our results suggest that both the presence and strength of social connections are positively associated with the business relationship durability. For example, the estimate in column 1 indicates that socially connected relationships have a 12.3% lower hazard rate than unconnected relationships. The estimates of the other explanatory variables have the expected signs. For example, we find that larger suppliers, suppliers that have higher growth potential and better operating performance, and those that make a larger proportion of sales to the customers maintain more durable business relationships.

In columns 5 and 6, we report the results from linear probability models using relationship-year observations where the dependent variable is a dummy variable

¹⁷To account for the technological aspect of the business relationship, we partition the sample based on industry R&D-to-assets ratio and find similar results in both subsamples. We also additionally control for supplier R&D in the regressions and again obtain similar results. These results are reported in Table A1 of the Supplementary Material.

Social Connections and Relationship Duration

Table 2 reports the results from regressions of supplier-customer relationship duration on the social connections between suppliers and customers. In columns 1–4, the unit of observation is a relationship and duration analysis techniques are used to estimate the hazard function describing relationship duration. We treat relationships that last until the last year of the sample period. All explanatory variables are measured in the first year that we observe the relationship duration mour sample period. All explanatory variables are measured in the first year that we observe the relationship during the sample period. All explanatory variables are measured in the first year that we observe the relationship during the sample period. Columns 1 and 2 report the results from the Cox proportional hazards model and columns 3 and 4 report the results from the Cox proportional hazards model and columns 3 and 4 report the results from the veibul distribution model. In columns 5 and 6, the unit of observation is relationship-year and the OLS regression is used to predict whether the relationship terminates in the next year. The dependent variable is a dummy variable which equals 1 if the relationship terminates in the next year fixed effects in columns 5 and 6. *p*-values based on robust standard errors (White (1980)) are reported in parentheses and the standard errors are adjusted for supplier-customer-pair clustering in columns 5 and 6 (Petersen (2009)). *, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

	C	OX	Weibull		OLS	
Model	1	2	3	4	5	6
CONNECTED	0.877*** (0.002)		0.861*** (0.003)		-0.021** (0.014)	
In(PAIRWISE_CONNECTIONS)		0.921** (0.035)		0.888*** (0.008)		-0.012* (0.080)
In(SUPP_CONNECTIONS)	1.087**	1.074*	1.094*	1.085*	0.010	0.009
	(0.047)	(0.086)	(0.073)	(0.099)	(0.239)	(0.311)
SUPP_SIZE	0.889***	0.888***	0.880***	0.880***	-0.022***	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUPP_LEVERAGE	1.106	1.107	1.083	1.081	0.026	0.027
	(0.330)	(0.327)	(0.505)	(0.514)	(0.218)	(0.197)
SUPP_MB	0.975***	0.975**	0.967***	0.967***	-0.004	-0.004
	(0.009)	(0.010)	(0.004)	(0.004)	(0.149)	(0.149)
SUPP_TANGIBILITY	0.868	0.876	0.798	0.807	-0.040	-0.040
	(0.373)	(0.404)	(0.217)	(0.241)	(0.219)	(0.221)
SUPP_ROA	0.724***	0.724***	0.683***	0.683***	-0.110***	-0.109***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUPP_CAPEX	1.520	1.553	1.467	1.496	0.077	0.077
	(0.337)	(0.315)	(0.454)	(0.433)	(0.450)	(0.450)
HHI	1.098	1.154	1.112	1.168	0.086	0.086
	(0.886)	(0.826)	(0.891)	(0.841)	(0.434)	(0.430)
In(CUST_CONNECTIONS)	1.014	1.013	1.030	1.030	-0.009	-0.010
	(0.808)	(0.824)	(0.674)	(0.672)	(0.484)	(0.457)
CUST_R&D	2.555*	2.590*	2.576	2.623*	0.282*	0.281*
	(0.055)	(0.053)	(0.103)	(0.099)	(0.053)	(0.054)
CUST_LEVERAGE	0.784*	0.784*	0.715**	0.710**	-0.053*	-0.055*
	(0.080)	(0.081)	(0.039)	(0.036)	(0.062)	(0.054)
SALES_TO_CUSTOMER	0.203***	0.206***	0.153***	0.156***	-0.327***	-0.327***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In(DISTANCE)	1.001	1.000	1.000	0.997	0.000	-0.000
	(0.923)	(0.977)	(0.991)	(0.840)	(0.949)	(0.988)
Year FE Industry FE	Yes	Yes	Yes	Yes	Yes Yes	Yes Yes
No. of obs.	3,477	3,477	3,477	3,477	11,722	11,722

indicating if the trade relationship is terminated (drop out of the Segment File) in the next year. We find that a relationship is less likely to be terminated if it is associated with (stronger) social connections. This evidence corroborates the findings in the duration analysis that the presence and strength of social connections reduce the likelihood of relationship termination.¹⁸

¹⁸According to the coefficient estimate in column 5 of Table 2, socially connected relationships are 2.1% less likely to terminate than unconnected ones in a given year. Given that the unconditional

B. Supplier-Level Innovation Activities

Here we conduct multivariate regressions in which we regress the supplierlevel innovation proxies on the pairwise social connections between trading partners. The regression specification is described as follows:

(1) SUPP_INNOVATION_{*i*,*t*+1} = α_1 SC_{*i*,*j*,*t*} + $X_{i,t}\beta$ + $Y_{j,t}\gamma$ + $Z_{i,j,t}\delta$ + $u_{i,j}$ + v_t + $\epsilon_{i,t}$,

where *i* denotes supplier *i*, *j* denotes customer *j*, and *t* denotes year *t*. SUPP INNOVATION_{i,t+1} represents the supplier-level innovation measures defined in Section II.B (i.e., supplier-level R&D investment and patenting outcomes). We measure the dependent variables in year t + 1 since it takes time for innovative ideas to materialize. $SC_{i,j,t}$ is the main variable of interest that captures the presence or strength of pre-existing social connections between senior managers and directors of the supplier and customer (CONNECTED and $\ln(\text{PAIRWISE}_\text{CONNECTIONS})$). We include a series of supplier-level $(X_{i,t})$, customer-level $(Y_{i,t})$, and supplier-customer pair-level $(Z_{i,t,t})$ characteristics that might affect supplier innovation. Finally, we include year fixed effects (v_t) to capture the time-trend of innovation activities and the possible effect of overall economic conditions. We also control for supplier-customer pair fixed effects $(u_{i,i})$ to remove the impact of any unobserved but time-invariant heterogeneity at the relationship level (e.g., unobserved relationship productivity).¹⁹ The inclusion of pair fixed effects ensures that our results capture the effect of within-relationship variations in social connections on supplier innovation. We cluster standard errors at the supplier firm level to account for the repetition of the same supplier-years across supplier-customer pairs and the within-supplier serial correlation of the residuals (Petersen (2009)).

1. Supplier R&D Expenses

Table 3 reports the regression results on supplier R&D investment. As we can see from the results, no matter how we measure social connections (the dummy variable or the continuous measure), we consistently observe a significantly positive effect of pairwise social connections on supplier R&D investment. For example, the estimation in column 1 suggests that, holding all else equal, socially unconnected suppliers' R&D spending will increase by 0.3% of assets when they become connected with their customers, a 3.4% (7.9%) increase relative to the sample mean (median).

To deal with the limitation that we only observe supplier R&D at the firm level rather than at the relationship level, we further examine how social connections affect the *sensitivity* between supplier R&D and customer R&D. A higher comovement of R&D spending in the bilateral relationship indicates a higher degree of customization and cooperation between the upstream and downstream firms. Specifically, we add an interaction term between customer R&D and the

probability of relationship termination is 20% in our sample, this estimate represents a 10% reduction in the probability of relationship termination relative to the sample average.

¹⁹Our results are also robust to the inclusion of supplier industry fixed effects or supplier firm fixed effects. These results are not reported but are available upon request.

Social Connections and Supplier R&D

Table 3 reports the results from regressions of supplier R&D on the social connections between suppliers and customers. The dependent variable is supplier R&D expenses (XRD) over book value of total assets (AT). Other variable definitions are in the Appendix. We control for year and supplier-customer pair fixed effects in all regressions. In parentheses are *p*-values based on standard errors adjusted for heteroscedasticity (White (1980)) and firm clustering (Petersen (2009)). *, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

			_R&D	
Dependent Variable	1	2	3	4
CONNECTED	0.003* (0.077)	-0.002 (0.484)		
$CONNECTED \times CUST_{R\&D}$		0.152*** (0.010)		
In(PAIRWISE_CONNECTIONS)			0.004** (0.033)	0.000 (0.975)
$In(PAIRWISE_CONNECTIONS) \times CUST_R\&D$				0.130** (0.034)
In(SUPP_CONNECTIONS)	0.004	0.004	0.004	0.004
	(0.134)	(0.296)	(0.308)	(0.324)
SUPP_SIZE	-0.039***	-0.039***	-0.039***	-0.039***
	(0.000)	(0.000)	(0.000)	(0.000)
SUPP_LEVERAGE	-0.023*	-0.022	-0.022	-0.022
	(0.079)	(0.311)	(0.311)	(0.325)
SUPP_MB	0.005***	0.005**	0.005**	0.005**
	(0.002)	(0.022)	(0.025)	(0.024)
SUPP_TANGIBILITY	0.108***	0.108**	0.108**	0.107**
	(0.000)	(0.017)	(0.018)	(0.018)
SUPP_ROA	-0.150***	-0.150***	-0.150***	-0.150***
	(0.000)	(0.000)	(0.000)	(0.000)
SUPP_CAPEX	0.055***	0.055*	0.055*	0.055*
	(0.007)	(0.081)	(0.080)	(0.080)
HHI	0.146*	0.156	0.151	0.153
	(0.065)	(0.275)	(0.289)	(0.284)
HHI ²	-0.673**	-0.702	-0.684	-0.696
	(0.013)	(0.129)	(0.139)	(0.133)
In(CUST_CONNECTIONS)	0.002	0.002	0.001	0.002
	(0.600)	(0.719)	(0.747)	(0.710)
CUST_R&D	0.093	0.011	0.095	-0.009
	(0.389)	(0.927)	(0.398)	(0.939)
CUST_LEVERAGE	-0.018	-0.019	-0.018	-0.019
	(0.146)	(0.265)	(0.288)	(0.279)
SALES_TO_CUSTOMER	0.031**	0.031*	0.031*	0.032*
	(0.024)	(0.087)	(0.089)	(0.085)
In(DISTANCE)	0.000	0.000	0.001	0.000
	(0.937)	(0.932)	(0.905)	(0.941)
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
No. of obs.	12,568	12,568	12,568	12,568
Adj. <i>R</i> ²	0.853	0.853	0.853	0.853

connection dummy in column 2 or the continuous connection measure in column 4 of Table 3. The results show that supplier R&D is more sensitive to customer R&D when they are socially connected or when their pairwise connections are stronger. Taken together, the results on R&D level and R&D sensitivity suggest that social connections promote supplier innovation (probably tailored for key customers), given that R&D expenses are considered as an important input of innovation activities and are highly correlated with innovation outcomes in subsequent periods (Griffith et al. (2004)).

2. Supplier Patents and Innovation Specificity

Table 4 reports the regression results of patent counts on pairwise social connections. Consistent with the previous results on supplier R&D spending, we find that the coefficients on both connection measures are positive, and statistically significant at conventional levels. Based on the coefficients in columns 1 and 2, the economic magnitude corresponds to a 6.1% increase in produced patents when the

TABLE 4

Social Connections, Supplier Patents, and Innovation Specificity

Table 4 reports the results from regressions of supplier innovation outputs on the social connections between suppliers and customers. The dependent variable in columns 1 and 2 is the natural logarithm of 1 plus supplier total number of patents filed (and eventually granted) in year *t* + 1. In columns 3–6, we classify the patents produced by the supplier into nontradable and tradable patents. (Non) Tradable patents are defined as those patents that belong to the technology classes with (below-) above-median reassignment rates (i.e., the percentage of patents that are reassigned in each technology classes with (below-) above-median reassignment rates (i.e., the percentage of patents that are reassigned in each technology classes according to the USPTO Patent Assignment Database. One-tailed *t*-tests are used to compare the coefficients on CONNECTED (In (PAIRWISE_CONNECTIONS)) in columns 3–4 (5–6) and the corresponding *p*-values are reported in the end of the table. Other variable definitions are in the Appendix. We control for year and supplier-customer pair fixed effects in all regressions. In parentheses are *p*-values based on standard errors adjusted for heteroscedasticity (White (1980)) and firm clustering (Petersen (2009)). *, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

	In(PAT	ENTS)	NON_ TRADABLE	TRADABLE	NON_ TRADABLE	TRADABLE
Dependent Variable	1	2	3	4	5	6
CONNECTED	0.061* (0.063)		0.078** (0.016)	0.024 (0.412)		
In(PAIRWISE_CONNECTIONS)		0.075** (0.026)			0.095*** (0.005)	0.029 (0.397)
In(SUPP_CONNECTIONS)	0.031	0.028	0.033	0.010	0.030	0.009
	(0.700)	(0.717)	(0.660)	(0.864)	(0.680)	(0.874)
SUPP_SIZE	0.218***	0.216***	0.132**	0.142**	0.130**	0.141**
	(0.000)	(0.000)	(0.012)	(0.011)	(0.013)	(0.011)
SUPP_LEVERAGE	-0.124	-0.119	-0.076	-0.157	-0.069	-0.155
	(0.378)	(0.400)	(0.628)	(0.254)	(0.660)	(0.261)
SUPP_MB	0.026*	0.026*	0.017	0.025*	0.016	0.025*
	(0.085)	(0.086)	(0.254)	(0.078)	(0.257)	(0.078)
SUPP_TANGIBILITY	-0.634*	-0.640*	-0.648**	-0.057	-0.655**	-0.059
	(0.058)	(0.056)	(0.047)	(0.830)	(0.045)	(0.823)
SUPP_ROA	-0.076	-0.075	-0.137*	0.000	-0.136*	0.000
	(0.415)	(0.419)	(0.092)	(1.000)	(0.093)	(0.997)
SUPP_CAPEX	0.464	0.462	0.595	0.215	0.591	0.214
	(0.278)	(0.281)	(0.138)	(0.556)	(0.139)	(0.559)
HHI	10.188**	10.304**	8.166*	8.849*	8.312**	8.895*
	(0.021)	(0.019)	(0.053)	(0.067)	(0.048)	(0.065)
HHI ²	-36.146**	-36.480**	-32.899**	-29.836	-33.323**	-29.969
	(0.027)	(0.025)	(0.050)	(0.140)	(0.046)	(0.138)
In(CUST_CONNECTIONS)	-0.056	-0.059	-0.065	-0.060	-0.070	-0.062
	(0.587)	(0.556)	(0.502)	(0.417)	(0.463)	(0.401)
CUST_R&D	0.890	0.907	0.615	0.926	0.636	0.933
	(0.501)	(0.493)	(0.612)	(0.436)	(0.602)	(0.434)
CUST_LEVERAGE	-0.186	-0.180	-0.001	-0.163	0.006	-0.161
	(0.384)	(0.396)	(0.996)	(0.371)	(0.978)	(0.377)
SALES_TO_CUSTOMER	0.359***	0.361***	0.298**	0.143	0.301**	0.144
	(0.007)	(0.007)	(0.019)	(0.200)	(0.018)	(0.196)
In(DISTANCE)	-0.009	-0.005	-0.011	0.178	-0.006	0.180
	(0.927)	(0.963)	(0.928)	(0.368)	(0.965)	(0.366)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs. Adj. R ² <i>p</i> -value of testing coefficient differences	8,748 0.854	8,748 0.854	8,748 0.823 0.030	8,748 0.730	8,748 0.823 0.016	8,748 0.730

connection dummy switches from off to on, or an elasticity of 7.5% for patent production with respect to social connection strength. These results reinforce the previous findings on supplier R&D investment and lend further support to our main hypothesis that pre-existing social connections are beneficial to the innovation activities by the upstream firm.

Next, we delve deeper into the specificity (or generalizability) of suppliers' patents to shed light on the underlying channels for the positive association between social connections and supplier innovation. If social connections mitigate hold-up and facilitate corporation in R&D effort, then we should observe a stronger effect of social connections on more specific innovations than generalizable ones. We take advantage of patent assignment records maintained by the USPTO to gauge the specificity.²⁰ Reassigned patents are presumably deployed by other companies after reassignment, hence less specific. For example, Serrano (2010) finds that the probability of a patent being traded increases with its generality. Akcigit, Celik, and Greenwood (2016) document that a patent is more likely to be sold if it is more distant from the seller's patent portfolio in the technology space. We classify a patent as (non) tradable if it belongs to a technology class with (below-) abovemedian reassignment rate (i.e. the proportion of patents that are reassigned among all patents in each technology-class-year).²¹ We then count the number of nontradable and tradable patents for each firm-year and use this as the dependent variable in equation (1).

We present the results in columns 3-6 of Table 4. The model specifications are the same as those in columns 1 and 2 except that we replace the dependent variables with the number of nontradable patents in columns 3 and 5 and the number of tradable patents in columns 4 and 6. Consistent with our expectations, we find a significantly positive impact of social connections on nontradable patents, but not on tradable patents. One-tailed *t*-tests comparing the network effect on nontradable versus tradable patents show that the coefficient differences are statistically significant at the 5% level. This evidence provides further support to our main hypothesis that social connections foster relationship-specific innovation by upstream suppliers.

C. Supplier Cross-Citations and Technological Proximity

To further capture the relationship-specificity of the innovation conducted by the supplier, we take advantage of the richness of the patent data and construct several pair-level innovation measures that reflect the extent to which suppliers tailor their innovation to customers' needs. As defined in Section II.B, the pair-level innovation measures we use are: i) the presence and intensity of cross-citations

²⁰The data contain detailed information on patent right transfers, including the types of the transfer (for our purpose, we only focus on "change in ownership"), patent identity, the parties involved, and transaction date. One drawback of the data is that the record of patent rights transfer is voluntary hence probably incomplete, even though patent laws provide strong incentives for parties to disclose assignments with the USPTO (Marco et al. (2015)). The data are obtained from https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-assignment-dataset.

²¹For robustness checks, we also use an alternative definition of patent tradability according to whether the patent is actually traded at least once or not. The results (not tabulated) remain similar.

between suppliers and customers;²² and ii) technological proximity based on the technology class distribution of patents produced by suppliers and customers. The multivariate regression model is represented as follows:

(2) RELATION_SPECIFIC_INNOVATION_{*i*,*j*,*t*+1} =
$$\alpha_1 SC_{i,j,t} + X_{i,t}\beta + Y_{j,t}\gamma$$

+ $Z_{i,j,t}\delta + u_i + v_t + \epsilon_{i,j,t}$

where the dependent variable RELATION_SPECIFIC_INNOVATION_{*i,j,t*+1} denotes pairwise innovation proxies between supplier *i* and customer *j* measured in year t + 1. The right-hand side variables are similar to those used in the previous regression analysis. In order to exploit the rich cross-sectional heterogeneity in the pairwise innovation proxies between connected and unconnected pairs for the same supplier firm, we control for supplier fixed effects (u_i) here. This helps to deal with any unobserved but time-invariant heterogeneity at the supplier level that might drive our results (e.g., unobserved supplier innovation potential). Since the dependent variables are measured at the pair level, we adjust the standard errors with supplier-customer-pair clustering (Petersen (2009)).

We present the regression results on cross-citations in columns 1–4 of Table 5. In columns 1 and 2, the dependent variable is a dummy variable (CROSS_CITATION_DUMMY), which equals 1 if the supplier produces any patent in year t + 1 that cites the customer's patent portfolio, and 0 otherwise. The estimates of the linear probability model in column 1 show that connected suppliers are 2.8% more likely to produce patents that cite customer patent portfolios than unconnected ones.²³ We observe a similar network effect on cross-citations when we use social connection counts to measure the network strength in column 2. These findings are confirmed when we use a continuous cross-citation measure (ln(CROSS_CITATIONS)), defined as the natural logarithm of 1 plus the total number of cross-citations) in columns 3 and 4. Based on the coefficient estimates in column 3, the number of cross-citations by connected suppliers is 7.8% higher than unconnected ones.

Alternatively, we measure the closeness of innovation activities between the supplier and customer by the overlap of technology classes of patents produced by these two firms (Jaffe (1986), Bena and Li (2014)). We then regress this pair-level innovation proximity (TECH_PROXIMITY) on our social connection measures after controlling for the same set of right-hand side variables as in the cross-citation regressions and report the results in columns 5 and 6 of Table 5. Consistent with the results on cross-citations, we find that connected suppliers and customers have a larger overlap in the technological scope of innovation activities than for unconnected pairs. The estimates in column 5 where the CONNECTED dummy indicator is the main variable of interest suggest that the technological proximity of

²²The cross-citation measure provides a reasonable and valid estimate of the technological relatedness. For example, Gomes-Casseres, Hagedoorn, and Jaffe (2006) point out that "patent citations have the advantage that they perform a legal function related to the validity of the patent and the technology to which it applies, so that they are not contaminated by unnecessary citations to friends, colleagues, or famous people."

²³The results from probit regressions after controlling for year and supplier industry fixed effects are qualitatively similar.

Social Connections and Relation-Specific Innovation

Table 5 reports the results from OLS regressions of supplier cross-citations (technological proximity) on the social connections between suppliers and customers in columns 1–4 (5–6). Supplier cross-citations are measured based on the supplier's patent that cites the customer's patent portfolio in year t + 1. The dependent variable in columns 1 and 2 is a dummy indicator measuring the presence of cross-citations and the dependent variable in columns 3 and 4 is the natural logarithm of 1 plus the number of cross-citations. In columns 5 and 6, the dependent variable is measured as technological proximity between the supplier's patents in year t + 1 and customer's patent portfolio following Jaffe (1986). Other variable definitions are in the Appendix. We control for year and supplier fixed effects in all regressions. In parentheses are p-values based on standard errors adjusted for heteroscedasticity (White (1980)) and supplier-customer-pair clustering (Petersen (2009)).

	CROSS_CITATION_DUMMY		In(CROSS_CITATIONS)		TECH_PROXIMITY	
Dependent Variable	1	2	3	4	5	6
CONNECTED	0.028*** (0.000)		0.078*** (0.000)		0.016*** (0.006)	
In(PAIRWISE_CONNECTIONS)		0.036*** (0.000)		0.100*** (0.000)		0.025*** (0.000)
In(SUPP_CONNECTIONS)	-0.019	-0.021*	-0.083***	-0.088***	-0.008	-0.010
	(0.109)	(0.070)	(0.002)	(0.001)	(0.462)	(0.340)
SUPP_SIZE	0.052***	0.052***	0.124***	0.122***	0.056***	0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SUPP_LEVERAGE	-0.021	-0.020	-0.045	-0.042	-0.037	-0.036
	(0.486)	(0.503)	(0.528)	(0.550)	(0.134)	(0.139)
SUPP_MB	0.006*	0.006*	0.007	0.007	0.004	0.004
	(0.062)	(0.063)	(0.324)	(0.330)	(0.182)	(0.179)
SUPP_TANGIBILITY	0.015	0.015	0.123	0.124	0.037	0.037
	(0.814)	(0.809)	(0.399)	(0.395)	(0.495)	(0.497)
SUPP_ROA	-0.021	-0.021	-0.029	-0.029	-0.005	-0.005
	(0.296)	(0.294)	(0.515)	(0.508)	(0.755)	(0.753)
SUPP_CAPEX	-0.030	-0.026	-0.224	-0.213	0.100	0.103
	(0.776)	(0.805)	(0.321)	(0.344)	(0.271)	(0.256)
HHI	2.808****	2.855***	8.320***	8.450***	2.472***	2.499***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.000)	(0.000)
HHI ²	-7.440**	-7.533**	-27.311**	-27.579**	-7.274***	-7.312***
	(0.022)	(0.020)	(0.035)	(0.032)	(0.001)	(0.001)
In(CUST_CONNECTIONS)	-0.043***	-0.045***	-0.139***	-0.142***	0.017*	0.016
	(0.003)	(0.002)	(0.000)	(0.000)	(0.088)	(0.113)
CUST_R&D	0.848***	0.827***	1.865***	1.807***	0.760***	0.744***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CUST_LEVERAGE	0.098***	0.100***	0.316***	0.321***	-0.029	-0.027
	(0.001)	(0.001)	(0.000)	(0.000)	(0.302)	(0.323)
SALES_TO_CUSTOMER	0.063**	0.062**	0.098	0.094	0.045**	0.044*
	(0.027)	(0.030)	(0.139)	(0.154)	(0.046)	(0.052)
In(DISTANCE)	-0.002	-0.001	-0.018*	-0.016*	-0.001	-0.000
	(0.467)	(0.659)	(0.060)	(0.085)	(0.743)	(0.972)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	8,748	8,748	8,748	8,748	8,748	8,748
Adj. <i>R</i> ²	0.500	0.501	0.613	0.614	0.556	0.557

innovation activities is 1.6 percentage points higher for connected pairs. Given that the sample average of TECH_PROXIMITY is 0.118, this estimate represents an economically important difference.

D. The Role of Third-Party Common Connections

So far, we focus on the *direct* social connections between executives and directors at the supplier and customer and find that they have a positive impact on supplier innovation and relation-specific investment. Supplier and customer

members can also be *indirectly* connected through common third-party friends in their social network. Since one of our arguments relies on the reputation among common social circles serving as a disciplinary mechanism to deter opportunistic behaviors under incomplete contracting, we predict that social connections will matter more when the individuals share a larger common social circle.

To test the conjecture above, we examine whether the impact of direct social connections on supplier innovation varies with common third-party connections between supplier and customer members.²⁴ Specifically, for any two members (executives and directors) from either side, we count the common connections they have outside the business relationship (e.g., third-party individuals that are socially connected with the supplier member and the customer member prior to the initiation of the trading relationship in question) and then aggregate them to obtain the total number of third-party common connections between the two firms in each year. To capture the strength of such indirect connections, we construct a dummy indicator (HIGH_3RD_CONNECTIONS), which is equal to 1 if the aggregate number of third-party connections with one of the two direct connection measures (CONNECTED or ln(PAIRWISE_CONNECTIONS)) to the baseline regressions and report the results in Table 6.

The results show that the coefficient estimates of the interaction terms are positive in all regressions and they are statistically significant at conventional levels for 7 out of 8 specifications. This evidence supports the complementary role of indirect connections and suggests that direct social connections are more effective in promoting supplier innovation when there are more third-party common connections between the supplier and customer members.²⁵ Importantly, these results speak directly to the reputation deterrent effects on breaching implicit contracts and exploiting sensitive information, suggesting that the broader notion of hold-up mitigation is one of the underlying channels through which social connections promote supplier innovation.

E. Further Analysis and Robustness Checks

In this section, we design additional tests to further test our hypothesis and conduct a battery of sensitivity tests to establish the robustness of our findings. These results are presented in Tables A3–A7 of the Supplementary Material.

Our first set of tests explore different types of social connections to strengthen the inferences that pre-existing social connections promote supplier (relationshipspecific) innovation. First, since executives are presumably more involved in

²⁴We thank the referee for suggesting this test.

²⁵We also construct a pairwise connection measure weighted by indirect connections between the supplier and customer members. Specifically, for any two connected members (executives and directors) from the supplier and customer, we use the decile rank of indirect connections (we divide the rank by 10 to make it range from 0.1 to 1) as the weight to aggregate the pairwise direct connections across all member pairs in each business relationship during the year. Then we regress the innovation outcomes on the weighted pairwise connections and report the results in Table A2 of the Supplementary Material. We find that the weighted connection measure has a significant and positive impact on supplier (relationship-specific) innovation and its coefficient estimates are generally larger in magnitude than those on the unweighted network measures in Tables 3–5.

TABLE 6 The Role of Third-Party Common Connections

Table 6 reports the results from regressions in which we interact direct social connections between supplier and customer members with their common third-party connections. HIGH_3RD_CONNECTIONS is a dummy variable, which takes the value of 1 if the aggregate number of third-party common connections between executives and directors at the supplier and customer is above the sample median, and 0 otherwise. The dependent variables are inflicated in the table header. We include the same set of control variables as in Table 3 and the coefficients of these control variables are suppressed for brevity. In parentheses are *p*-values based on robust standard errors (White (1980)) clustered by supplier-firm if the dependent variable is measured at the supplier firm-level or by supplier-customer pair if the dependent variable is at the pair-level (Petersen (2009)), **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

	SUP	P_R&D	In(PA1	ENTS)	In(CROSS_	CITATIONS)	TECH_PF	ROXIMITY
Dependent Variable	1	2	3	4	5	6	7	8
CONNECTED	0.000 (0.998)		0.025 (0.415)		0.041** (0.042)		0.003 (0.611)	
CONNECTED × HIGH_3RD_CONNECTIONS	0.011* (0.058)		0.091* (0.071)		0.072* (0.065)		0.035*** (0.008)	
In(PAIRWISE_CONNECTIONS)		0.000 (0.907)		0.048 (0.146)		0.039* (0.082)		0.008 (0.286)
$\label{eq:linear} \mbox{In(PAIRWISE_CONNECTIONS)} \times \mbox{HIGH_3RD_CONNECTIONS}$		0.008** (0.050)		0.032 (0.466)		0.090** (0.043)		0.028** (0.018)
HIGH_3RD_CONNECTIONS	-0.009 (0.175)	-0.009 (0.138)	0.004 (0.931)	0.029 (0.561)	0.037 (0.262)	-0.001 (0.983)	-0.009 (0.453)	-0.013 (0.295)
Control variables Year FE Supplier FE Pair FE	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes
No. of obs. Adj. R ²	12,568 0.853	12,568 0.853	8,748 0.854	8,748 0.854	8,748 0.614	8,748 0.615	8,748 0.557	8,748 0.558

operational matters of the firm, we expect their social connections to be more effective than those of nonexecutive directors for corporate innovation and relationship-specific investment. To test this intuition, we decompose the pairwise social connection measures into two components: one involves at least one executive on either side of the trading relationship and the other involves nonexecutive directors only. Consistent with our expectation, Table A3 in the Supplementary Material shows that the coefficients on social connections involving executives are statistically significant while those that only involve nonexecutive directors are much smaller and less significant, although they are also positive in most cases. Second, to further ensure that the formation of social connections based on education connections only, which are more likely to be formed at a distant time and space. We find that education connections, reported in Table A4, have a similar impact as our main network measures, further mitigating the reverse causality concern.

Our second test checks if the impact of social connections on supplier (relationship-specific) innovation depends on the prior history of the business relationship. From the entire Segment Filings, we observe that some of the business relationships appear in our sample for the first time while others have been terminated and then reemerge. Presumably, the past experience may have built trust between the supplier and the customer which helps sustain implicit contracts and facilitate cooperation. Therefore, we expect social connections to play a more important role in mitigating hold-up and enhancing cooperation if the two firms are doing business for the first time. Consistently, we find that social connections significantly correlate with four different proxies for supplier innovation when the business relationship is reported for the first time in the Segment Filing, as shown in Panel A of Table A5 in the Supplementary Material. On the contrary, as shown in Panel B, for business relationships that re-emerge in the segment filings, the coefficients on social connections are much smaller and mostly insignificant, with the exception when the dependent variable is cross-sections, although it is only significant at the 10% level (column 3 of Panel B). Overall, these results generally support our expectation that social connections are particularly effective in mitigating hold-up and enhancing cooperation for first-time business relationships.

Our third test checks the robustness of results on supplier R&D and the validity of the R&D sensitivity measure. Specifically, we split the sample based on whether the supplier firm operates in manufacturing (SIC code between 2,000–3,990) or nonmanufacturing industries. The social connection effect should be stronger in manufacturing industries since these industries produce unique and specialized products for customers where hold-up is a big concern and cooperation is important, compared with nonmanufacturing sectors (Titman and Wessels (1988), Banerjee et al. (2008)). This is exactly what we find in Table A6 in the Supplementary Material. This evidence suggests that we are not just capturing some mechanical or spurious relationship, which lends further support to our hypothesis.

Our last set of tests investigate the robustness of findings on supplier patenting activities. First, since the majority of our sample firm-years do not have any patents produced, we exclude firm-years with zero patents and repeat the regressions with patent-based dependent variables. Panel A of Table A7 shows that all the previous findings continue to hold in this subsample with nonzero patents. Second, we

conduct negative binomial regressions instead of ordinary least squares (OLS) regressions, with the raw number of patents or cross-citations as the dependent variable, to address the issue that patent and cross-citation counts are nonnegative and discrete. Our results remain qualitatively unchanged as shown in Panel B of Table A7. Third, in addition to customer R&D expenses, we include customer patent count (ln(CUST_PATENTS)), defined as the natural logarithm of 1 plus the number of eventually granted patents that are filed by customers in each year) in regressions with patent-based dependent variables. As shown in Panel C of Table A7, the coefficients on our main variables of interest (CONNECTED and ln(PAIRWISE_CONNECTIONS)) remain unchanged. Interestingly, the coefficients on ln(CUST_PATENTS) are significantly positively across six regressions, indicative of comovement of patenting activities by the supplier and customer.²⁶

F. Placebo Test

The inclusion of relationship or supplier firm fixed effects is helpful to account for any *time-invariant* unobservables at the relationship or supplier firm level that might simultaneously affect suppliers' innovation and their social connections with major customers. But still, there could be some *time-varying* industry shocks (e.g., deregulation) that affect both the productivity of innovation activities and the executive/director labor market which could mechanically lead to the results we document. To deal with such possibilities, we replace year fixed effects with supplier-industry × customer-industry × year fixed effects in our regressions to control for time-varying industry shocks and find similar results, as reported in Table A8 of the Supplementary Material.

Alternatively, we conduct placebo tests on *fake* supplier-customer pairs where the pseudo supplier is a random firm that operates in the same industry as the actual supplier but does not have any disclosed trading relationship with the customer in the entire Compustat Segment File. Thus, we keep the industry-pairs fixed so that any unobserved industry shocks that also affect the actual supplier-customer-pairs are accounted for in our placebo sample. Therefore, it provides a good testing ground to rule out unobserved factors at the industry-pair-level that could mechanically drive our results. Moreover, the placebo tests also help address the concern that our results are in some way a manifestation of existing findings that socially well-connected firms tend to be more innovative in general (Faleye et al. (2014)). If the overall social connectivity of the pseudo supplier is reflected in its connectivity with the customer firm, then we should continue to find that the pairwise social connections positively correlate with supplier innovation in this placebo sample.

The placebo results are reported in Panel A and B of Table 7. First, we find that only 30% of the *fake* trading relationships are socially connected by our definition, a number much smaller compared with the social connectedness we observe for the *real* supplier-customer relationships. Second, we find that the "within-pair" changes in social connections do not have any significant impact on the innovation

²⁶In an untabulated regression, we include the interaction term between ln(CUST_PATENTS) and the social connection measures. The coefficient of the interaction term is positive and marginally significant.

Social Connections and Supplier Innovation: Placebo Tests

Table 7 reports the regression results from placebo tests. The placebo sample is constructed by selecting a random firm in the same SIC 2-digit industry as the supplier for each supplier-customer pair in our sample. We require the random firm not to disclose the customer firm as key customer in the entire segment fillings. All regression specifications are the same as in Tables 3–5 except that we cannot control for the sales between "fake" suppliers and customers in the placebo sample. Dependent variables are indicated in each table header. In parentheses are *p*-values based on robust standard errors (White (1980)) clustered by supplier-firm if the dependent variable is measured at the supplier firm-level or by supplier-customer pair if the dependent variable is at the pair-level (Petersen (2009)). *, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

Panel A. Supplier R&D in Placebo Sample

			SUPP_R&D					
Dependent Variable		1	2	_	3	4		
CONNECTED		-0.006 (0.388)	-0.00 (0.79					
CONNECTED × CUST_R&D			-0.14 (0.40					
In(PAIRWISE_CONNECTIONS)					-0.003 (0.586)	0.001 (0.852)		
$In(PAIRWISE_CONNECTIONS) \times C$	UST_R&D					-0.140 (0.315)		
Control variables Year FE Pair FE		Yes Yes Yes	Yes Yes Yes		Yes Yes Yes	Yes Yes Yes		
No. of obs. Adj. <i>R</i> ²		10,265 0.874	10,26 0.87		10,265 0.874	10,265 0.874		
Panel B. Supplier Innovation Output	ts in Placebo S	Sample						
	In(PAT	ENTS)	In(CROSS_C	ITATIONS)	TECH_F	ROXIMITY		
Dependent Variable	1	2	3	4	5	6		
CONNECTED	-0.016 (0.644)		-0.003 (0.713)		0.006 (0.302)			
In(PAIRWISE_CONNECTIONS)		-0.004 (0.915)		0.008 (0.534)		0.010 (0.122)		
Control variables Year FE Supplier FE Pair FE	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes	Yes Yes Yes		
No. of obs. Adj. <i>R</i> ²	7,431 0.900	7,431 0.900	7,431 0.717	7,431 0.717	7,431 0.578	7,431 0.578		

activities of the randomly-chosen fake suppliers. Third, in this sample of fake trading relationships, connected suppliers do not significantly make more crosscitations and they do not produce patents that are more relevant to the customer's technology area (columns 3–6 of Panel B). These nonresults confirm that our baseline findings are not driven by unobserved industry shocks. They are also helpful to mitigate the concern that our results are driven by the overall large networks of supplier and customer members since we find that those connections between fake trading partners have no impact on the R&D and innovation by the pseudo supplier.

G. Identification Strategy

So far, our empirical approach has accounted for endogeneity concerns coming from unobserved time-invariant cross-sectional heterogeneity at the

relationship or supplier firm level by including pair or firm fixed effects. To rule out the possibility that time-varying sectoral shocks are driving our results, we control for suppler-industry × customer-industry × year fixed effects or conduct placebo tests by randomly picking "fake suppliers" from the same industry as the actual supplier. However, our strategies may not completely address the endogenous nature of connection changes, which could be a response to the anticipated changes in the strength of the trading relationship. For example, a socially connected supplier executive may be brought in to manage a trading relationship if the business is expected to grow bigger. This might be associated with an increase in supplier innovation stemming from the promise of future business with the customer; meanwhile, social connections also increase due to the arrival of the new executive. However, the relationship between social connections and supplier innovation is noncausal *since the connected executive is not the reason for the growth in the business*.

To further establish that social connections *causally* facilitate supplier innovation, we isolate a sample of departures from boards and managerial positions due to deaths or retirements. We employ a difference-in-differences (DID) design similar to Fracassi and Tate (2012) as discussed below, to isolate the impact of social connections on supplier innovation. Specifically, around each departure, we examine whether innovation (including the number of cross-citations and technological relatedness between the supplier's and customer's produced patents) drops for the affected supplier whose connection with its customer is weakened by the departure, relative to those suppliers whose connectedness to their customers remain unaffected.

We identify deaths and retirements of senior managers and directors from their profiles in BoardEx. To reduce the likelihood that the retirements are triggered by fundamental economic shocks, we define retirements as managers or directors leaving the firm at the age of 65 or above *and* having no positions in other firms afterward. We choose a 5-year investigation-window centered on the event year and remove those events that are confounded by other event(s) in the 5-year windows. Only those suppliers for which we can observe at least one firm-year observation before and at least one firm-year observation after the event are kept. The regressions are specified as follows:

(3) SUPP_INNOVATION_{*i*,*i*+1} or RELATION_SPECIFIC_INNOVATION_{*i*,*j*,*i*+1} = $\alpha_1 AFTER + \alpha_2 AFTER \times CONNECTED_DEPARTURE$ $+ \alpha_3 CONNECTED_DEPARTURE + X_{i,t}\beta + Y_{j,t}\gamma$ $+ Z_{i,i,t}\delta + u_{i,t} + v_t + \epsilon_{i,t} \text{ or } \epsilon_{i,i,t}.$

The outcome variables include both supplier-level innovation measures (supplier R&D spending and number of patent produced) and the other pair-level proxies (number of supplier cross-citations and technological proximity) as defined in Section II.B. AFTER is a dummy variable which takes the value of 1 for years after the event (retirement or death), and 0 otherwise. CONNECTED_DEPARTURE

is equal to 1 if the leaving member is socially connected with at least one member of the trading counterparty, and 0 otherwise.²⁷ We include an additional interaction term between AFTER and CONNECTED_DEPARTURE to capture the DID effect. Specifically, the coefficient on AFTER reflects the average within-firm changes in innovation activities around the events involving unaffected suppliers. The coefficient of the interaction term (AFTER × CONNECTED_DEPARTURE) will capture any incremental effect of these events on the affected suppliers' innovation activities. We control for the same set of supplier, customer, and pairlevel characteristics as before, in addition to year fixed effects and suppliercustomer-pair fixed effects.

We first examine departures at customer firms, which are typically much larger than the supplier firms in our sample (the mean ratio of supplier size to customer size is 10.2%, and the median is 1.5%, as reported in Panel B of Table 1).²⁸ The baseline regression results are reported in Panel A of Table 8. Column 1 reveals that R&D spending tapers off for affected suppliers after the departure of socially connected customer members. No significant changes in R&D investment are observed for those suppliers who are not connected with the leaving manager or director. Similarly, we find that the number of produced patents also declines for suppliers who share social connections with the leaving customer members. Moreover, after the departure, affected suppliers make fewer cross-citations toward their customers' patent portfolio and the patents they produce are less related to the subsample of departures caused by deaths to further ensure that the departures are exogenous to the trading relationship. Even though this sample is much smaller, most of our results continue to hold.²⁹

In addition to departures at the customer side, we also conduct the DID analyses around the departures of supplier's members.³⁰ The results, reported in Table 9, are weaker, but generally consistent with the results obtained from departures at the customer side. In Table A9 (A10) of the Supplementary Material, we conduct cross-sectional analyses based on the length of the business relationship at the time of the customer (supplier) member departure and find that the decrease in the innovation after the connected departures is more pronounced in the earlier years of business relationship. Overall, these results support the causal interpretation of the positive effect of social connections on supplier (relation-specific) innovation.

²⁷The CONNECTED_DEPARTURE variable can be estimated in regressions with pair fixed effects if the same supplier-customer pair has multiple events and the value of CONNECTED_DEPARTURE varies across events. Otherwise, it will drop out of the regression as in the case of the death sample analysis reported in Panel B of Tables 8 and 9.

²⁸Chu et al. (2019) rely on the size asymmetry in the bilateral relationship to identify changes that stem from customers and impose relatively exogenous variations on suppliers.

²⁹In untabulated results, we find that our results hold in the subsamples where the business relationships last at least 3 more years, mitigating the concern that the reduction in supplier innovation we document is driven by the (anticipated) business relationship termination.

³⁰We thank the referee for suggesting this test and the cross-sectional test based on the length of business relationship.

Supplier Innovation Around Departures of Customers' Members

Table 8 reports the DID analysis that exploits plausibly exogenous variations in social connections. Events are the retirements or deaths of directors and senior managers at the customer firm. Retirements are defined as customer managers or directors leaving the firm at the age of 65 or above and having no positions in other firms afterward. The event window contains 5 years centered on the retirement or death year ([-2, 2]). AFTER is a dummy variable which equals 1 for fiscal years after the retirement or death, and 0 otherwise. CONNECTED_DEPARTURE is a dummy variable which equals 1 if at least one education connection or prior employment connection exists between the retiree or deceased member at the customer and the directors or senior managers at the supplier, and 0 otherwise. Panel A reports the results using the full sample of departures (retirements and deaths) while Panel B focuses on director or senior manager deaths only. We include the same set of control variables as in Table 3 and the coefficients of these control variables are suppressed for brevity. In parentheses are *p*-values based on robust standard errors (White (1980)) clustered by supplier-firm if the dependent variable is measured at the supplier firm-level or by supplier-customer pair if the dependent variable is at the pair-level (Petersen (2009)).*, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

	SUPP_R&D	In(PATENTS)	In(CROSS_CITATIONS)	TECH_PROXIMITY
Dependent Variable	1	2	3	4
Panel A. Full Sample (Retirements and D	eaths of Custor	mers' Members)		
AFTER	0.004	0.029	0.032	0.004
	(0.182)	(0.130)	(0.214)	(0.640)
$AFTER \times CONNECTED_DEPARTURE$	-0.020***	-0.243**	-0.381**	-0.050*
	(0.010)	(0.043)	(0.045)	(0.058)
CONNECTED_DEPARTURE	-0.006	0.100**	0.160**	0.015
	(0.409)	(0.024)	(0.026)	(0.687)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
No. of obs.	4,225	3,305	3,305	3,305
Adj. <i>R</i> ²	0.821	0.743	0.738	0.719
Panel B. Departures Due to Deaths				
AFTER	0.006*	0.021	0.019	0.027
	(0.083)	(0.628)	(0.750)	(0.269)
$AFTER \times CONNECTED_DEPARTURE$	-0.006*	-0.276*	-0.537*	-0.111**
	(0.075)	(0.072)	(0.067)	(0.038)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
No. of obs.	871	536	536	536
Adj. <i>R</i> ²	0.936	0.553	0.570	0.727

H. Additional Investigations

So far, we have identified a significantly positive effect of pairwise connections on supplier innovation that has survived a comprehensive set of sensitivity tests and is robust to an identification strategy that exploits plausibly-exogenous variations in social connections.

Our results may potentially resolve a puzzle that has emerged in the literature on the finance and governance of firms in vertical relationships. Given that customer firms can benefit from their suppliers' relationship-specific investment and that there is the well-documented cost of full vertical integration, it might appear natural that contractual incompleteness could be better resolved via some form of partial integration, such as equity ownership or board representation by the downstream customer firms in their upstream suppliers. However, several authors have documented that this is extremely uncommon in the customer-supplier data compiled from Compustat. In fact, less than 3% of the relationships involve equity ownership by the customer, and a similar percentage involve board

Supplier Innovation Around Departures of Suppliers' Members

Table 9 reports the DID analysis that exploits plausibly exogenous variations in social connections. Events are the retirements or deaths of directors and senior managers at the supplier firm. Retirements are defined as supplier managers or directors leaving the firm at the age of 65 or above and having no positions in other firms afterward. The event window contains 5 years centered on the retirement or death year ([-2, 2]).AFTER is a dummy variable which equals 1 for fiscal years after the retirement or death, and 0 otherwise. CONNECTED_DEPARTURE is a dummy variable which equals 1 if at least one education connection exists between the retiree or deceased member at the supplier and the directors or senior managers at the customer and, 0 otherwise. Panel A reports the results using the full sample of departures (retirements and deaths) while Panel B focuses on director or senior manager deaths only. We include the same set of control variables as in Table 3 and the coefficients of these control variables are *p*-values based on robust standard errors (White (1980)) clustered by supplier-firm if the dependent variable is measured at the supplier firm-level or by supplier-customer pair if the dependent variable is at the pair-level (Petersen (2009)). *, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

	SUPP_R&D	In(PATENTS)	In(CROSS_CITATIONS)	TECH_PROXIMITY
Dependent Variable	1	2	3	4
Panel A. Full Sample (Retirements and D	eaths of Suppli	ers' Members)		
AFTER	0.001	0.047	0.028	-0.006
	(0.363)	(0.114)	(0.134)	(0.467)
$AFTER \times CONNECTED_DEPARTURE$	-0.004	-0.164**	-0.148**	-0.065**
	(0.230)	(0.048)	(0.025)	(0.042)
CONNECTED_DEPARTURE	-0.003	0.062	0.056	-0.018
	(0.377)	(0.592)	(0.594)	(0.690)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
No. of obs.	3,175	2,367	2,367	2,367
Adj. <i>R</i> ²	0.929	0.892	0.856	0.595
Panel B. Departures Due to Deaths				
AFTER	-0.013*	-0.124**	-0.069	-0.026
	(0.084)	(0.010)	(0.224)	(0.358)
$AFTER \times CONNECTED_DEPARTURE$	-0.015	-0.227*	-0.302*	-0.084*
	(0.382)	(0.092)	(0.094)	(0.067)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	Yes	Yes
No. of obs.	432	321	321	321
Adj. <i>R</i> ²	0.794	0.883	0.869	0.671

representation.³¹ It is possible that partial integration with smaller suppliers is not observed as it is too costly to do so for numerous small suppliers.³² Our results suggest that social connections are an effective and less costly mechanism to mitigate problems associated with contractual incompleteness. As noted before, in contrast to the lack of evidence in favor of partial integration, nearly half of customer-supplier relationships in our sample involve at least one social connection.

Social connections can have other interesting implications for vertical relationships. For example, firms could engage in a joint venture or strategic alliance to conduct innovative research and development (Seru (2014)). Does the presence or strength of social connections affect the way suppliers develop innovation with

³¹Fee et al. (2006) report that only 3.31% of customers hold a 5% or above equity stake at their suppliers for a sample of supplier-customer relationships identified from Compustat Segment files from 1988 to 2001. Minnick and Raman (2017) report that 4% (5%) of firms have directors/managers from customers (suppliers). Similarly, Dass, Kini, Nanda, Onal, and Wang (2014) document that only 1.2% of firms include executives or directors from suppliers or customers on the board.

³²Partial integration is likely to have its own costs. For example, a principal customer that holds equity stake or a board seat in the supplier may exert too much influence, which might impair the supplier's relationships with other (principal) customers.

Social Connections and the Boundary of the Firm

Table 10 reports the results from OLS regressions of supplier-customer-pair-level JV-Alliance on the social connections between suppliers and customers. The dependent variable is a dummy variable which equals 1 if the supplier has established a joint venture or strategic alliance with the customer, and 0 otherwise. Other variable definitions are in the Appendix. We control for year and supplier fixed effects in both specifications. In parentheses are *p*-values based on standard errors adjusted for heteroscedasticity (White (1980)) and supplier-customer-pair clustering (Petersen (2009)).*, **, and *** stand for statistical significance based on 2-sided tests at the 10%, 5%, and 1% levels, respectively.

	JV_ALLIANCE_DUMMY				
Dependent Variable	1	2			
CONNECTED	0.014** (0.011)				
In(PAIRWISE_CONNECTIONS)		0.011** (0.040)			
In(SUPP_CONNECTIONS)	-0.018*** (0.006)	-0.018*** (0.006)			
SUPP_SIZE	0.006 (0.298)	0.006 (0.291)			
SUPP_LEVERAGE	-0.024 (0.167)	-0.024 (0.177)			
SUPP_MB	0.000 (0.879)	0.000 (0.888)			
SUPP_TANGIBILITY	0.028 (0.566)	0.028 (0.570)			
SUPP_ROA	-0.018* (0.071)	-0.018* (0.069)			
SUPP_CAPEX	-0.117** (0.013)	-0.115** (0.014)			
HHI	0.516 (0.459)	0.532 (0.447)			
HHI ²	- 1.935 (0.555)	1.979 (0.548)			
In(CUST_CONNECTIONS)	-0.005 (0.568)	-0.004 (0.575)			
CUST_R&D	0.375** (0.013)	0.373** (0.014)			
CUST_LEVERAGE	0.056** (0.032)	0.057** (0.030)			
SALES_TO_CUSTOMER	-0.001 (0.941)	-0.001 (0.946)			
In(DISTANCE)	-0.001 (0.842)	-0.001 (0.881)			
Year FE Supplier FE	Yes Yes	Yes Yes			
No. of obs. Adj. <i>R</i> ²	12,568 0.533	12,568 0.533			

their major customers? Answering such questions would speak to the boundary of their operations and thus enrich the scope of our empirical analysis.

We collect the information on all the joint ventures and strategic alliances (JV-Alliance) between the suppliers and customers in our sample from the SDC Platinum Database. The establishment of JV-Alliance is considered as an avenue to conduct R&D-intensive innovation activities (Seru (2014)). If social connections could encourage such cooperation in innovative projects, we should observe that connected pairs are more likely to form JV-Alliance. The results from linear probability models reported in Table 10 confirm the above conjectures. Specifically, we find that socially connected suppliers and customers are more likely to establish R&D-intensive joint ventures or strategic alliances for cooperative innovative projects. Overall, these additional investigations complement our previous findings on supplier innovation activities and suggest that the impact of social connections extends to other important aspects of vertical relationships.

IV. Conclusion

In this paper, we offer one explanation for why innovative upstream firms can remain independent even though contracts may be incomplete. We find that preexisting social connections between upstream suppliers and their downstream customers are quite common. We show that (relation-specific) innovative activities by suppliers increase when they have social connections with their customers and when the social connections are stronger, suggesting that social connections mitigate the hold-up problem associated with contractual incompleteness and facilitate cooperation in vertical relationships.

One caveat of our study is that our data do not identify the full set of suppliers of the customer firms, but only those for whom the customer contributes a major part of their sales. It would be interesting in future work to examine whether social connections play a similar role for relationships with "important suppliers," or other mechanisms such as partial integration (e.g., equity ownership or board representation in the supplier firms) are more common ways to mitigate problems stemming from contractual incompleteness in relationships with "important suppliers." Such mechanisms are very uncommon in our data, possibly because the suppliers that we are able to identify are small suppliers and it may be too costly for the customer to partially integrate with so many of them.

Appendix. Variable Definitions

Dependent Variables

SUPP_R&D: Supplier's R&D expenses (XRD) over book value of total assets (AT).

- NUM_OF_PATENTS: Supplier's total number of patents filed (and eventually granted) in year t + 1.
- ln(PATENTS): Natural logarithm of 1 plus a firm's total number of patents filed (and eventually granted) in year t + 1.
- CROSS_CITATION_DUMMY: Dummy variable: 1 if the supplier has produced any patent that cites the customer's patent portfolio in year t + 1, and 0 otherwise.
- NUM_OF_CROSS_CITATIONS: Number of citations made by supplier's patents filed (and eventually granted) in year t + 1 toward customer's patent portfolio.
- ln(CROSS_CITATIONS): Natural logarithm of 1 plus the number of citations made by supplier's patents filed (and eventually granted) in year t + 1 toward customer's patent portfolio.
- TECH_PROXIMITY: Following Jaffe (1986), the technology proximity between supplier i and customer j is defined as:

TECH_PROXIMITY_{*ij*} =
$$\frac{N_i N_j'}{(N_i N_i')^{1/2} (N_j N_j')^{1/2}}$$
,

where $N_i = (N_{i1}, N_{i2}, ..., N_{i37})$ is a vector indicating the scope of innovation activities by supplier *i* with each element is the share of patents applied (eventually granted) in year t + 1 in each technology class. We match the 426 technology classes assigned by USPTO to 37 subcategories using the mapping in Hall et al. (2001). N_j is the scope of patent portfolios produced by the customer in the past 3 years.

JV_ALLIANCE_DUMMY: Dummy variable: 1 if the supplier has established a joint venture or strategic alliance with the customer, and 0 otherwise.

Social Connections

- CONNECTED: Dummy variable: 1 if at least one education connection or prior employment connection exists between the supplier and customer, and 0 otherwise.
- NUM_OF_PAIRWISE_CONNECTIONS: Number of total education and prior employment connections between the supplier and customer.
- In(PAIRWISE_CONNECTIONS): Natural logarithm of 1 plus the detrended number of total education and prior employment connections between the supplier and customer.
- In(SUPP_CONNECTIONS): Natural logarithm of 1 plus the detrended number of unique education and prior employment connections that the supplier's senior managers and directors have in BoardEx.
- In(CUST_CONNECTIONS): Natural logarithm of 1 plus the detrended number of unique education and prior employment connections that the customer's senior managers and directors have in BoardEx.
- HIGH_3RD_CONNECTIONS: Dummy variable: 1 if the aggregate number of third-party common connections between the supplier and customer members is above sample median, and 0 otherwise. We define third-party common connections as individuals outside the trading relationship that are connected to at least one supplier member and one customer member prior to the initiation of the trading relationship.

Supplier Characteristics

- SUPP_SIZE: Natural logarithm of the supplier's book value of total assets (AT).
- SUPP_LEVERAGE: Supplier's book value of debts (DLTT + DLC) over market value of total assets (AT CEQ + CSHO × PRCC).
- SUPP_MB: Supplier's market value of total assets (AT $CEQ + CSHO \times PRCC$) over book value of total assets (AT).
- SUPP_TANGIBILITY: Supplier's net PPE (property, plant and equipment) (PPENT) over book value of total assets (AT).
- SUPP_ROA: Supplier's income before extraordinary items (IB) over book value of total assets (AT).
- SUPP_CAPEX: Supplier's capital expenditures (CAPX) over book value of total assets (AT).

- HHI: The sum of squared market shares in sales (SALE) of the supplier's industry. Industry is defined using 2-digit SIC code.
- **Customer Characteristics**
- CUST R&D: Customer's R&D expenses (XRD) over book value of total assets (AT).
- CUST_LEVERAGE: Customer's book value of debts (DLTT + DLC) over market value of total assets (AT CEQ + CSHO \times PRCC).

Pair-Level Characteristics

- SALES_TO_CUSTOMER: Supplier's sales to the customer (SALECS) firm scaled by supplier's book value of total assets (AT).
- DISTANCE: The geographical distance (in miles) between the headquarters of the supplier and its customer.
- SUPP_CUST_SIZE_RATIO: Supplier's book value of total assets over customer's book value of total assets.

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/ 10.1017/S002210902000068X.

References

- Akcigit, U.; M. A. Celik; and J. Greenwood. "Buy, Keep, or Sell: Economic Growth and the Market for Ideas." *Econometrica*, 84 (2016), 943–984.
- Allen, F., and A. Babus. The Network Challenge (Chapter 21): Networks in Finance. Pearson Education (2009).
- Allen, J. W., and G. M. Phillips. "Corporate Equity Ownership, Strategic Alliances, and Product Market Relationships." *Journal of Finance*, 55 (2000), 2791–2815.
- Banerjee, S.; S. Dasgupta; and Y. Kim. "Buyer-Supplier Relationships and the Stakeholder Theory of Capital Structure." *Journal of Finance*, 63 (2008), 2507–2552.
- Barrot, J.-N., and J. Sauvagnat. "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks." *Quarterly Journal of Economics*, 131 (2016), 1543–1592.
- Bena, J., and K. Li. "Corporate Innovations and Mergers and Acquisitions." Journal of Finance, 69 (2014), 1923–1960.
- Brown, D. T.; C. E. Fee; and S. E. Thomas. "Financial Leverage and Bargaining Power with Suppliers: Evidence from Leveraged Buyouts." *Journal of Corporate Finance*, 15 (2009), 196–211.
- Cai, Y., and M. Sevilir. "Board Connections and M&A Transactions." Journal of Financial Economics, 103 (2012), 327–349.
- Chu, Y.; X. Tian; and W. Wang. "Corporate Innovation along the Supply Chain." Management Science, 65 (2019), 2445–2466.
- Dass, N.; J. R. Kale; and V. Nanda. "Trade Credit, Relationship-Specific Investment, and Product Market Power." *Review of Finance*, 19 (2014), 1867–1923.
- Dass, N.; O. Kini; V. Nanda; B. Onal; and J. Wang. "Board Expertise: Do Directors from Related Industries Help Bridge the Information Gap?" *Review of Financial Studies*, 27 (2014), 1533–1592.
- Duchin, R., and D. Sosyura. "Divisional Managers and Internal Capital Markets." *Journal of Finance*, 68 (2013), 387–429.
- Dyer, J. H., and H. Singh. "The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage." Academy of Management Review, 23 (1998), 660–679.
- Ellis, J. A.; C. E. Fee; and S. E. Thomas. "Proprietary Costs and the Disclosure of Information about Customers." *Journal of Accounting Research*, 50 (2012), 685–727.

- Engelberg, J.; P. Gao; and C. A. Parsons. "Friends with Money." Journal of Financial Economics, 103 (2012), 169–188.
- Engelberg, J.; P. Gao; and C. A. Parsons. "The Price of a CEO's Rolodex." *Review of Financial Studies*, 26 (2013), 79–114.
- Faleye, O.; T. Kovacs; and A. Venkateswaran. "Do Better-Connected CEOs Innovate More?" Journal of Financial and Quantitative Analysis, 49 (2014), 1201–1225.
- Fee, C. E.; C. J. Hadlock; and S. Thomas. "Corporate Equity Ownership and the Governance of Product Market Relationships." *Journal of Finance*, 61 (2006), 1217–1251.
- Fee, C. E., and S. Thomas. "Sources of Gains in Horizontal Mergers: Evidence from Customer, Supplier, and Rival Firms." *Journal of Financial Economics*, 74 (2004), 423–460.
- Fracassi, C., and G. Tate. "External Networking and Internal Firm Governance." Journal of Finance, 67 (2012), 153–194.
- Frésard, L.; G. Hoberg; and G. M. Phillips. "Innovation Activities and Integration through Vertical Acquisitions." *Review of Financial Studies*, 33 (2020), 2937–2976.
- Glaeser, E. L., D. I. Laibson; J. A. Scheinkman; and C. L. Soutter. "Measuring Trust." *Quarterly Journal of Economics*, 115 (2000), 811–846.
- Gomes-Casseres, B.; J. Hagedoorn; and A. B. Jaffe. "Do Alliances Promote Knowledge Flows?" Journal of Financial Economics, 80 (2006), 5–33.
- Griffith, R.; S. Redding; and J. Van Reenen. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics*, 86 (2004), 883–895.
- Hall, B. H.; A. B. Jaffe; and M. Trajtenberg. "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools." NBER Working Paper No. 8498 (2001).
- Henke, J. W., and C. Zhang. "Increasing Supplier-Driven Innovation." MIT Sloan Management Review, 51 (2010), 41.
- Hertzel, M. G.; Z. Li; M. S. Officer, and K. J. Rodgers. "Inter-Firm Linkages and the Wealth Effects of Financial Distress along the Supply Chain." *Journal of Financial Economics*, 87 (2008), 374–387.
- Holmström, B. "Agency Costs and Innovation." Journal of Economic Behavior & Organization, 12 (1989), 305–327.
- Huston, L., and N. Sakkab. "Connect and Develop." Harvard Business Review, 84 (2006), 58-66.
- Ishii, J., and Y. Xuan. "Acquirer-Target Social Ties and Merger Outcomes." Journal of Financial Economics, 112 (2014), 344–363.
- Jaffe, A. B. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value." *American Economic Review*, 76 (1986), 984–1001.
- Jaffe, A. B.; M. Trajtenberg; and M. S. Fogarty. "Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors." *American Economic Review*, 90 (2000), 215–218.
- Kale, J. R., and H. Shahrur. "Corporate Capital Structure and the Characteristics of Suppliers and Customers." *Journal of Financial Economics*, 83 (2007), 321–365.
- Klein, B.; R. G. Crawford; and A. A. Alchian. "Vertical Integration, Appropriable Rents, and the Competitive Contracting Process." *Journal of Law & Economics*, 21 (1978), 297–326.
- Kogan, L.; D. Papanikolaou; A. Seru; and N. Stoffman. "Technological Innovation, Resource Allocation, and Growth." *Quarterly Journal of Economics*, 132 (2017), 665–712.
- Liang, L.; R. Williams; and S. C. Xiao. "Stock Market Information and Innovative Investment in the Supply Chain." Working Paper, University of Arizona (2020).
- Marco, A. C.; A. F. Myers; S. J. Graham; P. A. D'Agostino; and K. Apple. "The USPTO Patent Assignment Dataset: Descriptions and Analysis." Working Paper, Georgia Institute of Technology (2015).
- Minnick, K., and K. Raman. "Board Composition and Relationship-Specific Investments by Customers and Suppliers." *Financial Management*, 46 (2017), 203–239.
- Petersen, M. A. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies*, 22 (2009), 435–480.
- Serrano, C. J. "The Dynamics of the Transfer and Renewal of Patents." *RAND Journal of Economics*, 41 (2010), 686–708.
- Seru, A. "Firm Boundaries Matter: Evidence from Conglomerates and R&D Activity." Journal of Financial Economics, 111 (2014), 381–405.
- Titman, S., and R. Wessels. "The Determinants of Capital Structure Choice." *Journal of Finance*, 43 (1988), 1–19.
- White, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica*, 48 (1980), 817–838.