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The Dark Side of Stakeholder Influence: The Surprising Effect of Customer Fraud on Suppliers

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JEL Classification: G14, G3, L14, L24

Keywords: Playing it safe, Corporate Fraud, Explorative innovation, Exploitative innovation, Supply Chain

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The Dark Side of Stakeholder Influence: The Surprising Effect of Customer Fraud on Suppliers[#]

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1. Introduction

The role of non-financial stakeholders – that is, customers, suppliers, employees, and communities – in corporate governance is now a subject of considerable debate. The influential Business Roundtable in 2019 embraced a new statement of "corporate purpose", namely, that corporations should consider the interests and be accountable to not only shareholders but all other constituencies affected by corporate decisions. The statement, endorsed by the CEOs of more than 180 major public companies, has raised controversy. For example, it has been argued that (a) the support for stakeholder governance may be motivated by a desire to reduce accountability to shareholders, and would serve the private interests of corporate managers, and (b) corporations are not the best agents for solving social problems when externalities are involved, and the task is best left to regulators (Bebchuk and Tallarita, 2020).

In this paper, we provide evidence on the dark side of stakeholder influence. We argue that when influential stakeholders cannot commit to long-term relationships with the firm, they may have a distortionary effect on corporate policies. Our evidence suggests that managers are vulnerable to stakeholder pressure, and this can manifest in weaker firm performance and lower survival likelihood. In other words, more stakeholder influence, instead of "growing the pie", can in fact shrink it and can undermine the very "stakeholderism" model it is supposed to promote.

The stakeholders we consider are an upstream (supplier) firm's major downstream corporate customers, often accounting for at least 10 percent of the upstream firm's sales. About a third of all listed firms (half of all manufacturing firms) sell to a major customer (henceforth, "principal customer") in any given year. We find that the presence of these stakeholders causes the supplier firms to focus on innovation activities that are beneficial mainly to the customer, at the expense of a more diversified innovation strategy that could have value outside the relationship. We show that when these major customers become less important for a supplier firm's prospects due to reasons that are exogenous to the supplier, the latter pursues a more diversified innovation strategy, attracts more customers, enjoys faster sales growth, has higher Tobin's Q, and improves its long-term survival likelihood.

We argue that a possible reason for these results is a preference by supplier managers for "safety" in the short-term. Gormley and Matsa (2016) argue that many corporate decisions can be understood from the perspective of managers wanting to "play it safe", i.e., reducing firm risk, possibly at the expense of shareholder wealth, so that they are not confronted with the prospect of default and losing their jobs. Our results are consistent with such a "play-it-safe" motive; however, as we explain below, they are likely driven by a preference for safety in the shorter term by managers with short decision horizons. Indeed, these managerial actions, as we show, make the firm *less* safe in the longer term, while destroying shareholder value.

In our context, supplier managers' preference for safety in the shorter rather than the longer term affects their choice of innovation strategy. Innovation can be either *explorative* or *exploitative* (March, 1991). Explorative innovation (or, more broadly, *experimentation*) "involves search, risk-taking, and experimentation with new technologies or new areas of knowledge." Exploitation (or more broadly, *developing known opportunities*), on the other hand, "… is the refinement of existing and familiar technologies." (Manso, Balsmeier, and Fleming, 2019). Exploration may be perceived to be riskier in the short term as the path to success is only known through experimentation and possible failure, but once successful, it can enable a firm to generate more diversified revenue streams or create niche markets more immune to competitive threats.

Figure 1 shows possible cumulative firm failure probabilities as a function of time from these two alternative strategies. Here, Strategy A (experimentation) is riskier than strategy B (developing known opportunities) in the short term, but safer in the longer term. Managers could prefer strategy B if their horizons are short and are evaluated on the basis of their short-term performance. We argue that this is plausible – a recent literature finds extensive evidence that short-termism affects managerial behavior and can distort managerial incentives.[1] Managers could also be "uncertainty averse" in the short term.[2] Thus, managerial preference for safety in the short term could impede experimentation and ultimately make the firm riskier in the longer term. Not only could this destroy shareholder value, but when the firm itself becomes riskier in the longer term, various stakeholders are also adversely affected. Such a possibility undermines the entire stakeholder governance model. In this paper, we provide evidence consistent with these possibilities.[3]

While the preference for exploitative over explorative innovation could manifest even in the absence of major customers, any distortion is likely to be exacerbated when the latter are present. It is well-recognized that upstream suppliers often make non-transferable investments in production processes and innovation to meet their downstream customers' specific requirements.[4] Transaction cost economics argues that relationship-specificity subjects the suppliers to hold-up problems and customer opportunism (Klein, Crawford, and Alchian, 1978). The principal customers in our sample are much larger firms, delegate much of their

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[1] The effects of short-termism on corporate policy have been documented, (e.g., Asker, Farre-Mensa, and Ljungqvist, 2015; Edmans, Fang, and Lewellen, 2017, among others). Some researchers attribute short-termism to the importance of "short-term prices" (Stein, 1989; Bushee, 1998; Derrien, Kecskés, and Thesmar, 2013) or short-term goals of certain types of institutional investors. Others argue that it is driven by the focus on short-term performance targets such as earnings per share (Almeida, Fos, and Kronlund, 2016) and their inclusion in executive compensation contracts (Cheng, Harford and Zhang, 2015; Bennett, Bettis, Gopalan, and Milbourn, 2017). See also Almeida (2018).

[2] Uncertainty aversion, or a preference for known risks over unknown risks, is also referred to as "ambiguity aversion" and has been formalized by Schmeidler (1989) and Gilboa and Schmeidler (1989). Massari and Newton (2020) and Marinacci and Massari (2019) show that, under some conditions, ambiguity fades away via learning in the long term. However, managers with short horizons may not have the incentive to learn via experimentation.

[3] Chen, Su, Tian and Xu (2021) provide evidence that supplier managers with a concentrated customer base are provided risk-taking incentives, especially when the cost of losing large customers is high.

[4] The importance of such relationship-specific investments has been extensively discussed in the literature on transaction cost economics and property rights in understanding the boundary of the firm (Williamson, 1975; Klein, Crawford, and Alchian, 1978; Dyer and Singh, 1998).

innovation requirements to their suppliers, and enjoy bargaining power.[5] However, the length of the typical customer-supplier relationship is not very long-term – only about six years (Costello, 2013; Cen, Dasgupta, and Sen, 2016). Relationship continuation is likely to depend on the supplier's ability to fulfill the customer's expectation of innovation that improves the latter's products or production processes. Even when the customer changes its product or production technology, suppliers that were successful in generating relationship-specific innovation may expect to be rewarded with contract extension or new contracts.

The loss of a major customer can have a serious negative impact on the career prospects of a supplier CEO: the typical CEO tenure (Cziraki and Jenter, 2020) is of the order of five to seven years.[6] As a result, exploitative innovation that is more incremental and directly beneficial to the customer (e.g., improvements specific to a product manufactured by the customer) could be prioritized at the expense of explorative innovation that is valuable outside the relationship, or to a broader customer base. However, exploitative customer-specific innovation may not confer major long-term benefits to shareholders since the customer cannot commit to a long-term relationship. Therefore, the incentive of supplier managers to prioritize short-term safety and cater to the principal customer could result in insufficient explorative innovation, with potentially adverse consequences for firm value and survival in the longer term.

Our empirical strategy exploits the impact of the revelation of financial fraud by principal customers on the incentives of supplier managers to pursue explorative, rather than exploitative, innovation. The revelations of customer frauds are associated with significant

[5] As several authors note, customer-specific innovation by upstream firms is increasingly becoming the norm (Henke and Zhang, 2010; Pihlajamaa, Kaipia, Aminoffd, and Tanskanen, 2019).

[6] Cziraki and Jenter (2020) report that CEOs of smaller firms move to non-CEO executive positions at larger firms. The career goals of the managers of the supplier firms could be similar, i.e., find executive positions in larger firms.

reputational costs for these firms. In our sample, fraud revelations are associated with significant shareholder value loss for the customer firms (around 10%). Such shocks could potentially impact the supplier firm's incentive to engage in innovation in different ways. It is important to realize that such shocks could lead to more shareholder-preferred outcomes for the supplier only if either (or both) of two conditions are satisfied: (a) customer bargaining power decreases, and (b) the shocks reduce the manager's benefit from pursuing actions that destroy shareholder value.[7]

First, the revelation of fraud could lower the customer's bargaining power. The customer may not be able to attract new suppliers, and is likely to need the current supplier even more than before to produce dedicated innovation. This weakened bargaining power could result in price concessions or other guarantees from the customer, and the supplier, as a result, would engage in even more relationship-specific innovation. This, other things unchanged, is a "positive shock" to both the supplier firm's shareholders and the manager (especially one who is sensitive to short-term outcomes).

Second, the fraudulent customer might have to slow down its own growth and its purchases from its suppliers as it recovers from the adverse consequences of the fraud. As a result, the return from exploitative customer-specific innovation could be lower. A manager acting in the interest of shareholders would then engage in less customer-specific innovation. In this case, the revelation of the customer fraud is a negative shock to the firm's shareholders, as well as the manager.

Third, the outcome could be driven by the very nature of innovation activity, namely, that it is difficult to write complete contracts, since the deliverables are difficult to specify ex-

[7] There is a significant literature on customer bargaining power and supply chain outcomes. See, for example, Bhattacharyya and Nain (2011).

ante. Thus, the relationship has to be sustained via implicit contracts. The supplier manager would engage in exploitative innovation that benefits the customer as long as there is an expectation that the customer would honor the implicit contract and "reward" the supplier by continuing the relationship if the latter produces relationship-specific innovation. However, a fraud event is likely to be associated with managerial turnover in the customer firm, with new personnel in decision-making roles who may have no knowledge of previous implicit arrangements, and a general breakdown of trust. Under these circumstances, there is less certainty that the customer will not engage in opportunistic behavior after its fraud is revealed. In this case, the supplier's incentive to engage in customer-specific exploitative innovation would be reduced. This is a negative shock to the manager, as it exposes the manager to more risk or uncertainty in the short term. However, it could be a positive shock for the shareholders if managerial preference for short-term safety and reluctance to engage in experimentation was responsible for a sub-optimally diversified innovation strategy prior to the shock.

This third scenario is the only one in which customer fraud would lead to more shareholder-preferred outcomes for the supplier firm in the longer term (e.g., more sales growth, higher Tobin's Q, lower risk, and higher long-term survival likelihood), together with lower R&D expenditure, more explorative and less exploitative innovation. In the first scenario, shareholder preferred outcomes could be observed, but this should be associated with more relationship-specific innovation and possibly more R&D and overall innovation activity, as measured by total patent counts. It is also unlikely that such a shock would lead to more sales to other customers relative to the affected customer. In the second scenario, while more explorative innovation would occur, more shareholder-preferred outcomes are unlikely to emerge, as the shock is a negative shock (and there are no managerial agency problems in this scenario).[8]

For our empirical tests, we identify a sample of financial frauds committed by publicly listed firms and obtain information on their suppliers from the FactSet Revere and Compustat databases. We then manually compile the dates when the financial fraud was first publicly revealed.[9] For each fraud event, we match each affected supplier to another firm in the same 2-digit SIC industry as the supplier. In a stacked difference-in-difference setting, we examine how the innovation activities, sales growth, diversity of customer base, Tobin's Q, and firm risk of the treated suppliers are affected relative to the control group. We then examine the effect of innovation strategy on the 10-year survival probability in cross-sectional regressions, and establish the mechanism through which survival likelihood is affected.

We find that, subsequent to customer fraud revelation, suppliers spend less on R&D and generate fewer patents. Moreover, they shift their innovation areas away from those of the fraudulent principal customer. They also engage in more explorative innovation and less exploitative innovation. This is what we expect, irrespective of the existence of managerial agency issues. However, while their sales to the fraudulent customer flattens out, they add new customers and outperform the control firms in terms of overall sales growth. They also outperform control firms in terms of Tobin's Q, and overall firm risk (as measured by the annualized standard deviation of daily stock returns) is lower. Compared to suppliers in the same industry, their survival likelihood is higher over a 10-year period.[10] The survival effect is

[8] One caveat for the third scenario is that the manager's decision to engage in excessive customer-specific innovation prior to the shock may also be in the best interest of the shareholders. We discuss this issue further at the end of this section and in section 3.6.1.

[9] We use information from the Security and Exchange Commission's website to obtain enforcement releases in order to identify fraudulent customers and their initial public revelation dates. Details are provided in section 2.1.

[10] The effect is quantitatively important. Univariate comparisons show that while the failure rate of the affected suppliers over the ten-year period is 8.17%, that for the control group is 12% -- this nearly 4% difference is substantial in the context of an overall failure rate of the two groups combined of 11%.

nuanced: while in the first three years, more of the suppliers of fraudulent customers exit, the *cumulative* survival rate for the suppliers of fraudulent customers is above that of the control group after the first three years.

We show that our results are unlikely to be due to common shocks that cause customer fraud prior to fraud revelation and could affect suppliers at the same time. Since the period over which fraud is committed typically precedes the year fraud is revealed, we are able to check whether the suppliers' innovation activities change when fraud is actually being committed (possibly due to prevailing industry conditions). We find no such evidence.

We find that engaging in more explorative innovation improves survival likelihood. First, we show that in a matched sample of suppliers with fraudulent principal customers and other suppliers from the same 2-digit SIC industry, those generating more explorative innovation are more likely to survive than those generating more exploitative innovation. Second, we use the causal mediation analysis procedure developed by Dippel, Gold, Heblich, and Pinto (2019) to see if explorative innovation contributes to higher survival likelihood. We consider the change in sales to all principal customers in the year of the fraud revelation compared to one year before as the treatment, and explorative innovation as the mediator variable, respectively. Both are instrumented by an indicator variable which takes the value of 1 if the supplier's customer committed fraud, and zero otherwise. We find that both the indirect effect of the treatment via the mediator (explorative innovation) on the 10-year survival probability is significantly positive. We do not find corresponding significant effects for alternative mediation variables such as sales, general and administrative expenses or R&D.

Overall, these results support the view that the myopic incentive of managers to prolong an ongoing relationship with a principal customer leads to over-investment in customer-specific innovation at the cost of a more diversified innovation strategy which could be more beneficial in the longer term. We emphasize that our results *do not* suggest that firms should avoid business relationships with customers who place large orders with them. Indeed, attracting more principal customers is a way firms grow and develop reputation (Cen, Dasgupta, Elkamhi, and Pungaliya, 2015).[11] What we show is that together with the beneficial effects, there is a "dark side" to reliance on principal customers. A combination of managerial agency problems, customer bargaining power, and the inability of the customers to commit to a long-term relationship prevents optimal diversification of innovation, and undermines long-term growth and survival. Identifying these problems associated with powerful stakeholders goes to the heart of the recent debate on "stakeholderism", i.e., the risks of making managers accountable to stakeholders as opposed to shareholders.

1.1 Contribution and Relationship to Recent Literature

Aside from addressing the recent debate on stakeholder governance, our study is related to several strands of literature. We now discuss these connections, and our contribution.

First, our paper is most closely related to several papers that address the choice between explorative and exploitative innovation. Our results are consistent with the arguments in Manso, Balsmeier, and Fleming (2019), who present a model that is based on the tension between exploration and exploitation that is inherent in innovation activity. When future sales are likely to be lower, the return from exploitation (e.g., process innovation that lowers production costs) declines. At the same time, the cost of failure from exploration is lower, since profits are low anyway. As a consequence, more explorative innovation occurs at the expense of exploitative innovation. A similar mechanism is likely to be at work in our context, reinforced by the fact that the affected customer might need to scale down its operations and

[11] Chen, Dasgupta, Huynh and Xia (2021) show that suppliers relocate near principal customers and increase relationship-specific innovation to insulate themselves from foreign competition.

even exit if the consequences of the fraud are serious enough. This reduces the return from exploitative innovation and encourages explorative innovation. Moreover, as Balsmeier, Fleming, and Manso (2017) suggest, firms in general (and not only the suppliers) may be innovating sub-optimally due to other types of frictions, and their survival might improve when the tradeoff changes against exploitative innovation. For example, managers may have incentives to generate more patents that are incremental rather than aim for riskier, higher-impact patents, especially when boards over-scrutinize managers; both boards and managers may be myopic and sensitive to the fact that the stock market does not properly recognize the long-term value of new types of innovation. As Manso, Balsmeier, and Fleming (2019) observe, there may exist "inherent biases towards exploitation, for example, due to the imperfect protection of property rights, or the difficulty of commercializing new technologies and appropriating their profits for the inventing firm." If the return to exploitation decreases, such biases are less likely to be important, and firms can be better off.

Our results are also related to Almeida et al. (2021) who examine the effect of share repurchase programs on firms' innovation. Using a regression discontinuity design that allows them to examine the effect of opportunistic use of share repurchases to boost earnings per share marginally above analysts' median estimates, the authors find that such repurchases are associated with lower R&D, but higher patenting activity. In addition, the patents are of higher quality, as indicated by citations and stock market reactions to the patent grants. There is a significant shift to explorative patents and innovation in new technological areas. The authors argue that the results suggest that short-term earnings pressure causes managers to cut R&D spending, but work harder within their existing R&D budgets. By focusing on more novel and productive innovation, they "can balance the interests of both short-term and long-term investors".

Our results are different from those documented in a contemporaneous paper by Selvam and Tan (2020) who examine the effect of covenant violations by customers on the suppliers' innovation. The authors find that suppliers innovate more, cite the customer patents more, and increase the overlap with the customer's innovation areas. This is attributed to the "bonding hypothesis," namely, due to its weakened bargaining power, the customer provides monetary and non-monetary incentives (e.g., in the form of more information sharing) to retain its supplier relationships. Financially impaired customers may also have an incentive to outsource innovation to suppliers. In contrast, we find that following financial fraud by the customer, suppliers innovate less, and move their innovation away from the affected customer by engaging in more diversified innovation. One possible reason why our results are different is that the expectation that implicit contracts would be honored is necessary for suppliers to engage in relationship-specific innovation. However, it is this crucial component of the relationship that is most called into question when the customer's reputation is affected. Related, the magnitude of the shock to the customer's reputation and the implications for its future cash flows in our case is also substantial – in our sample, the customers suffer abnormal returns of -10% around the revelation of fraud.

Second, we add to a growing literature on innovation in the supply chain. Using mutual fund flow-driven price pressure to identify exogenous negative shocks to stock prices, Williams and Xiao (2016) find that suppliers decrease subsequent R&D investment and produce fewer patents following declines in their key customers' market values. Chu, Tian, and Wang (2019) demonstrate that geographical proximity of customers and suppliers facilitates knowledge spillover through interaction among employees and researchers and leads to more customer-specific innovation. Dasgupta, Zhang, and Zhu (2020) demonstrate that prior social connections among high-rank executives and directors of the trading partners mitigate opportunism and hold-up. Chen, Dasgupta, Huynh, and Xia (2020) examine how upstream competition causes suppliers to relocate plants closer to their principal customers in order to cooperate more on innovation and forge closer ties with the customer. Selvam and Tan (2020) examine how customer financial distress affects supplier innovation. Our paper focuses on how the *nature* of supplier innovation changes following an adverse reputational shock to the customer and how this affects the supplier's survival likelihood. Our results suggest that supplier innovation is suboptimally diversified, possibly reflecting customer bargaining power and supplier managerial myopia.

Third, we contribute to the understanding of the wider real effects of corporate fraud going beyond the firms that commit financial misconduct. Giannetti and Wang (2016) show that the revelation of financial misconduct by firms can have widespread effects on the stock market. Following fraud revelation, households' stock market participation in the state where the fraudulent firm is headquartered decreases, even in firms that did not engage in fraud. Kedia and Philippon (2009) show that firms that manipulate earnings invest and hire more than levels warranted by their productivity to signal to the market that earnings are consistent with their real decisions; however, they do not examine peer effects. Beatty, Liao, and Yu (2013) find that peers of fraudulent firms mistakenly increase investment during the fraud periods, and equity analysts potentially contribute to this spillover effect. Their results indicate that even close peers do not suspect financial fraud and adjust their investment decisions in response to their fraudulent competitor's perceived overperformance. To the best of our knowledge, there is no study on the changes in investment decisions of stakeholders after the revelation of financial misconduct.

Finally, there is also a growing literature on the propagation of shocks through vertical linkages in the economy (Hertzel, Li, Officer, and Rodgers, 2008; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Acemoglu, Ozdaglar, and Alireza Tahbaz-Salehi, 2017), as well as the effect of supply chain disruptions (mostly in operations management). Several authors leverage natural disasters to study the propagation of shocks to upstream as well as downstream firms and find large (and sometimes asymmetric) effects (Barrot and Sauvagnat, 2016; Boehm, Flaaen, and Pandalai-Nayar, 2019; Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2016). Our results suggest that the long-term effect of such disruptions on the suppliers depends on the flexibility with which the latter can adjust their innovation and may not be as serious as one might suppose.

The rest of the paper is organized as follows. Section 2 describes sample construction, variable description, and empirical methodology. Section 3 discusses summary statistics and the results. We conclude in Section 4.

2. Data and Empirical Methodology

2.1 Data source and sample

Our sample is based on all U.S. firms available in Compustat from 1990 to 2015. We exclude financial firms (SIC: 6000-6999), utility firms (SIC: 4900-4999), and government organizations (SIC: 9000-9999) as they are subject to different sets of regulatory requirements. Since we group firms by industry in our empirical set-up, we also drop the conglomerates (GICS: 201050). We use information from the SEC website to obtain enforcement releases in order to identify fraudulent customers and their initial public revelation dates.[12] We identify enforcement actions brought by the SEC and the Department of Justice (DOJ) based on charges of financial misrepresentation under Section 13(b) of the Securities Exchange Act of 1934.[13] Then, following Karpoff, Koester, Lee, and Martin (2017), we collect all fraud-related events available from enforcement releases, SEC filings, and news items (LexisNexis). These events

[12] The U.S. SEC website documents enforcement releases from 1995.
[13] These fraud cases include at least one charges of violating Section 13(b)(2)(a), Section 13(b)(2)(b), and Section 13(b)(5) provisions of the 1934 Securities Exchange Act and Rule 17 CFR 240.13b2-1 and Rule 17 CFR 240.13b2-2 of the Code of Federal Regulations. For more details, please see Karpoff et al. (2017).

include SEC informal/formal investigation, analyst report or whistle-blower information, restatement announcement, and press releases of a firm's internal investigation. Among these interrelated news items, we identify the news or public announcement that reveals a firm's fraud to the public for the first time. To alleviate the concern of look-back bias, we select the revelation events that are also identified in the enforcement releases, and the revelation events are publicly known in real time. Online Appendix Figure 1 shows the timeline of events pertaining to the fraud at Raytheon, a major U.S. defense contractor, from September 16, 1999, through March 28, 2007. In 1997 and 1998, Raytheon prematurely recognized revenue on Raytheon Aircraft Company's sale of unfinished aircraft through improper "bill and hold" transactions. Raytheon overstated approximately $190 million in net sales between 1997 and 2001. Raytheon also failed to fully and accurately disclose material trends and uncertainties. On September 16, 1999, Raytheon announced that its third-quarter earnings would be below analysts' projections, and that it expected to take a pre-tax, third-quarter charge of between $350 million and $450 million. Shares in Raytheon fell by 12% on the same day. On October 12, 1999, Raytheon announced a shortfall of its earnings projections for 1999 and 2000 -- the EPS would be between $1.40 and $1.50, well below Wall Street expectation of $3.56 per share. The company's share plunged more than 40% in the afternoon. For Raytheon, we consider the first event (September 16) – identified in the enforcement releases – as the revelation date.

We retrieve information on the customer-supplier relationships from both the FactSet Revere database and the Compustat segment customer file. The FactSet Revere database is a novel database that has comprehensive coverage for each inter-firm relationship. FactSet collects principal customers' information from firms' annual reports. In addition, FactSet analysts also collect data from various sources such as quarterly filings, press releases, investor presentations, and corporate announcements. FactSet Revere database includes comprehensive start and end dates between two inter-related firms. Suppliers can disclose their customers, and customers can also disclose their suppliers, but we do not require a relationship to be disclosed by both firms. FactSet Revere Relationship database starts from April 3, 2003. The Compustat segment customer file is publicly available as the Statement of Financial Accounting Standards No. 14 (before 1997) and the Statement of Financial Accounting Standards No. 131 (after 1997) require firms to disclose the existence and sales to principal customers representing more than 10% of the firm's total revenues. However, the database reports only the name of the principal customers without identifiers, and the reported principal customer names are not consistent. Sometimes the same customer is reported in a different abbreviated form in different years and by different suppliers. We follow Banerjee, Dasgupta, and Kim (2008) to manually match customers to their Compustat identifier (i.e., GVKEY) when possible. We use both the FactSet Revere Relationship database and Compustat Customer Segment Files to identify the suppliers of fraudulent customers (affected suppliers). Affected suppliers are identified as those who supply to a fraudulent customer in the year when the customer's fraud is revealed to the public. Some supplier firms might be subject to multiple announcement events. We only include the first event in order to clearly construct the before- and after-event periods.

The patent data used in Kogan et al. (2017), which has a longer and wider coverage than the patent dataset available in the NBER, is made available to researchers by the authors. They provide this enlarged patent dataset between 1926 and 2010, which carefully matches the patents granted by USPTO with the CRSP stock identifier (PERMNO). We use this dataset as the basis of our analysis of innovation. However, any patent dataset is heavily truncated because it typically takes several years to process a patent application. The patent is not recorded by the USPTO until it is granted. Thus, the number of patents falls towards 2010 because the patents have not been granted yet. Following Hall, Jaffe, and Trajtenberg (2001), we use the historical distribution of application-grant time-lag to predict the missing number of patent applications. Dass, Nanda, and Xiao (2017) summarize the truncation bias corrections in patent data. They use updated patent data to examine the NBER-2006 sample. They find that truncation bias in the number of patent applications has worsened in recent years. We check the robustness of the results by using two historical distributions of application-grant lag. The first historical distribution of application-grant lag is from 2003-2006. The 2003-2006 historical distribution of application-grant lag is used to correct truncation bias of the number of patents from 2007 to 2010. For example, 88.82% of patents are expected to be missing in 2007 based on the distribution in the 2003-2006 period because only 11.28% of patents tend to be granted within one year (0.52% in the same year as application year (2003), 10.66% in 2004). To adjust truncation bias in year 2007 using the historical patterns between 2003 and 2006, the number of patents that are granted in 2007 should be divided by 11.28%. We also use the distribution of application-grant lag in the 1990-2000 period. We then compute the truncation-adjusted number of patents from 2001 to 2010. We get similar results using both historical patterns to adjust truncation bias in the number of patents.

2.2 Variables

R&D expenses have been widely used in the literature as a proxy for innovation input (Allen and Phillips, 2000; Griffith, Redding, and Reenen, 2004). Specifically, we treat R&D expenses as zero if R&D is missing, and we scale R&D expenses by the book value of total assets. Following the existing literature on corporate innovation, we measure the scale of innovation output by counting the number of patents that are filed by firms and are eventually granted for each firm-year observation. We use the patent application year rather than the grant year because the application year is closer to the time when the innovation is produced (Hall et al., 2001). We use the standard method to adjust the above innovation output measure to deal with the truncation problem associated with the patent data (Hall et al., 2001). Since we only observe the patents that are finally granted, towards the end of our sample period, those patents that are still in process are not observed.

Following existing literature, we define innovation style by classifying patents into exploitative vs. explorative patents.[14] Exploitative patents cite at least 60% of patents that are either the firm's own patents or patents that are cited by the firm in the past five years. Explorative patents cite at least 60% of patents that are neither firm's own patents nor the patents that are cited by the firm in the past five years. We also use a stricter citation requirement (80%) for classifying the style of innovation as a robustness test. Following Jaffe (1986) and Bena and Li (2014), to calculate technological proximity between supplier and customer, we calculate the closeness of their innovation activities in the technology space based on their patents' technology class distribution. The technology proximity variable takes a value between 0 and 1.

For firm characteristics, we compute all variables for firm *i* in fiscal year *t*. Our variables include firm size (the natural logarithm of the book value of total assets), growth opportunities (market-to-book ratio), profitability (Roa), asset tangibility (net PPE scaled by total assets), capital expenditures, leverage, and industry concentration (the Herfindahl index based on sales). Aghion et al. (2005) point out a non-linear effect of product market competition on innovation output. Hence, we include the squared Herfindahl index in our regressions. Detailed definitions of variables can be found in Appendix Table A1.

2.3 Empirical methodology

Supplier firms of fraudulent customers are classified as the treated group. We determine the control firms based on their Standard Industry Classification (SIC) codes in Compustat.

[14] See for example: Levinthal and March (1993), McGrath (2001), Benner and Tushman (2002), Smith and Tushman (2005), Gao, et al. (2018) and Liu et al. (2017).

Control firms operate in the same 2-digit SIC code as the treated suppliers. Following Gormley and Matsa (2011), we analyze the treated suppliers' response to their corresponding customers' announcement of fraud. Specifically, we compare changes in their behavior relative to other firms' behavior in the same 2-digit SIC industry around the time of the announcement of fraud. For every year, in each affected industry, we construct a cohort of treated suppliers and matched control firms using firm-year observations for the five years before and five years after the announcement. In the case of the revelation of Raytheon's financial misconduct, among Raytheon's suppliers, Mercury Systems, Inc and Ducommun Incorporated operate in two-digit SIC industries 36 and 37, respectively. Then, we construct two cohorts for Mercury Systems, Inc and Ducommun Incorporated separately since the control firms come from different two-digit SIC industries. In the control group, firm-year observations are removed if they become treated by other revelations of financial misconduct. Firms are not required to be in the sample for the full ten years around the event. We then "stack" all cohorts of treated and control firms into one dataset. In total, we identify 77 fraudulent customers and 477 affected suppliers in 202 cohorts. They come from 38 different 2-digit SIC industries. Customers can have suppliers operating in different 2-digit SIC industries. Thus, the size of our control group is large for each event. Having a large control group enables us to select firms that share similar ex-ante characteristics with the treated one. For each treated firm, we select firms in the same quartile of size, leverage, sales, and trade receivables in the same 2-digit SIC industry in year t-5.[15] Control firms are required to have at least one identifiable corporate customer between years $t-5$ and $t-1$. Treated and matched control firms for the same customer fraud revelation event belong to the same cohort, indexed by c. Since both treated and control firms in each cohort are from the same 2-digit SIC industry, any industry trend that potentially biases our results

[15] Year t is the event year when a customer's fraud becomes known to the public.

can be absorbed.[16] We then estimate the average treatment effect in a "stacked difference-in-difference" setting. Specifically, we estimate the following firm-panel regression:

$$Y_{ict} = \beta_0 + \beta_1 Post_{ict} * Treated_{ic} + \sum_{k=2}^{N} \beta_k Controls_{ict} + \gamma_{ic} + \omega_{tc} + \varepsilon_{ict} \qquad (1)$$

where *y* is one of several dependent variables of interest for firm *i* in cohort *c* and year *t*, $Treated_{ic}$ is an indicator that equals one for treated suppliers in cohort *c*, and *Post* is an indicator variable that takes a value of 1 in the five years after the fraud announcement for firms in cohort *c*, and zero otherwise. We include a set of variables, lagged by one period, to control for observable differences among the sample firms as well as firm-cohort fixed effects, γ_{ic}, to ensure that the estimated impact of customer's fraud is controlled for any fixed differences between firms; however, all our results are also reported for specifications that drop potentially endogenous control variables (Angrist and Pischke, 2009). We also include year-cohort fixed effects, ω_{tc} to control for any secular time trend.

3 Empirical Results

3.1 Summary statistics

The disclosure of fraudulent activity has a significant price impact on customer firms, as shown in Online Appendix Figure 2(a). On average, fraudulent customers lose more than 10% of their market values. Thus, for the fraudulent customer firms, investors respond to the information in the trigger news item quickly, and the expected loss of value is substantial. (Karpoff, Lee, and Martin, 2008). Online Appendix Figure 2(b) shows that the direct suppliers of these fraudulent firms also have a negative price impact but of a lower magnitude.[17]

[16] However, this approach does not absorb common shocks that could affect both the fraudulent customer and the treated suppliers. This issue is discussed and addressed in section 3.5.

[17] The average cumulative abnormal buy and hold return between day -5 and day +5 is minus 1.794% with *t*-value of -3.469 (*p*-value=0.0006). The average cumulative abnormal buy and hold return on the event day is minus 0.560% with *t*-value of -2.844 (*p*-value=0.0046).

Figure 2a plots the year-on-year growth rate of sales of the affected suppliers to the fraudulent customer (red line) and that of all other sales (blue line). The growth rate of sales to the fraudulent customer drops to almost negative 5 percent in the initial year, and remains negative for the first three years, before settling to a slightly positive level for the subsequent years. The major impact of the customer fraud appears to be the *lost growth in sales* to that customer in the next several years, if compared to the growth of sales to all other customers. The growth rate of all other sales is almost 10 percent in the initial year, possibly reflecting an effort to bolster sales to other customers and utilize excess capacity created by the drop in demand from the fraudulent customer. Since the subsequent growth of all other sales is on a higher base, the growth rate slows, but then jumps again after four years. Our later results will show that new principal customers emerge precisely around this time. Figure 2b compares treated (red line) and control (blue line) supplier firms in terms of the percentage increase in sales in year t, where t = -5, -4, …, +5, over its sales six years prior to the fraud event, i.e. $(S_t - S_{-6})/S_{-6}$. Sales dip for the treated suppliers in year 0, but start to diverge from year 4. Overall, the evidence suggests that on average, the suppliers are able to compensate for the loss in sales growth to the fraudulent principal customer by increasing sales to other customers relatively quickly.

[Insert Figure 2a and Figure 2b here]

Table 1 presents summary statistics for our sample treated supplier firms and their 2-digit SIC industry peers. As shown in Table 1, an average supplier in our regression sample invests 9.5% of their total assets in R&D expenses, and these innovation inputs translate into 9.7 granted patents per year. The average percentage of exploitative (explorative) patents is 33% (59%). The summary statistics of treated firms and matched control firms averaged over the five years prior to the revelation of fraud are reported in Table 2. The table shows that treated suppliers and control firms have similar R&D expenses. On average, treated suppliers spend 8.97% of their assets on R&D, whereas control firms spend 8.80% of their assets. None of the characteristics are significantly different for the treated suppliers and their control firms. The main regression analysis is based on the matched sample of control firms, but our results remain similar using the full sample of control firms (same industry peers).

[Insert Table 1 and Table 2 here]

3.2 Effect of customer financial misconduct on suppliers' R&D and innovation strategy

We begin by analyzing how firms adjust their R&D investment in response to the disclosure of fraudulent activities of their customers. We do this by using a difference-in-difference analysis of R&D spending, after controlling for cohort-year and firm-cohort fixed effects. The control group includes matched firms in the same 2-digit SIC industry as the treated firms. The results for the matched sample are reported in the first two columns of Table 3. To address the concern that our estimates will be biased if control variables are affected by the treatment, we report results without any other firm-specific controls in the first column, and add additional control variables in the second column. We find that R&D investment decreases for the treated group in the post-treatment period. Treated suppliers decrease R&D investment by 0.8% of their total assets. The fall in R&D investment accounts for 10% of the average R&D spending by the treated suppliers prior to the event.

We next examine whether the negative effect of customers' announcement of fraud on supplier R&D is also transmitted to innovation output. We calculate the natural logarithm of one plus the number of patents produced by firms. In columns (3) and (4) of Table 3, the coefficient of treated*post corresponds to a 15.76% decrease in produced patents for treated suppliers relative to matched industry peers per year in the five-year window after their customers' announcement of fraud. The results based on patenting outcomes reinforce the previous findings on treated suppliers' R&D investment.

We show below that the nature of innovation changes for the treated suppliers, in that they engage in more explorative and riskier innovation in new areas. If innovation becomes riskier, for a given dollar amount spent on R&D innovation input, the number of patents generated will be fewer. To test whether this is the case, we define a new dependent variable as the difference between the natural logarithm of one plus a firm's total number of patents in a year and the natural logarithm of one plus the total R&D expenditure in the past five years. Columns (5) and (6) report the results for the matched sample. The coefficient of treated*post is negative and significant, suggesting that the treated suppliers engage in riskier innovation relative to the matched control group.

In Online Appendix Table OA1, we find similar results from the full sample in which the control firms are those that operate in the same 2-digit SIC industries as the treated suppliers.

[Insert Table 3 here]

Following the literature on R&D, we treat missing values of R&D as firms having no significant R&D to report.[18] However, one concern is that our estimates could be biased if these missing observations do not mean zero R&D investment. In view of this concern, we redo the analysis by dropping firms that do not report R&D expenses in any year in the sample, and the results remain very similar. Columns (1) and (2) in Online Appendix Table OA2 report the main R&D results where firms with missing R&D are dropped. We also focus on firms with non-missing patent information to re-examine the effect of the revelation of customer fraud on

[18] In the treated group, 77% of firms report R&D and have median (average) R&D of 0.077(0.106), 72% of firms have patent data with median (average) Log(Patents) of 1.386 (1.921). In the control group, 82% of firms report R&D and have median (average) R&D of 0.068 (0.101), 59% of firms have patent data with median (average) Log(Patents) of 1.099(1.680).

suppliers' innovation output. Columns (3) and (4) in Online Appendix Table OA2 show that treated suppliers produce fewer patents after the event. In Columns (5) and (6), we show that innovation becomes riskier if we focus on the firms that report R&D expense and produce patents.

In Figure 3, we present our tests of parallel trends. We regress R&D expenses and innovation output on the treatment dummy interacted with year dummies representing t-5, t-4, t-3, t-2, t-1, t, t+1, t+2, t+3, t+4, t+5. Year t-6 is included and is the reference year. We find that there is no significant difference in either R&D investment or innovation output between the treated suppliers and control firms before the event. The decrease in treated suppliers' R&D investment coincides with the event year, whereas the decrease in their innovation output occurs two years later, possibly in response to lower R&D.

[Insert Figure 3 here]

Overall, these results show that the affected suppliers adjust down the scale of their innovation activity when a major customer's financial fraud is revealed. This could reflect the fact that the value of relationship-specific investment is lower, from the supplier's point of view, when the customer's financial fraud is revealed. The results also suggest that it is highly unlikely that the weakening of the customer's bargaining power creates a positive shock for the supplier that encourages more relationship-specific R&D and innovation.

However, since we do not observe treated suppliers' R&D investment at the relationship level, we cannot directly test whether the supplier's investment that is specific to the fraudulent customer is affected. For example, it is possible that treated suppliers reduce R&D investment in order to improve earnings outlook. To deal with the limitation of R&D data, we take advantage of the richness of patent data to further examine: 1) change in technological proximity between suppliers and their fraudulent customers; 2) change in treated suppliers' innovation style. We show that treated suppliers start to shift their innovation activities away from fraudulent customers, and engage in more explorative innovation and less exploitative innovation.

3.3 *Do suppliers adjust their innovation activities?*

First, in order to understand if suppliers move their innovation away from fraudulent corporate customers, panel A of Table 4 presents a univariate comparison of technology proximity between treated suppliers and their customers before and after the disclosure of customers' fraud, and panel B presents regressions results. The univariate results show that there is a significant decrease in technological proximity between the treated suppliers and their fraudulent customers after the event and an insignificant increase in the proximity between treated suppliers and their non-fraudulent customers. The difference of changes in treated suppliers' technological proximity with the fraudulent group and with the non-fraudulent group of customers is significant at 5% level. This suggests that treated suppliers adjust their innovation activities away from the fraudulent customers. The regression estimates presented in panel B with technological proximity as the dependent variable show a very similar pattern.[19]

[Insert Table 4 here]

Next, we test whether treated suppliers' "style" of innovation changes. Patents are classified into "exploratory" and "exploitative" categories as defined in Section 2.2. We calculate exploitative (explorative) scores as the percentage of a firm's number of exploitative (explorative) patents to its total number of patents each year. In column (1) of Table 5, we find that treated suppliers decrease the proportion of exploitative patents by approximately 13% (relative to sample average) after the revelation of fraudulent customers' fraud. On the other

[19] The regression in panel B is done only for the treated suppliers, and for those with at least another non-fraudulent principal customer.

hand, the disclosure of fraudulent behavior of customers drives their suppliers to explore new areas of innovation that could be potentially valuable to a broader customer base. As a result, they create 7.9% more explorative patents relative to matched firms in the same 2-digit SIC industries. Treated suppliers divert their resources towards new knowledge domains.[20]

To further check whether the treated suppliers' innovation becomes more diverse, we construct a Hirschman-Herfindahl Index (HHI) based on new patents granted every year. To do so, use the technology subcategories provided by Hall et al. (2001). Our stacked DiD analysis with this technological HHI as the dependent variable, reported in Appendix Table A2, shows that treated firms increase the diversity of their patenting activity after the revelation of customer fraud.

[Insert Table 5 here]

The results based on innovation style suggest that previous findings on treated suppliers' R&D investment and subsequent innovation output represent a shift not only in the scale, but also the scope of their innovation activity. The shift of the treated suppliers' technological focus from fraudulent customers to other customers is consistent with the hypothesis that the value from relationship-specific investment is likely to be lower after the revelation of the fraud. This, in turn, could arise from several channels, e.g., (a) the fraud firm could face greater uncertainties, and the relationship could be terminated or scaled down earlier than expected (a negative shock), or (b) the fraud firm could be less likely to honor implicit contracts with the supplier, which could expose the latter to hold-up, which is a negative shock to a short-term oriented manager sensitive to safety or averse to uncertainty, but potentially a positive shock

[20] The number of observations is much lower compared with Table 3 because, to compute the dependent variables, (i) there has to be at least one patent application in the firm-year, and (ii) the firm has to have patents in the past five years. The results are similar in the full sample, reported in Online Appendix Table OA3. The results are also similar if we use 80% threshold to define exploitative and explorative patents (see Online Appendix Table OA4).

to the firm's shareholders if the manager did not engage in the optimal amount of experimentation prior to the fraud. In the following sections, we provide evidence in support of this latter interpretation.

3.4 *Financial Constraints*

Our arguments regarding suboptimal diversification of innovation implicitly assume that the suppliers are financially constrained – otherwise, there is no reason why exploitative innovation has to occur at the expense of explorative innovation. Accordingly, we examine whether our results are more pronounced for firms that are more likely to be financially constrained. We consider firm size (as measured by total assets) to be an inverse measure of financial constraints. A supplier is considered financially constrained if it is in the bottom third when firms are sorted by their size at the fraud revelation year. We interact post and treated*post with an indicator variable FC denoting a financially constrained supplier. The results for the matched sample are reported in Appendix Table A3 in the Appendix.[21] We find that the treatment effects for R&D, patents, and innovation style are significantly stronger for financially constrained firms.

3.5 *Could common (industry) shocks explain our results?*

For a causal interpretation of our results, it is important to show that common industry or other shocks do not simultaneously cause fraudulent behavior by the customer firms and affect the innovation activity of the suppliers relative to their controls. To address this issue, we take advantage of the fact that the period during which fraud is committed typically precedes the year the fraud is revealed. If industry shocks induced both fraud by the high-profile firm and affected the innovation activities of their suppliers, we should find that the outcome variables

[21] Results for the full sample are in Online Appendix Table OA5.

for the treated suppliers begin to diverge from those of their peers when the fraud was actually committed. To further rule out the possibility that the fraud was not committed *in anticipation of* future industry conditions (that materialized at the time the fraud was revealed), we focus on a sample where the last reported year that fraud was committed (as per the SEC's Accounting and Auditing Enforcement Releases (AAERs)) is at least two years prior to the revelation of the fraud. Since the average duration of contractions from peak to trough in the U.S. over the last forty-five years has averaged only twelve months, it seems unlikely that the fraud firms were engaging in fraud two or more years ahead of an anticipated change in industry conditions. Using the year before the commencement of fraud by the high-profile firm as the reference year, we augment the regression specification in Eqn. (1) by adding the interaction of *Treated* and two indicator variables, "*During-Fraud*", which takes a value of one for each of the years prior to the revelation of fraud when the fraud was being committed, and zero otherwise, and *After-Fraud*, which is 1 for the two years after the last reported year of fraud but before the revelation of fraud. In Appendix Table A4, we report the regression results with supplier R&D and innovation variables as our dependent variables. The coefficients of *Treated*During-Fraud* and *Treated*After-Fraud* are both insignificant in all regressions, but that of *Treated*Post* remains significant, and similar in magnitude and sign to those in our main tables.[22]

Fraud may be the outcome of some long-term industry trends, such as industries in decline. If so, innovation activity could be falling or changing subsequent to the fraud because the return from current innovation is low. To further address this possibility, we augment our baseline specifications by interacting *Treated*Post* with a dummy variable *High Growth*, which takes the value of one if the median value of the market to book ratio of the fraud customer industry

[22] The reference year is the year before the start of customer misconduct, as identified in the AAERs.

is above the corresponding median across all events in the year prior to the revelation of fraud, and zero otherwise. Our results are stronger (and in some cases, while the triple interaction is significant, *Treated*Post* becomes insignificant) in the high growth industries. Thus, the "declining industry" phenomenon is not driving our results. These results are presented in the Online Appendix Table OA6.

3.6 The Evolution of Sales Growth, Tobin's Q, and Risk

In Tables 6-9, we provide additional evidence of the benefits of a more diversified innovation strategy. In Table 6, we examine how the number of customers that can be identified in our database changes for the affected suppliers vis-a-vis the control group. The dependent variable in columns (1) and (3) is the number of corporate principal customers, while that in columns (2) and (4) is the logarithm of (one plus) the number of identifiable principal customers. The results are reported for the regressions that include the control variables; however, they are similar when the control variables are not included. We find from columns (1) (column (2)) that compared to the control group, the treated suppliers experience on average 0.3 additional principal customers per year (7 percent increase in the number of customers) after the revelation of customer fraud. The result is consistent with the observation that the suppliers try to diversify their customer base when a major customer is impaired, and our subsequent evidence that the long-term survival rate of the affected suppliers increases relative to the control group. We expect that it might take the suppliers some time to widen their customer base after the shift in innovation style, and this is what we find in columns (3) and (4), where we find that the number of principal customers starts to increase from the third year after the fraud revelation. In Table 7, the dependent variable is the natural logarithm of supplier's sales in period *t* minus the natural logarithm of its sales six years before the event. The results show that the treated suppliers experience more rapid sales growth relative to the baseline year than the control group.[23] The last two columns explore the dynamics. We find that the sales growths of the treated and control groups start to diverge after year 2.

[Insert Tables 6 and 7 here]

In Tables 8 and 9, we study the impact in firm value (as measured by Tobin's Q), and total firm risk (as measured by the annualized standard deviation of daily stock returns), respectively. We create two indicator variables for the first five-year period after the event, and for the second five-year period after the event. In Table 8, we see that Tobin's Q for the treated suppliers is significantly higher in both five-year periods compared to the five-year period before the event. Figure 4 shows that the Tobin's Q begins to diverge roughly three years after the event, i.e., around the time the firm begins to attract new customers and sales growth begins to pick up (Tables 6 and 7).[24]

[Insert Figure 4 and Figure 5 here]

In Table 9, we see a similar pattern for firm risk. Firm risk for the treated suppliers is lower after the event. However, here, the effect is twice as large in the second five-year period than in the first. Figure 5 indicates that here also, the risk-reduction sets in around the third year after the event. [25]

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[23] In Table 7, the magnitudes of the coefficient of treated*post in column (1) (when controls are excluded) and in (2) (when controls are included) are somewhat different, though both are significant at 1 percent level.

[24] As we noted in section 3.1, the cumulative abnormal returns to suppliers around the fraud revelation dates of their customers are negative, though much smaller in magnitude in comparison to those of the fraudulent customer itself. This negative market reaction could reflect the possibility of immediate loss or slowing down of sales to a major customer, and uncertainty about the success of alternative innovation or marketing strategies. In view of our results on various supplier performance metrics such as sales growth and Tobin's Q, it appears that the average negative abnormal returns for the suppliers reflect the market's focus on short-term profits, which are likely to be adversely affected by the event.

[25] Overall, in the first five years after the event, the affected suppliers outperform the control group in terms of explorative innovation, the number of major customers, sales growth, Tobin's Q, while firm risk is also lower. While a slightly higher fraction of the affected suppliers do exit in the first three years after the shock than their matched counterparts, the difference is small, and more than 95 percent of the firms from both groups survive after the first three years of the shock. Thus, the magnitude of the difference-in-difference coefficients are too large to be attributed to survival bias. In fact, by the third year after the shock, the cumulative survival rates of the

[Insert Tables 8 and 9 here]

3.6.1 *Managerial risk/uncertainty aversion and customer bargaining power*

Our arguments have been based on the premise that for an *adverse* shock to the firm (e.g., the revelation of customer fraud) to translate to shareholder-preferred outcomes, one of two conditions must be satisfied: (a) there is some kind of managerial agency problem, and the shock lowers the manager's benefit from pursuing a type of behavior that is not in the best interest of the shareholders, and (b) the shock weakens customer bargaining power. Is it possible that only one of these effects drive our results? We argue that while this is possible, it is not very likely in our context.

Consider first the possibility that the manager is acting in the best interest of shareholders. It is possible that the manager pursues more relationship-specific investment because not heeding the customer's demand for such innovation would result in losing the customer's business, and this would impose a greater loss to shareholders than the alternative of engaging in more explorative innovation. This issue reduces to one of how the customer could "punish" the supplier for not engaging in sufficient relationship-specific innovation. The customer's threat of abruptly walking away from the supplier is unlikely to be credible, since the customer also has to make relationship-specific investments and find alternative suppliers. However, even though such a threat is not credible, an uncertainty-averse manager sensitive to the short-term impact of such actions (e.g., due to career concerns) might still want to avoid such an unlikely possibility – which would be consistent with our interpretation of the results. Alternatively, the customer could (more credibly) threaten not to renew or extend an existing contract. While this could impose costs on shareholders, suppliers in our sample appear quite

two groups are about equal (see Figure 6), and it is also around this point that the increase in customer base and sales growth for the affected suppliers begin to show up.

attuned to customer turnover: the customer relationships in our sample are not very long-term (on average, about 6 years). Therefore, a lower likelihood of being able to renew or extend the contract may not impose significant costs on the shareholders. Moreover, as our results show, the explorative innovation pays off in the form of higher sales growth fairly quickly. Thus, we argue that it is more the manager's short-term risk or uncertainty aversion, rather than any significant negative impact on shareholder value, that explains how customer bargaining power affects the nature of innovation.

Next, consider the possibility that the manager's actions are motivated by a desire to hold on to the customer longer and deliver the type of innovation that is more beneficial to the customer, without any implicit of explicit pressure from the customer. The problem here is that the customer is not able to commit to a long-term relationship – otherwise, what is beneficial for the customer would presumably also be beneficial for the supplier. When long-term contracts cannot be written, the possibility of customer opportunism is likely to affect and distort managerial actions.

3.7 *Impact on the supplier's survival*

After observing strategic shifts in R&D investment and innovation style, we investigate the effect it has on the affected suppliers' survival in the shorter and the longer term. In Figure 6, we plot the cumulative failure rates of affected suppliers for the ten-year period after the financial misconduct of their customer firms become publicly known. We define firm failures as performance-related stock market delistings, liquidations, and distressed mergers (with delisting codes 400-490 and 5200584). Figure 6 is very similar to the hypothetical Figure 1. From Figure 6, we observe an immediate increase of the fraction of failed firms in the treated group compared with the control group following the event, but over the longer term, the fraction of failed firms increases at a slower rate compared to the control group. This suggests that once they survive the first few years following the fraud, treated suppliers actually have better survival prospects than matched firms in the same industry. Over a 10-year period, while 12% of the control group exit, that percentage is only 8% for the treated group. Importantly, the groups are balanced in terms of the importance of principal customers. While the percentage of firm-year observations before the fraud revelation associated with principal customers that account for more than 10% of the supplier's sales for the treated group is 84 percent, for the control sample, it is 83 percent, and the difference is statistically insignificant.

[Insert Figure 6 here]

To examine the link between innovation style and survival, we do a series of tests. First, in Table 10, we report linear probability and probit regressions where we predict a firm's likelihood to fail after the revelation of customers' financial misconduct. Specifically, we examine failure likelihood in two sub-periods. When we confine attention to the first three years after the event (Columns (1) and (3)), we find that treated suppliers are more likely to fail in the following year than the control group. Beyond the first three years and until ten years after the event, we find that treated suppliers are less likely to fail in the following year than firms in the control group ((Column (2) and (4)). These results are consistent with Figure 6, in which we observe a flip in treated suppliers' survival rates. The estimates indicate that in the first three years, the affected suppliers have a 1.86% higher likelihood of exit in the following year; however, for the next seven years, they have a 1.13% lower likelihood of exit the following year. These magnitudes are economically significant given that only about 10% of the sample firms exit over the ten-year period after the revelation of the customer fraud.

[Insert Table 10 here]

The explanation for this result may lie in the significant changes in the nature of innovation activities of the treated firms, noted earlier. In order to test the effect of innovation style on survival, in Table 11, we perform survival analysis for the ten-year post-event period. The results based on Cox proportional hazard model are reported in column (1), results based on the hazard function that assumes Weibull distribution are reported in columns (2), while column (3) reports results based on the linear probability model. The dependent variable takes a value of one if a failure occurs (i.e., a firm exits). The variables of interest are those corresponding to innovation style, i.e., *CExplore* and *CExploit*. *CExploit* (*CExplore*) is the natural logarithm of one plus the percentage of the cumulative number of exploitative (explorative) patents after the revelation of customer fraud. We find that likelihood of failure decreases if the firm engages in more explorative innovation (higher values of *CExplore*) in all regressions. The treated firms are less likely to fail even after controlling for innovation style, although the results are marginal for the matched sample. Table OA7 in the Online Appendix reports results for the full sample, which includes all the industry peers of the affected suppliers. The results are similar.

[Insert Table 11 here]

Since innovation style is endogenously chosen by firms, a causal interpretation of the results of Table 11 is problematic. For example, it could be the case that suppliers who are more likely to survive take more risk and engage in more explorative innovation. To address this concern, we perform causal mediation analysis following Dippel et al. (2019).

First, in Table 12, Panel A, we first run cross-sectional linear probability and probit regressions, where the dependent variable takes a value of one if the firm exits the sample at the end of ten years after the fraud event is revealed, and is zero otherwise. The sample includes both the treated and the control firms. Results reported in the first two columns show that treated firms are less likely to fail over the ten-year horizon. The economic magnitude in column (1) is significant: the failure rate of the treated firms is 3.91% lower than for control firms, in the context of an 10% failure rate for all sample firms.

We next try to establish a possible channel through which the affected suppliers improve their survival likelihood. To motivate this analysis, in columns (3)-(6) of Panel A, we show various effects of customer fraud on the treated suppliers compared to the control group. In column (3), we find that the change in sales to all principal customers in the event year compared to a year before, scaled by the latter sales (CS_PC), is negatively related to the treated dummy. Columns (4)-(6) examine the effect of customer fraud on three “mediator” variables that could potentially affect survival likelihood: explorative innovation, sales, general and administrative expenses (SG&A), and R&D. Firms can engage in more SG&A to promote sales, and could cut R&D to improve earnings, so these, along with explorative innovation, are potential mediating variables.

The dependent variable in column (4), *Explore5*, is defined, for both the treated firms and their controls, as the *per-year average* of the natural logarithm of one plus the total percentage of the explorative patents up to five years after the revelation of customer fraud, or the year prior to its exit, if the latter event is earlier. In columns (5) and (6), the dependent variables *SG&A5* and *R&D5*, are similar measures based on SG&A expenses over assets and R&D over assets. Consistent with earlier results, we find that the treated firms step up explorative innovation. We do not find any difference in the way treated firms adjust SG&A expenses relative to the control firms; however, R&D investment is lower.

In panel B, we change the treatment variable to CS_PC, i.e., *change in principal customer sales*, and instrument it with the dummy variable *Customer Fraud*, which takes a value of 1 if the supplier firm has a principal customer revealed to have committed fraud, and zero otherwise. CS_PC can affect firm survival directly, or indirectly, via any of the mediating variables. We follow the method of Dippel et al. (2019) to conduct a causal mediation analysis. The purpose is to disentangle the effect of an intermediate variable like *Explore5* from the direct effect of the treatment CS_PC. The method requires a single instrument, which in our case is *Customer Fraud*.[26]

Since the method can accommodate only one mediating variable, we consider the role of each of the three alternative mediating variables in turn. Since we do not find in column (5) *SG&A5* to respond to customer fraud, we do not expect it to play any mediating role. However, as noted, *R&D5* does respond to customer fraud, and lower or more efficient R&D could improve earnings and improve the survival likelihood.

Panel B of Table 12 reports the results. We focus on the first set of results (first two columns) where the mediating variable in *Explore5*. We find that the indirect effect of a decrease in *Explore5* associated with an increase in CS_PC explains more than 100 percent of the decrease in survival likelihood. The direct effect of an increase in CS_PC contributes a 7 percent reduction (= -0.015/0.216) to the total effect in survival likelihood, but the effect is not significant.[27] In contrast to *Explore5*, we find no mediation effect attributable to *SG&A5* or *R&D5*.[28] Overall, these results suggest a causal role of explorative innovation in lowering supplier default.

[Insert Table 12 here]

[26] The estimation method utilizes a system of two 2SLS regressions. The STATA code is provided in Dippel, Ferrara and Heblich (2020). See Chen, Ma, Sun and Xu (2021) for a recent application in the Finance literature.
[27] As Dipple et al. (2020) note, "It is also worth noting that in the mediation framework …. there is nothing logically inconsistent about having a positive total effect which is composed of a (larger) positive indirect effect that is partly offset by a negative direct effect, or vice versa." (page 6).
[28] The last panel provides the F-statistics for test of weak instruments in the two first stages. It is possible that the direct effect is not identified precisely. Simulations reported in Dippel et al. (2020) indicate that while the indirect effect (our main interest here) is recovered accurately when the F-statics of both first stages reach the value of 5, a high value for the F-statistic for the second stage is required to recover the total (and hence the direct) effect.

4. Conclusion

Stakeholder governance or stakeholder capitalism as a framework for corporate purpose is very much in the discussion. The analysis in this paper suggests potential pitfalls of making managers accountable to stakeholders. When stakeholders have too much influence, managerial decisions could get distorted to the point where the firm's long-term survival is adversely affected. This hurts not only the shareholders, but also other stakeholders, thereby undermining the entire premise of stakeholder capitalism.

We examine the role of influential (principal) customers. The managers of the upstream suppliers of these principal customers have strong incentives to hold on to these customers, since their departure would have adverse consequences on their firm's profits, and possibly their own careers. Therefore, the type of innovation activity undertaken by these suppliers is primarily tailored to benefit the customer. However, innovation is by its very nature non-contractible, and the customer cannot commit to a long-term relationship. Thus, the supplier managers, by foregoing a more diversified innovation strategy, are essentially giving up long-term safety for more safety in the short term.

An adverse shock to the customer changes the tradeoffs. We find that suppliers make significant adjustments to innovation when their customer firms are revealed to have committed financial misconduct. Suppliers diversify their innovation away from the fraudulent customers and engage in more explorative innovation. Interestingly, these adjustments increase their sales growth, Tobin's Q, and long-term survival rate as they engage in more explorative innovation. The results indicate that the supplier firms might be trapped into doing too much exploitative innovation as their managers prioritize short-term profits and safety at the expense of better long-term survival prospects, sales growth, and firm value.

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Figure 1. Cumulative failure rates from two strategies

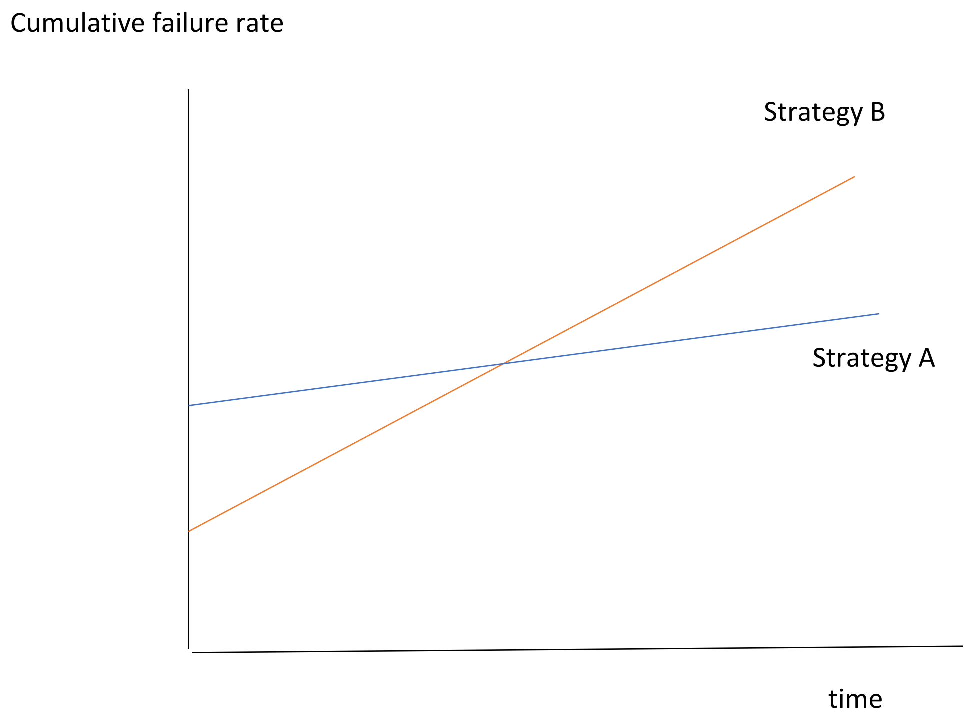


Figure 2a: Year-on-year percentage change in sales and sales to fraud customers.
This figure shows the average year-on-year percentage change in treated suppliers' sales and sales to fraud customers. The percentage change in the sales (sales to fraud customers) in year *t* (*t* = 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10) is the difference between the sales (sales to fraud customers) in year *t* and the sales (sales to fraud customers) in year *t* - 1 scaled by sales (sales to fraud customers) in year *t* - 1, i.e., $\frac{S_t}{S_{t-1}} - 1$, where *S* is raw total sales (sales to fraud customers). *t* = 0 is the fraud revelation year.

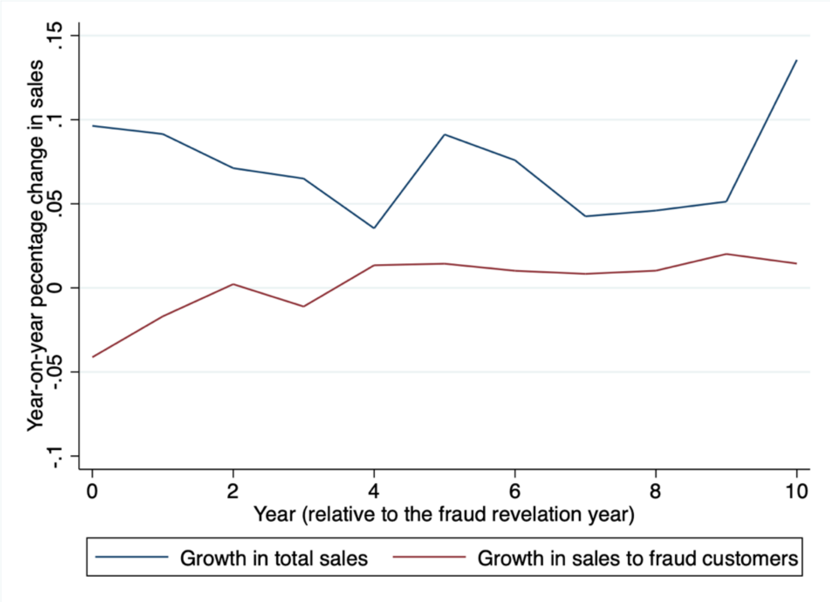


Figure 2b: Percentage change in sales for treated and control group.
This figure shows the average percentage change in sales for the treated suppliers and the matched firms. The percentage change in the sales in year *t* (*t* = -5, -4. -3, -2, -1, 0, 1, 2, 3, 4, 5) is the difference between the sales in year *t* and the sales in year *t* = -6 scaled by sales in year *t* = -6, i.e., $\frac{S_t}{S_{-6}} - 1$, where *S* is raw total sales. *t*=0 is the fraud revelation year.

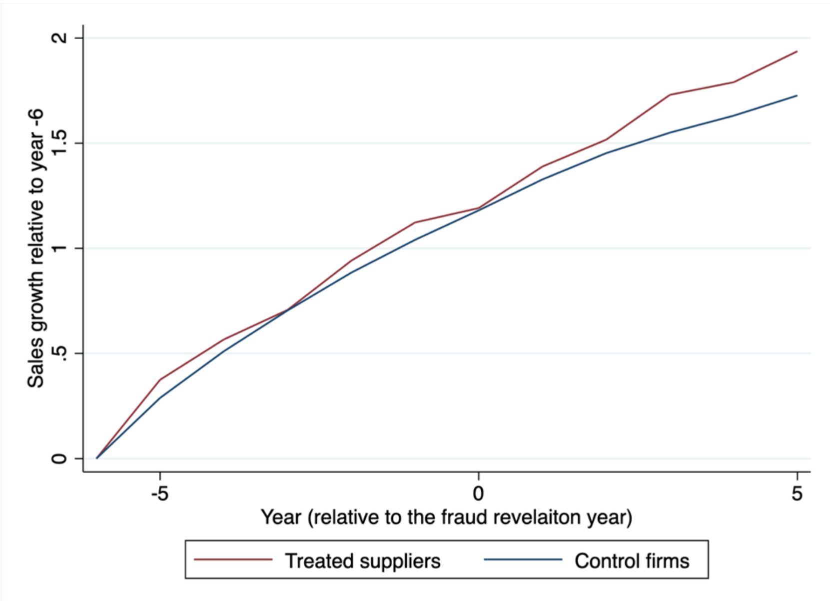
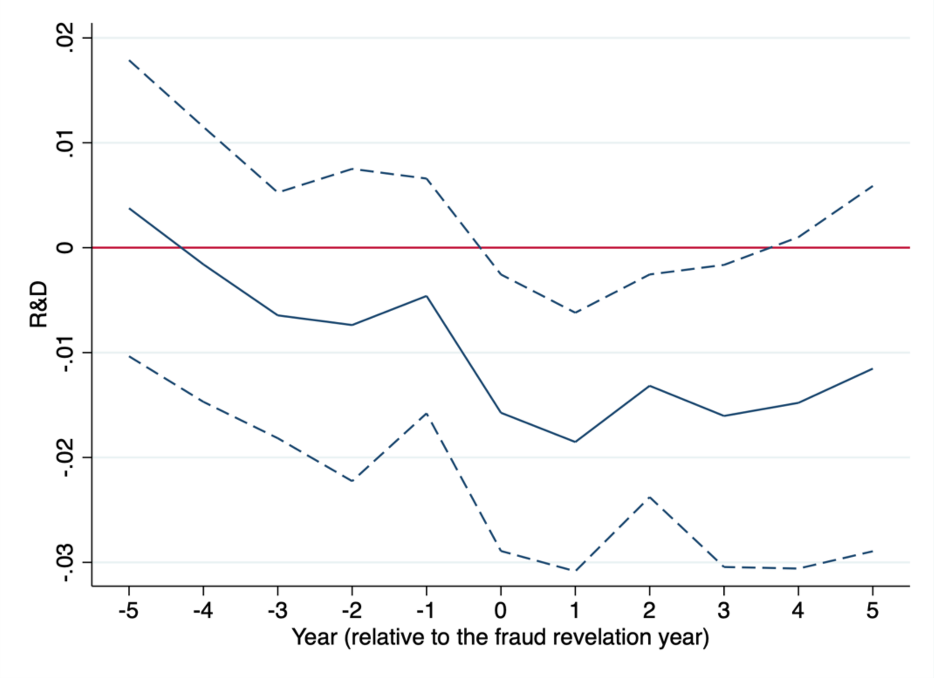


Figure 3: The effect of revelation of fraud on R&D and innovation output

The following figures plot the regression point estimates from a firm-panel regression of R&D spending (upper panel) and the number of patents (lower panel) on the treatment dummy interacted with year dummies representing years *t-5*, *t-4*, *t-3*, *t-2*, *t-1*, *t*, *t+1*, *t+2*, *t+3*, *t+4*, *t+5*. Year *t-6* is included and is the reference year. The sample includes the affected suppliers and the matched control firms. We include firm-cohort fixed effects, and year-cohort fixed effects. Ninety-five-percent confidence intervals are plotted as dotted lines. Standard errors are clustered at the industry level.



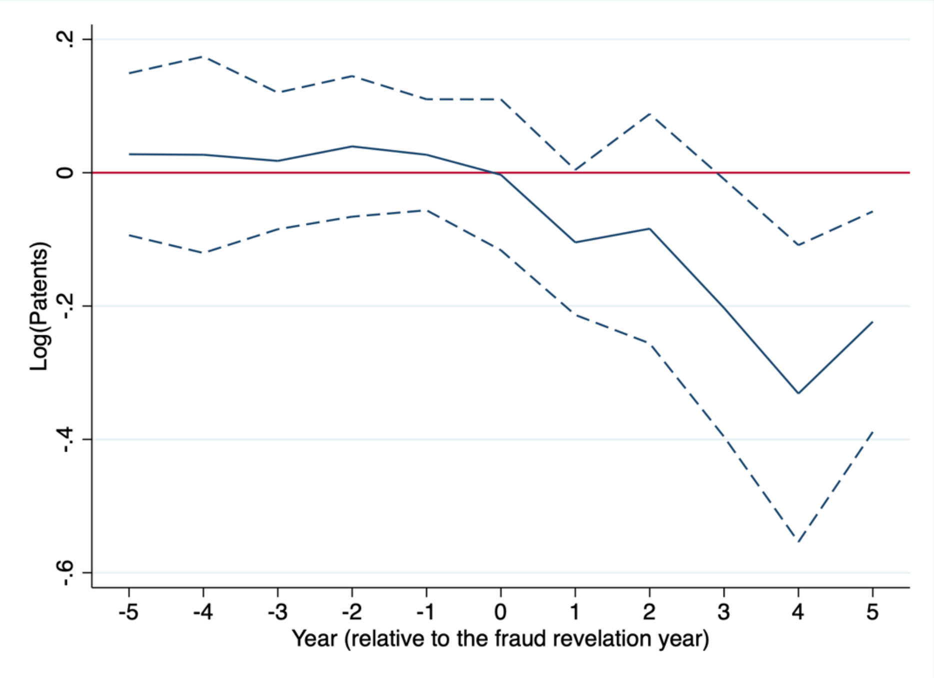


Figure 4: Tobin's Q

This figure shows the average Tobin's Q of the affected suppliers and their matched firms from five years prior to the fraud revelation to ten years after the fraud revelation. Year 0 is the fraud revelation year. Tobin's Q is measured as the sum of market value of equity and book value of total debt divided by total assets.

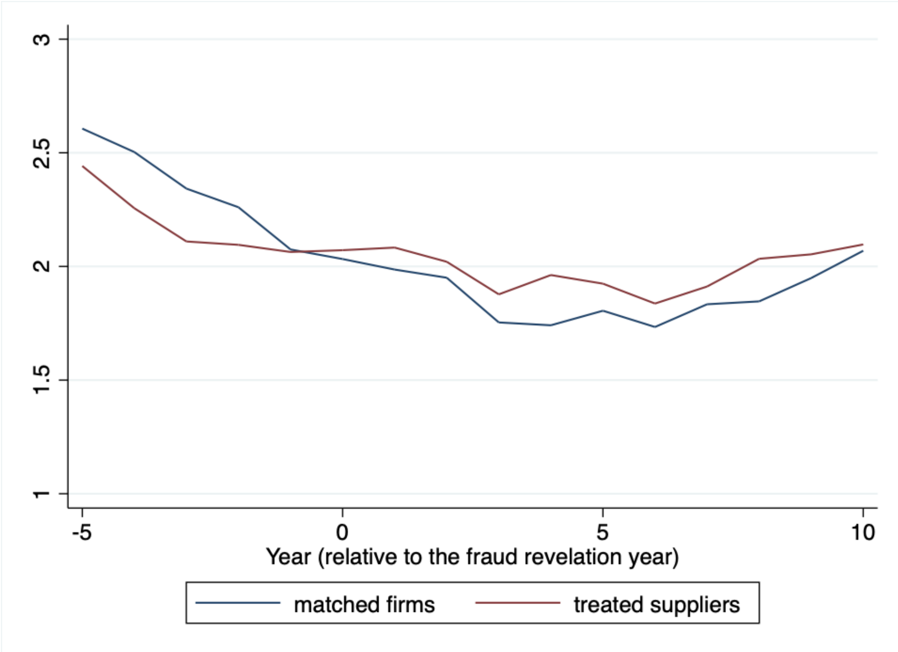


Figure 5: Firm risk

This figure shows the average firm risk of the affected suppliers and their matched firms from five years prior to the fraud revelation to ten years after the fraud revelation. Year 0 is the fraud revelation year. Firm risk is measured as the natural logarithm of the variance of daily stock returns over firm fiscal year.

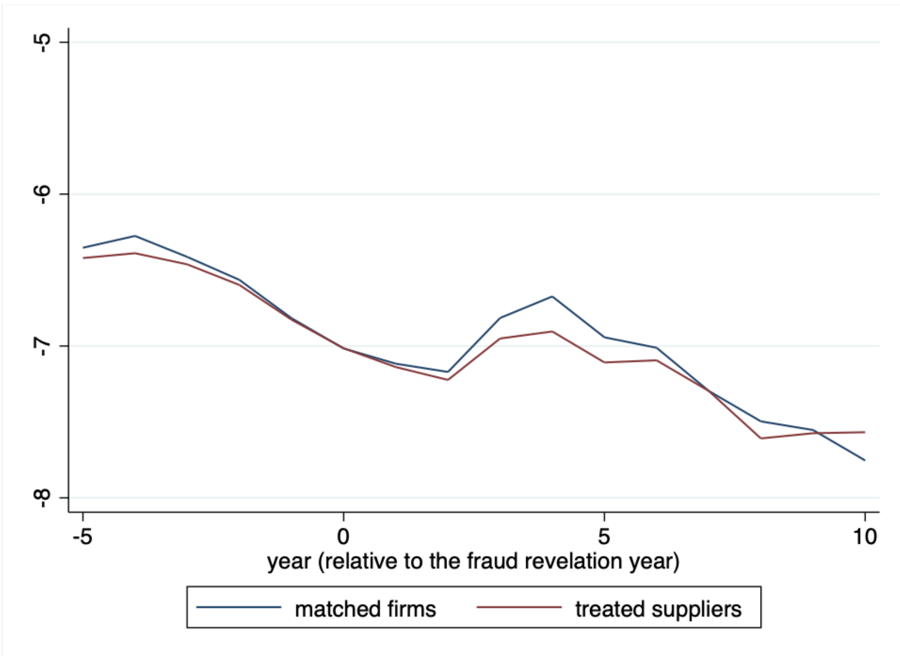


Figure 6: Cumulative failure rates of suppliers

This figure plots cumulative failure rates for the suppliers of fraud customers (treated suppliers) and the matched industry peers of treated suppliers for 10 years after the event year. We define failures as performance-related stock market delistings, liquidations, and distressed mergers (delisting codes 400-490 and 520-584).

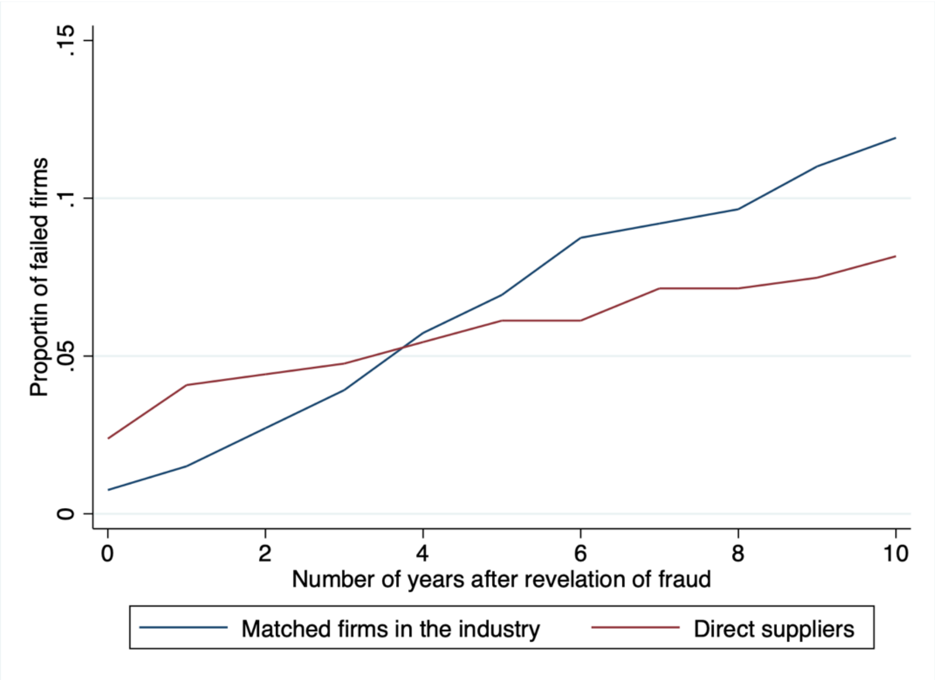


Table 1: Firm characteristics before the revelation of customers' fraud

This table reports summary statistics for regression variables for the full sample. Variable definitions are in Appendix Table A1.

	N	Mean	Std. Dev.	Q1	Median	Q3
R&D	463,794	0.0955	0.1381	0.0000	0.0458	0.1331
Log(Patents)	423,984	0.5896	1.1551	0.0000	0.0000	0.6931
Exploitative	77,519	0.3310	0.3337	0.0000	0.2500	0.5064
Explorative	77,519	0.5987	0.3515	0.3333	0.6316	1.0000
Size	463,794	5.0239	2.2076	3.4012	4.8656	6.4837
Mtb	463,794	2.3678	2.1600	1.1696	1.6651	2.6685
Leverage	463,794	0.1214	0.1575	0.0007	0.0554	0.1872
Roa	463,794	-0.0748	0.3279	-0.1331	0.0186	0.0837
Capex	463,794	0.4449	0.5850	0.1367	0.2599	0.5055
Tangibility	463,794	0.2049	0.2084	0.0617	0.1345	0.2703
HIndex	463,794	0.2226	0.1696	0.1004	0.1822	0.2901

Table 2: Summary statistics for the matched sample

This table reports summary statistics (five-year averages) of firm characteristics in the five years before the revelation of fraud. The means are reported separately for the two samples of firms. We restrict the control group to firms that are ex-ante similar to treated suppliers by matching each firm in the treatment group with firms belonging to the same quartile of size, leverage, sales, and receivables to sales at year *t-5* in the same 2-digit SIC industry, where *t* is the event year. The *p*-value of the difference between treated suppliers and control firms is reported in brackets in the last column. The standard errors are clustered by SIC 2-digit industry.

	Suppliers		Control Firms		
	N	Mean	N	Mean	Difference (p-value)
R&D	1,441	0.0897	5,986	0.0880	0.0017 (0.911)
Log(Patents)	1,365	1.0916	5,646	1.0011	0.0905 (0.248)
Exploitative	656	0.3269	2,062	0.3068	0.0201 (0.193)
Explorative	656	0.5939	2,062	0.5655	0.0284 (0.120)
Size	1,441	5.9806	5,986	6.0049	-0.0243 (0.923)
Mtb	1,441	2.3794	5,986	2.1778	0.2016 (0.433)
Leverage	1,441	0.1324	5,986	0.1222	0.0102 (0.585)
Roa	1,441	-0.0155	5,986	-0.0299	0.0144 (0.182)
Capex	1,441	0.4132	5,986	0.3685	0.0447 (0.296)
Tangibility	1,441	0.2425	5,986	0.2458	-0.0033 (0.870)
HIndex	1,441	0.2120	5,986	0.2119	0.0001 (0.998)

Table 3: R&D, innovation output, and innovation risk

This table reports the stacked DID results of the effect of the revelation of customers' fraud on their suppliers' R&D, innovation output, and risky R&D. In column (1) and (2), the dependent variable is R&D expense scaled by total asset. In column (3) and (4), the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted. In column (5) and (6), the dependent variable is the difference between the natural logarithm of one plus a firm's total number of patents in a year and the natural logarithm of one plus the total R&D expense in the past five years. *Treated* is a dummy variable indicating affected suppliers. *Treated* is zero for the matched control firms in the same SIC 2-digit industry as the affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Detailed variable definitions are in Appendix Table A1. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D		Dependent variable: Log(Patents)		Dependent variable: Risky R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post	-0.0120**	-0.0080**	-0.1502**	-0.1576***	-0.2885**	-0.2505**
	(-2.14)	(-2.43)	(-2.71)	(-2.86)	(-2.60)	(-2.19)
Controls	No	Yes	No	Yes	No	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,467	13,467	12,635	12,635	11,815	11,815
Adjusted R^2	0.719	0.777	0.896	0.898	0.916	0.918

Table 4: Technology proximity with fraudulent customers and non-fraudulent customers

This table reports the affected suppliers' technological proximity with fraudulent customers and non-fraudulent customers in the prior and post fraud revelation periods. For each affected supplier, its customers are identified in the year of the fraud revelation and sorted into fraudulent customer group and non-fraudulent customer group. In Panel A, the univariate results are reported. In Panel B, regression results are reported, with the supplier's technological proximity with a customer as the dependent variable. *t*-statistics are in parentheses. In Panel B, *Fraudulent Customer* is an indicator variable that takes a value of one if the customer is a fraudulent customer, and zero otherwise. *Post* is an indicator variable taking the value of one for up to five years after the fraud revelation, and zero for up to five years prior to the fraud revelation. Detailed variable definitions are in Appendix Table A1. The standard errors are clustered by SIC 2-digit industry.

Panel A: Technology proximity univariate analysis (5-year averages before and after fraud event)

Technology Proximity	Before Fraud Announcement	After Fraud Announcement	Difference
Fraudulent Customers	0.4347	0.3523	-0.0824** (-2.29)
Non-fraudulent Customers	0.3951	0.4047	0.0096 (0.41)
Difference	0.0396 (1.41)	-0.0524* (-1.69)	-0.0920** (-2.11)

Panel B: Technology proximity regression analysis

	(1)	(2)
Fraudulent Customer	0.0396	0.0401
	(1.38)	(1.32)
Post	0.0063	0.0062
	(0.30)	(0.26)
Fraudulent Customer * Post	-0.1056**	-0.0900**
	(-2.28)	(-2.07)
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,750	1,750
Adjusted R^2	0.443	0.596

Table 5: Innovation style

This table reports the stacked DID results of the matched sample. The dependent variable in columns (1) and (2) is the number of exploitative patents divided by the number of patents of a firm in a fiscal year. The dependent variable in columns (3) and (4) is the number of explorative patents divided by the number of patents of a firm in a fiscal year. *Treated* is a dummy variable indicating affected suppliers. *Treated* is zero for the matched control firms in the same SIC 2-digit industry as the affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Exploitative	(2) Exploitative	(3) Explorative	(4) Explorative
Treated*Post	-0.0441**	-0.0438**	0.0443**	0.0473**
	(-2.53)	(-2.51)	(2.02)	(2.08)
Size		0.0190		-0.0123
		(1.06)		(-0.71)
Mtb		-0.0011		0.0058
		(-0.20)		(0.78)
Leverage		0.1027**		-0.1062*
		(2.52)		(-1.94)
R&D		0.0854		0.0062
		(0.63)		(0.04)
Roa		0.0136		-0.0501
		(0.42)		(-1.52)
Capex		0.0723**		-0.0511*
		(2.79)		(-1.91)
Tangibility		-0.0650		0.0888
		(-0.40)		(0.49)
Hindex		0.2328		-0.1963
		(0.72)		(-0.55)
Hindex squared		-0.2279		0.2691
		(-0.64)		(0.75)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	4,334	4,334	4,334	4,334
Adjusted R^2	0.409	0.417	0.421	0.429

Table 6: Fraud revelation and diversification of suppliers' customer base

This table reports the stacked DID estimation results of the effect of the revelation of customers' fraud on the suppliers' customer base in the matched sample. In column (1) and (3), the dependent variable is the number of principal customers for each supplier in a year. In columns (2) and (4), the dependent variable is the natural logarithm of one plus the number of principal customers for each supplier in a year. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable taking the value of one for five years after the fraud revelation, and zero for five years prior to the fraud revelation. $Year_t$ is the fraud revelation year. Firm-cohort and year-cohort fixed effects are included. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Number of PCs	Log(1+ #PCs)	Number of PCs	Log(1+ #PCs)
	(1)	(2)	(3)	(4)
Treated*Post	0.3116**	0.0719**		
	(2.06)	(2.02)		
Treated*($Year_{t-1} = 1$)			0.0227	0.0165
			(0.28)	(0.46)
Treated*($Year_{t+1} = 1$)			0.0239	0.0050
			(0.30)	(0.39)
Treated*($Year_{t+2} = 1$)			0.0720	0.0046
			(0.81)	(0.11)
Treated*($Year_{t+3} = 1$)			0.3497***	0.1003**
			(3.37)	(2.20)
Treated*($Year_{t+4} = 1$)			0.3199***	0.0803*
			(3.12)	(1.77)
Treated*($Year_{t+5} = 1$)			0.6077***	0.1484***
			(6.00)	(3.10)
Size	-0.0363	-0.0245	-0.0360	-0.0244
	(-0.95)	(-1.37)	(-0.94)	(-1.37)
Mtb	0.0145	0.0063	0.0147	0.0064
	(1.07)	(1.02)	(1.08)	(1.03)
Leverage	-0.0495	-0.0163	-0.0505	-0.0156
	(-0.56)	(-0.40)	(-0.57)	(-0.38)
Roa	0.0781	0.0232	0.0778	0.0229
	(0.88)	(0.57)	(0.87)	(0.56)
Capex	0.0315	0.0045	0.0317	0.0048
	(0.71)	(0.22)	(0.71)	(0.23)
Tangibility	-0.7237***	-0.3226***	-0.7177***	-0.3206***
	(-4.10)	(-3.87)	(-4.07)	(-3.84)
Hindex	-0.5794	0.0255	-0.5843	0.0281
	(-0.59)	(0.06)	(-0.59)	(0.06)
Hindex squared	0.5580	-0.0927	0.5685	-0.0937
	(0.53)	(-0.16)	(0.54)	(-0.16)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	13,275	13,275	13,275	13,275
Adjusted R^2	0.508	0.482	0.508	0.481

Table 7: Supplier sales growth

This table reports stacked DID results for the matched sample. The dependent variable is growth in sales. Growth in sales is computed each year relative to year (*t* = -6), where year *t* = 0 is the fraud revelation year. That is, $Growth\ in\ sales_t = ln(sales_t) - ln(sales_{-6})$. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable equal to one for five years post the revelation of customer fraud and zero for five years before the revelation. Year *t* is the fraud revelation year. Firm-cohort and year-cohort fixed effects are included. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Growth in sales			
	(1)	(2)	(3)	(4)
Treated*Post	0.0887***	0.0364***		
	(4.90)	(2.92)		
Treated*($Year_{t-1} = 1$)			0.0106	0.0083
			(0.30)	(0.50)
Treated*($Year_{t+1} = 1$)			0.0117	0.0039
			(0.24)	(0.23)
Treated*($Year_{t+2} = 1$)			0.0964**	0.0294
			(2.07)	(1.60)
Treated*($Year_{t+3} = 1$)			0.1075**	0.0462**
			(2.25)	(2.19)
Treated*($Year_{t+4} = 1$)			0.1192**	0.0578**
			(2.31)	(2.32)
Treated*($Year_{t+5} = 1$)			0.1116*	0.0499*
			(1.84)	(1.70)
Size		0.6484***		0.6482***
		(15.43)		(15.37)
Mtb		0.0120***		0.0120***
		(2.98)		(2.98)
Leverage		-0.1107**		-0.1109**
		(-2.56)		(-2.56)
Roa		0.2191***		0.2191***
		(8.56)		(8,55)
Capex		-0.0005		-0.0006
		(-0.02)		(-0.02)
Tangibility		0.9374***		0.9369***
		(12.30)		(12.29)
Hindex		-0.2487		-0.2464
		(-1.48)		(-1.46)
Hindex squared		0.2372		0.2349
		(1.60)		(1.58)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	13,275	13,275	13,275	13,275
Adjusted R^2	0.404	0.707	0.397	0.707

Table 8: Tobin's Q

This table reports stacked DID results for the matched sample. The dependent variable is the Tobin's Q, measured as (market value of equity + book value of total debt) divided by total assets. *Treated* is a dummy variable indicating affected suppliers. Year *t* is the fraud revelation year. The reference period is from $Year_{t-5}$ to $Year_{t-1}$. $Year_{t+1\ to\ t+5}$ is one for the five years after the fraud revelation, and zero otherwise. $Year_{t+6\ to\ t+10}$ is one for the period between $Year_{t+6}$ and $Year_{t+10}$, and zero otherwise. Firm-cohort and year-cohort fixed effects are included. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Tobin's Q	
	(1)	(2)
*Treated**($Year_{t+1\ to\ t+5} = 1$)	0.3447***	0.2764***
	(2.83)	(3.19)
*Treated**($Year_{t+6\ to\ t+10} = 1$)	0.4094**	0.3775***
	(2.60)	(3.09)
Controls	No	Yes
Firm*Cohort FE	Yes	Yes
Year*Cohort FE	Yes	Yes
Observations	16,044	16,044
Adjusted R^2	0.471	0.536

Table 9: Firm Risk

This table reports the stacked DID results for the matched sample. The dependent variable is firm risk, measured as the natural logarithm of the variance of daily stock returns over firm fiscal year. *Treated* is a dummy variable indicating affected suppliers. Year *t* is the fraud revelation year. The reference period is from $Year_{t-5}$ to $Year_{t-1}$. $Year_{t+1\ to\ t+5}$ is one for the five years after the fraud revelation, and zero otherwise. $Year_{t+6\ to\ t+10}$ is one for the period between $Year_{t+6}$ and $Year_{t+10}$, and zero otherwise. Firm-cohort and year-cohort fixed effects are included. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: Firm risk	
	(1)	(2)
*Treated**($Year_{t+1\ to\ t+5} = 1$)	-0.0643**	-0.0524**
	(-2.52)	(-2.15)
*Treated**($Year_{t+6\ to\ t+10} = 1$)	-0.1269***	-0.0980***
	(-4.19)	(-3.40)
Controls	No	Yes
Firm*Cohort FE	Yes	Yes
Year*Cohort FE	Yes	Yes
Observations	13,113	13,113
Adjusted R^2	0.754	0.777

Table 10: Linear probability and probit models of survival

This table presents the results from linear probability and probit models of survival of the treated suppliers and their matched industry peers after the revelation of customer fraud. Failure is defined as performance-related stock market delisting, liquidation, and distressed merger (delisting codes 400-490 and 520-584). In columns (1) and (2), the results of the linear probability model are reported. In column (3) and (4), the results of the probit model are reported. The dependent variable is a dummy variable which equals one if a firm fails in the next year and zero otherwise. In columns (1) and (3), we report the survival of the suppliers in the first three years post the fraud revelation. In columns (2) and (4), we report the survival of the suppliers from year t = 4 to year t = 10 (t =0 is the fraud revelation year). Other variable definitions are in Appendix Table A1. The unit of observation is firm-year. *P*-values are reported in parentheses. Standard errors are clustered by SIC 2-digit industry. Industry fixed effects and year fixed effects are included. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	LPM	LPM	Probit	Probit
	(1)	(2)	(3)	(4)
	<=3 years	>3years	<=3 years	>3years
Treated	0.0186**	-0.0113***	0.6852***	-0.9922**
	(0.042)	(0.008)	(0.001)	(0.012)
Size	-0.0072***	-0.0051***	-0.3857***	-0.2307***
	(0.000)	(0.000)	(0.000)	(0.000)
Mtb	0.0000	0.0021	-0.1084	-0.0400
	(0.988)	(0.127)	(0.160)	(0.514)
Leverage	0.1229***	0.1479***	3.1626***	3.2761***
	(0.000)	(0.000)	(0.000)	(0.000)
Roa	-0.0153**	-0.0218*	-0.3071***	-0.4030***
	(0.041)	(0.059)	(0.006)	(0.008)
Capex	-0.0015	-0.0036	0.0167	-0.6924**
	(0.609)	(0.105)	(0.912)	(0.014)
Tangibility	-0.0122	-0.0178**	-0.7968	-0.8218
	(0.252)	(0.026)	(0.209)	(0.121)
Hindex	0.0077	-0.0014	0.1230	-0.0385
	(0.641)	(0.836)	(0.835)	(0.832)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,688	3,958	2,688	3,958

Table 11: Firm survival and explorative vs. exploitative innovation

This table presents the results from regressions of survival analysis on treated suppliers and matched industry peers after the revelation of customers' fraud. Failure is an indicator variable which is one if a firm has performance-related stock market delisting, liquidation, and distressed merger (delisting codes 400-490 and 520-584). *CExploit* (*CExplore*) is the natural logarithm of one plus the percentage of the cumulative number of exploitative (explorative) patents after the revelation of customers' fraud. *P*-values are reported in parentheses. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Survival Analysis		Failure (1/0)
	(1)	(2)	(3)
	Cox	Weibull	LPM
CExploit	1.3160	1.2358	0.0055
	(0.194)	(0.140)	(0.134)
CExplore	0.4512**	0.4463**	-0.0132***
	(0.021)	(0.020)	(0.007)
Treated	0.5813*	0.5761*	-0.0037
	(0.058)	(0.058)	(0.160)
Size	0.6725***	0.6700***	-0.0046***
	(0.000)	(0.001)	(0.000)
Mtb	0.8206***	0.8198***	-0.0011**
	(0.003)	(0.003)	(0.013)
Leverage	2.4277***	2.4382***	0.0303***
	(0.000)	(0.000)	(0.000)
Roa	0.6224***	0.6226***	-0.0187***
	(0.000)	(0.000)	(0.004)
Capex	0.6761	0.6719***	-0.0050**
	(0.190)	(0.182)	(0.035)
Tangibility	1.4721	1.5063	-0.0104
	(0.669)	(0.654)	(0.132)
Hindex	1.9028	1.9181	0.0042
	(0.337)	(0.339)	(0.609)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	7,595	7,595	7,595

Table 12: Cross-sectional regressions: Survival over a ten-year horizon and the effect of mediating variables.

This table reports the survival results based on cross-sectional linear probability and probit regressions, and mediation analysis in instrumental variable regressions. The sample comprises suppliers subject to customer fraud and the matched suppliers from the same cohort. In columns (1) and (2) of Panel A, we report the results of the linear probability model and probit model, respectively. The dependent variable is one if a firm has failed in the 10 years after the revelation of customer fraud; otherwise, it is zero. Failure is defined as performance-related stock market delisting, liquidation, and distressed merger (delisting codes 400-490 and 520-584). In Panel A, column 3, the dependent variable is *Change in sales to all principal customers* (*CS_PC*). *CS_PC* is the difference in the total sales to all principal customers in revelation year and the total sales to all principal customers in the year before the revelation of fraud, scaled by the latter sales. In Panel A, column 4, the dependent variable (*Explore5*) is the per-year average of the natural logarithm of one plus the total fraction of the explorative patents, from the first year after the fraud revelation to five years after the revelation (or up to the year before exit, if exit occurs earlier than in five years). In Panel A, column 5, the dependent variable (*SG&A5*) is the per-year average of the total SG&A expense scaled by total assets from the first year after the fraud revelation, from the first year after the fraud revelation to five years after the revelation (or up to the year before exit, if exit occurs earlier than in five years). In Panel A, column 6, the dependent variable (*R&D5*) is the per-year average of the total R&D expense scaled by total assets constructed in the same way. In Panel A, *Treated* is an indicator variable denoting direct suppliers of fraudulent customers. In Panel B, the results of the mediation analysis in instrumental variable regressions are reported. The dependent variable is the failure dummy. The treatment variable is *Change in sales to all principal customers* (*CS_PC*). The instrumental variable is the dummy indicating direct suppliers of fraudulent customers. In column (1), the mediator variable is *Explore5*; in column (2), it is *SG&A5*, and in column (3), it is *R&*D5. All explanatory variables are measured in the year before the revelation of customer fraud. *P*-values are reported in parentheses. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A						
Dependent variable =	Failure LPM	Failure Probit	CS_PC	Explore5	SG&A5	R&D5
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.0431**	-0.2127**	-0.0245**	0.0516***	-0.0020	-0.0079**
	(0.028)	(0.041)	(0.015)	(0.004)	(0.790)	(0.011)
Size	-0.0219***	-0.0674***	0.0049*	-0.0062**	-0.0126***	-0.0010**
	(0.000)	(0.000)	(0.056)	(0.040)	(0.000)	(0.021)
Mtb	-0.0196**	-0.0264**	0.0164**	-0.0003	-0.0019***	-0.0001
	(0.026)	(0.045)	(0.044)	(0.663)	(0.001)	(0.298)
Leverage	0.0642**	0.0987*	0.0105	0.0211*	0.0052	-0.0036
	(0.025)	(0.056)	(0.293)	(0.074)	(0.771)	(0.164)
Roa	-0.0830	-0.1468	0.0059	0.0215	-0.0654***	-0.0171***
	(0.105)	(0.130)	(0.739)	(0.139)	(0.005)	(0.001)
Capex	0.0113	0.0004	0.0055	-0.0777***	0.0294	0.0141***
	(0.822)	(0.998)	(0.852)	(0.003)	(0.231)	(0.003)
Tangibility	0.0139	0.0384	-0.0500	0.0328	-0.1144***	-0.0376***
	(0.871)	(0.918)	(0.372)	(0.422)	(0.000)	(0.000)
Hindex	0.0945	0.4266	0.0253	0.0206	-0.0187	-0.0136**
	(0.128)	(0.132)	(0.379)	(0.556)	(0.292)	(0.019)
R&D				0.0204		
				(0.317)		
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	923	923	923	923	923	923

Panel B: Dependent variable =Failure					
	(1)		(2)		(3)
Total effect (CS_PC)	0.2167** (0.028)	Total effect (CS_PC)	0.2167** (0.028)	Total effect (CS_PC)	0.2167** (0.028)
Direct effect (CS_PC)	-0.0153 (0.370)	Direct effect (CS_PC)	-0.0401 (0.229)	Direct effect (CS_PC)	-0.0322 (0.256)
Indirect effect (Explore5)	0.2321*** (0.036)	Indirect effect (SG&A5)	0.2568 (0.141)	Indirect effect (R&D5)	0.2489 (0.205)
F-statistic for excluded instruments in:					
First stage (1) (CS_PC on Treated)	8.218	First stage (1) (CS_PC on Treated)	8.218	First stage (1) (CS_PC on Treated)	8.218
First stage (2) (Explore5 on Treated | CS_PC)	5.397	First stage (2) (SG&A5 on Treated | CS_PC)	1.129	First stage (2) (R&D5 on Treated | CS_PC)	1.937
Controls	Yes		Yes		Yes

Appendix Table A1: Variable definitions

Dependent variables	Definitions
R&D	Firm's R&D expense (compustat item: xrd) scaled by lagged total asset (compustat item: at). If R&D is missing, then the ratio is replaced as zero.
Log(patents)	Natural logarithm of one plus a firm's total number of patents filed (and eventually granted) in a fiscal year (firm's total number of patents are corrected for truncation bias).
Exploitative	The number of exploitative patents filed (and eventually granted) divided by the number of all patents filed (eventually granted) by the firm in a fiscal year. For a patent to be an exploitative patent, at least 60% of its citations must be patents generated or cited by the firm in the past five years.
Explorative	The number of explorative patents filed (and eventually granted) divided by the number of all patents filed (eventually granted) by the firm in a fiscal year. For a patent to be an explorative patent, at least 60% of its citations must be neither the firm's own patents nor patents cited by the firm in the past five years.
Technological proximity	Following Jaffe (1986), the technology proximity between supplier i and customer j is computed as the uncentered correlation between their respective vectors of technological subcategories: $$T_{ij} = \frac{N_i N_j'}{(N_i N_i')^{1/2}(N_j N_j')^{1/2}}$$ Where $N_i = (N_{i1}, N_{i2}, \dots N_{i37})$ is a vector indicating the share of patents applied by supplier i in each technological subcategories every year. $N_j = (N_{j1}, N_{j2}, \dots N_{j37})$ is a vector indicating the share of patents applied by customer j in each technological subcategory in the past three years. We match the technology classes assigned by USPTO to 37 subcategories following the mapping in Hall et al. (2001). Technology proximity takes a value between 0 and 1 according to their common technology interests.
Technology HHI	The sum of the squared proportion of patents in each technology subcategories in a firm year.
Failure	We define failures as performance-related stock market delistings, liquidations, and distressed mergers (delisting codes 400-490 and 520-584).
Tobin's Q	Tobin's Q, measured as (market value of equity + book value of total debt) divided by total assets.
Firm risk	Firm risk is measured as the natural logarithm of the variance of daily stock returns over firm fiscal year.
Number of PCs	The number of principal customers for each supplier in a year.
Log(1+ #PCs)	The natural logarithm of one plus the number of principal customers for each supplier in a year.

Growth in sales	Growth in sales is computed each year relative to year (t = -6), where year t = 0 is the fraud revelation year. That is, $Growth\ in\ sales_t = ln(sales_t) - ln(sales_{-6})$.
SG&A5	The per-year average of the total SG&A expense scaled by total assets from the first year after the fraud revelation for up to five years after the revelation of customer fraud (or up to the year before exit, if exit occurs earlier than in five years).
Explore5	The per-year average of the natural logarithm of one plus the total fraction of the explorative patents by a treated or a matched supplier from the first year after the fraud revelation for up to five years after the revelation of customer fraud (or up to the year before exit, if exit occurs earlier than in five years).
CS_PC	The difference in the total sales to all principal customers in revelation year and the sales to all principal customers in the year before the revelation of fraud, scaled by the total sales in the latter year.
Other variables	
CExploit	Natural logarithm of one plus the percentage of cumulative number of exploitative patents after the revelation of customers' fraud.
CExplore	Natural logarithm of one plus the percentage of cumulative number of explorative patents after the revelation of customers' fraud.
Principal customers sales ratio	The ratio of total sales to all principal customers to supplier's total sales in the year before the revelation of fraud (for the treated supplier as well as its matched peer firm).
Change in sales to all principal customers	The difference between the average sales to all principal customers from the first year after the fraud revelation to two years after (alternatively, the year before exit, whichever is earlier) and the sales to all principal customers in the year before the revelation of fraud, scaled by the latter sales.
Size	Natural logarithm of total asset (compustat item: "at").
Mtb	The ratio of market value of total assets (compustat: "at" - "ceq" + "prcc_f" * "csho") to book value of total assets.
Leverage	Long-term debt (compustat item: dltt) and short-term debt (compustat item: dlcc) scaled by market value of total asset.
Roa	Income before extraordinary items (compustat item: ib) scaled by lagged total asset.
Capex	Capital expenditure (compustat item: capx) scaled by total value of property, plant and equipment (compustat item: ppent) at the beginning of the year.
Tangibility	The ratio of total value of property, plant and equipment to the lagged total asset (compustat item: "ppent").
HIndex	The sum of squared market shares in the 4-digit-SIC industry.

Appendix Table A2: Technology classification concentration.

This table reports the stacked DID results of the effect of the revelation of customer fraud on affected suppliers' technology classification concentration. The dependent variable is the sum of the squared proportion of patents in each technology subcategory in a firm year. We use the technology subcategories provided by Hall et al. (2001). In column (1) and (2), we report the results of the full sample. In column (3) and (4), we report the results of the matched sample. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent variable: Technology HHI				
	(1)	(2)	(3)	(4)
Treated*Post	-0.0322**	-0.0283**	-0.0349**	-0.0350**
	(-2.44)	(-2.08)	(-2.15)	(-1.99)
Size		0.0259***		0.0235**
		(3.71)		(2.11)
Mtb		0.0061**		0.0096**
		(2.50)		(2.34)
Leverage		-0.0562		-0.1449**
		(-1.50)		(-2.53)
R&D		-0.0540		0.1427
		(-0.58)		(1.35)
Roa		-0.0168		-0.0030
		(-1.15)		(-0.09)
Capex		0.0342*		0.0661*
		(1.91)		(1.88)
Tangibility		-0.1113*		-0.2095**
		(-1.71)		(-2.49)
Hindex		-0.2078*		0.1154
		(-1.70)		(0.47)
Hindex squared		0.2551*		0.0228
		(1.79)		(0.10)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	205,843	205,843	7,558	7,558
Adjusted R^2	0.214	0.216	0.249	0.252

Appendix Table A3: Financial constraint, R&D, patents, and innovation style.

This table reports the coefficients from the stacked DID regressions of the affected suppliers' R&D expenditure, patents, and innovation style on *Treated*Post* and its interactions with the financial constraints dummy. "FC" indicates whether a supplier is financial constrained and takes the value of one for firms that are in the bottom third sorted by their size in the fraud revelation year. The dependent variable in columns (1) and (2) is R&D expense scaled by total asset. The dependent variable in columns (3) and (4) is the natural logarithm of one plus a firm's total number of patents in a year. The dependent variable in columns (5) and (6) is the number of exploitative patents divided by the number of patents of a firm in a year. The dependent variable in columns (7) and (8) is the number of explorative patents divided by the number of patents of a firm in a year. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) R&D	(2) R&D	(3) Log(Patent)	(4) Log(Patent)	(5) Exploitative	(6) Exploitative	(7) Explorative	(8) Explorative
Treated*Post	-0.0065**	-0.0039**	-0.1066***	-0.1095***	-0.0335*	-0.0351**	0.0392**	0.0321*
	(-2.52)	(-1.98)	(-3.06)	(-3.14)	(-1.90)	(-2.04)	(2.19)	(1.98)
Treated*Post*	-0.0242***	-0.0191***	-0.1595***	-0.1329**	-0.0342*	-0.0356*	0.0470*	0.0457*
FC	(-3.30)	(-3.05)	(-3.01)	(-2.52)	(-1.72)	(-1.87)	(1.91)	(1.79)
Post*FC	0.0085	0.0010	0.0305	0.0340	-0.0144	-0.0137	0.0274	0.0297
	(0.53)	(0.33)	(1.27)	(1.32)	(-0.52)	(-0.47)	(0.89)	(0.83)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	12,948	12,948	12,136	12,136	3,573	3,573	3,573	3,573
Adjusted R^2	0.716	0.771	0.901	0.902	0.427	0.436	0.443	0.452

Appendix Table A4: "Fraud years", R&D, innovation output, and innovation style

We select customer misconduct cases that end at least two years prior to the revelation of misconduct. The reference year is the year before the start of the customer's misconduct. *Post* is an indicator variable equal to one for the five years post fraud revelation and zero otherwise. "During-Fraud" is equal to one for the years during the customer's misconduct and zero otherwise. "After-Fraud" is equal to one for the years after the misconduct and prior to the revelation of fraud. Treated is a dummy variable indicating affected suppliers. In column (1), the dependent variable is R&D expense scaled by total asset. In column (2), the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted. In column (3), the dependent variable is the number of exploitative patents divided by the number of patents of a firm in a year. In column (4), the dependent variable is the number of explorative patents divided by the number of patents of a firm in a year. Panel A shows the results for the matched sample, and Panel B sows the results for the full sample. The standard errors are clustered by SIC 2-digit industry. Firm-cohort and year-cohort fixed effects are included. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Matched Sample

	(1) R&D	(2) Log(Patents)	(3) Exploitative	(4) Explorative
Treated*During-Fraud	-0.0084	-0.0300	0.0081	-0.0087
	(-0.89)	(-0.39)	(0.12)	(-0.18)
Treated*After-Fraud	-0.0082	-0.0323	0.0030	-0.0070
	(-0.85)	(-0.44)	(0.06)	(-0.35)
Treated*Post	-0.0192**	-0.2398***	-0.0559**	0.0473**
	(-2.06)	(-3.19)	(-2.21)	(2.36)
Controls	No	No	No	No
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	4,909	4,811	1,909	1,909
Adjusted R^2	0.731	0.896	0.417	0.426

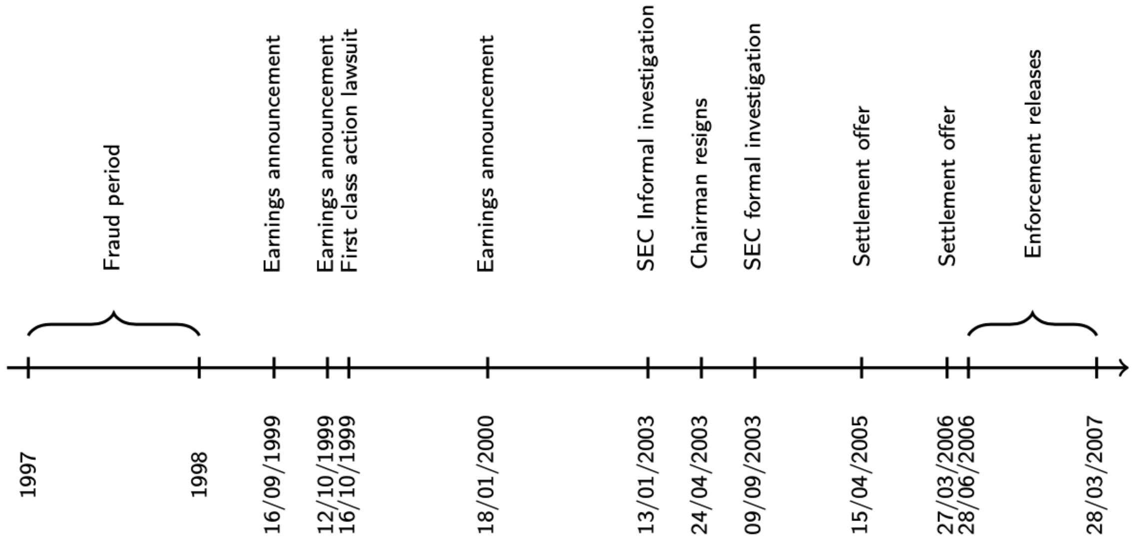
Panel B: Full Sample

	(1) R&D	(2) Log(Patents)	(3) Exploitative	(4) Explorative
Treated*During-Fraud	0.0002	0.0120	0.0053	-0.0045
	(0.02)	(0.19)	(0.13)	(-0.11)
Treated*After-Fraud	0.0008	0.0222	0.0016	-0.0011
	(0.09)	(0.36)	(0.04)	(-0.03)
Treated*Post	-0.0170**	-0.1360**	-0.0418**	0.0341**
	(-2.09)	(-2.18)	(-2.21)	(1.99)
Controls	No	No	No	No
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	91,499	88,039	14,649	14,649
Adjusted R^2	0.708	0.862	0.378	0.388

Online Appendix

Online Appendix Figure 1: Timeline of the key fraud related events of Raytheon

This figure provides the timeline of key informational events pertaining to Raytheon. The events are collected from enforcement releases, SEC filings, and LexisNexis. The fraud period is the period of financial misconduct. The "Enforcement releases" period is when the SEC concludes the investigation and issues the enforcement proceedings.



Online Appendix Figure 2: Average CAR around the public revelation of fraud

Figure OA2(a) and OA2(b) report the average cumulative buy and hold returns of the fraudulent customers and their direct suppliers, respectively. The period starts from twenty days prior to the public revelation of customers' fraud until twenty days after the revelation. Day zero is the revelation day.

Figure OA2(a) Average CAR of fraudulent customers from day -20 to +20

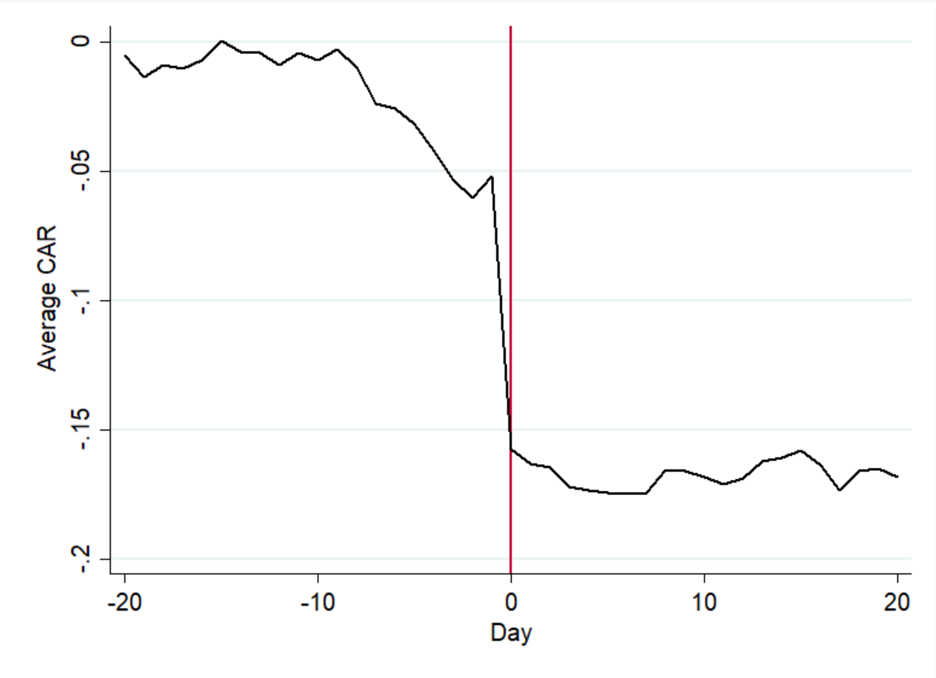
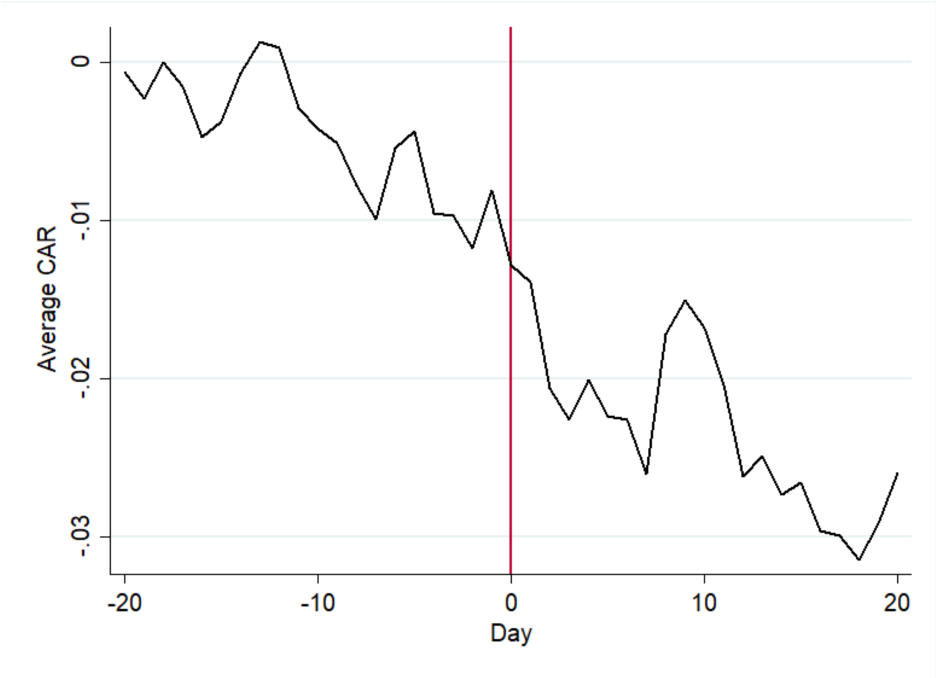


Figure OA2(b) Average CAR of affected suppliers from day -20 to +20



Online Appendix Table OA1: R&D, innovation output, and innovation risk (full sample)

This table reports the stacked DID results of the effect of the revelation of customers' fraud on their suppliers' R&D, innovation output, and risk of innovation. In column (1) and (2), the dependent variable is R&D expense scaled by total asset. In column (3) and (4), the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted. In column (5) and (6), the dependent variable is the difference between the natural logarithm of one plus a firm's total number of patents in a year and the natural logarithm of one plus the total R&D expense in the past five years. *Treated* is a dummy variable indicating affected suppliers. *Treated* is zero for the control firms in the same SIC 2-digit industry as the affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D		Dependent variable: Log(Patents)		Dependent variable: Risky R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post	-0.0122***	-0.0066**	-0.1108***	-0.1171***	-0.2766***	-0.2583***
	(-3.14)	(-2.44)	(-3.09)	(-3.39)	(-4.41)	(-4.13)
Controls	No	Yes	No	Yes	No	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	462,991	462,991	422,579	422,579	369,601	369,601
Adjusted R^2	0.679	0.751	0.850	0.852	0.911	0.913

Online Appendix Table OA2: Missing R&D and patent information

This table reports the stacked DID results of the effect of the revelation of customers' fraud on their suppliers' R&D, innovation output, and risk of innovation. In column (1) and (2), the dependent variable is R&D expense scaled by total asset. Firms are excluded if they do not report R&D expense in any year in the sample. In column (3) and (4), the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted. Firms are excluded if they do not produce any patents in any year in the sample. In column (5) and (6), the dependent variable is the difference between the natural logarithm of one plus a firm's total number of patents in a year and the natural logarithm of one plus the total R&D expense in the past five years. Firms are excluded if their R&D expense and patent information are missing in any year in the sample. *Treated* is a dummy variable indicating affected suppliers. *Treated* is zero for the matched control firms in the same SIC 2-digit industry as the affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D		Dependent variable: Log(Patents)		Dependent variable: Risky R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post	-0.0105***	-0.0097**	-0.0857**	-0.0884*	-0.2696**	-0.2218**
	(-3.11)	(-2.38)	(-2.18)	(-1.99)	(-2.19)	(-2.12)
Controls	No	Yes	No	Yes	No	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,829	10,829	7,558	7,558	6,391	6,391
Adjusted R^2	0.679	0.755	0.873	0.881	0.784	0.788

Online Appendix Table OA3: Innovation style (full sample)

This table reports the stacked DID results of the effect of the revelation of customer fraud on affected suppliers' innovation style. The dependent variable in columns (1) and (2) is the number of exploitative patents divided by the number of patents of a firm in a fiscal year. The dependent variable in columns (3) and (4) is the number of explorative patents divided by the number of patents of a firm in a fiscal year. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Exploitative	(2) Exploitative	(3) Explorative	(4) Explorative
Treated*Post	-0.0363**	-0.0377**	0.0316**	0.0334**
	(-2.54)	(-2.43)	(2.09)	(2.21)
Size		0.0180***		-0.0209***
		(2.82)		(-7.17)
Mtb		-0.0016		0.0021***
		(-0.81)		(2.66)
Leverage		0.0958***		-0.0979***
		(2.79)		(-6.04)
R&D		-0.0602		0.0058
		(-1.17)		(0.26)
Roa		-0.0351		0.0191**
		(-1.42)		(2.53)
Capex		0.0241		-0.0118
		(1.00)		(-1.40)
Tangibility		0.0642		-0.0292
		(1.08)		(-1.31)
Hindex		0.0978		-0.0783
		(0.49)		(-1.12)
Hindex squared		-0.1254		0.1533**
		(-0.73)		(2.03)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	74,365	74,365	74,365	74,365
Adjusted R^2	0.370	0.371	0.383	0.385

Online Appendix Table OA4: Innovation style (alternative cut-offs for the definition of exploitative and explorative patents)

This table reports the stacked DID results of the matched sample. An exploitative patent cites at least 80% of patents produced or cited by the firm in the past five years. For an explorative patent, at least 80% of its citations are neither firm's own patents nor patents cited by the firm in the past five years. The dependent variable in column (1) and (2) is the number of exploitative patents divided by the number of all patents of a firm in a year. The dependent variable in column (3) and (4) is the number of explorative patents divided by the number of all patents of a firm in a year. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable equal to one for five years post revelation of fraud and zero for five years before the revelation. Firm-cohort and year-cohort effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Exploitative	(2) Exploitative	(3) Explorative	(4) Explorative
Treated*Post	-0.0450***	-0.0449***	0.0336*	0.0375*
	(-3.85)	(-3.54)	(1.72)	(1.91)
Controls	No	Yes	No	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	4,334	4,334	4,334	4,334
Adjusted R^2	0.379	0.381	0.445	0.449

Online Appendix Table OA5: Financial constraint, R&D, patents, and innovation style (full sample).

This table reports the coefficients from the stacked DID regressions of the affected suppliers' R&D expenditure, patents, and innovation style on *Treated*Post* and its interactions with the financial constraint dummy. "FC" is an indicator for the supplier's financial constraint and takes the value of one for firms that are in the bottom third sorted by their size at the fraud revelation year. The dependent variable in columns (1) and (2) is R&D expense scaled by total asset. The dependent variable in columns (3) and (4) is the natural logarithm of one plus a firm's total number of patents in a year. The dependent variable in columns (5) and (6) is the number of exploitative patents divided by the number of patents of a firm in a year. The dependent variable in columns (7) and (8) is the number of explorative patents divided by the number of patents of a firm in a year. *Treated* is a dummy variable indicating affected suppliers. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R&D	R&D	Log(Patent)	Log(Patent)	Exploitative	Exploitative	Explorative	Explorative
Treated*Post	-0.0067**	-0.0062**	-0.0861***	-0.0890***	-0.0266**	-0.0280**	0.0234**	0.0231*
	(-2.55)	(-2.46)	(-3.85)	(-4.01)	(-1.98)	(-2.06)	(2.06)	(1.77)
Treated*Post*	-0.0174***	-0.0165**	-0.0883**	-0.0862**	-0.0270*	-0.0304*	0.0311*	0.0349**
FC	(-2.82)	(-2.07)	(-2.08)	(-2.04)	(-1.82)	(-1.86)	(1.84)	(1.99)
Post*FC	0.0004	0.0001	0.0044	0.0032	0.0022	0.0028	-0.0109	-0.0095
	(0.77)	(0.23)	(1.56)	(1.49)	(0.35)	(0.33)	(-1.64)	(-1.11)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	440,303	440,303	400,897	400,897	58,314	58,314	58,314	58,314
Adjusted R^2	0.680	0.749	0.850	0.852	0.387	0.389	0.396	0.396

Online Appendix Table OA6 (i): R&D, innovation output, innovation risk, and fraud customer industry growth opportunities (matched sample)

This table reports the coefficients from the stacked DID regressions of the affected suppliers' R&D expenditure, patents, and risk of innovation on Treated*Post and its interactions with the high growth opportunities dummy for the fraud customer industry. In column (1) and (2), the dependent variable is R&D expense scaled by total asset. In column (3) and (4), the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted. In column (5) and (6), the dependent variable is the difference between the natural logarithm of one plus a firm's total number of patents in a year and the natural logarithm of one plus the total R&D expense in the past five years. *Treated* is a dummy variable indicating affected suppliers. *Treated* is zero for the matched control firms in the same SIC 2-digit industry as the affected suppliers. *High growth* is one if the median value of the market to book ratio of the fraud customer industry is above the median value of this variable over all sample customer fraud events in the year prior to the revelation. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D		Dependent variable: Log(Patents)		Dependent variable: Risky R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post	-0.0010	-0.0015	-0.0316	-0.0299	-0.1784**	-0.1524*
	(-0.72)	(-0.34)	(-0.49)	(-0.46)	(-2.19)	(-1.87)
Treated*Post *High growth	-0.0181**	-0.0108**	-0.1889**	-0.2048**	-0.1771*	-0.1573*
	(-2.36)	(-2.09)	(-2.27)	(-2.63)	(-1.93)	(-1.68)
Post*High growth	0.0022	0.0024	-0.0417	-0.0280	-0.0064	-0.0081
	(0.62)	(0.42)	(-0.61)	(-0.39)	(-0.12)	(-0.16)
Controls	No	Yes	No	Yes	No	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,467	13,467	12,635	12,635	11,815	11,815
Adjusted R^2	0.719	0.777	0.896	0.898	0.916	0.918

Online Appendix Table OA6(ii): Innovation style and fraud customer industry growth opportunities (matched sample)

This table reports the coefficients from the stacked DID regressions of the affected suppliers' innovation style on Treated*Post and its interactions with the high growth opportunities dummy for the fraud customer industry. The dependent variable in columns (1) and (2) is the number of exploitative patents divided by the number of patents of a firm in a fiscal year. The dependent variable in columns (3) and (4) is the number of explorative patents divided by the number of patents of a firm in a fiscal year. *Treated* is a dummy variable indicating affected suppliers. *High growth* is one if the median value of the market to book ratio of the fraud customer industry is above the median value of this variable over all sample customer fraud events in the year prior to the revelation. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Exploitative	(2) Exploitative	(3) Explorative	(4) Explorative
Treated*Post	-0.0217**	-0.0184*	-0.0012	-0.0013
	(-2.06)	(-1.71)	(-0.08)	(-0.08)
Treated*Post *High growth	-0.0302**	-0.0356**	0.0798**	0.0853**
	(-2.50)	(-2.33)	(2.04)	(2.17)
Post*High growth	-0.0053	-0.0048	0.0094	0.0095
	(-0.19)	(-0.17)	(0.26)	(0.26)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	4,334	4,334	4,334	4,334
Adjusted R^2	0.409	0.417	0.421	0.429

Online Appendix Table OA6(iii): R&D, innovation output, innovation risk, and fraud customer industry growth opportunities (full sample)

This table reports the coefficients from the stacked DID regressions of the affected suppliers' R&D expenditure, patents, and risk of innovation on Treated*Post and its interactions with the high growth opportunities dummy for the fraud customer industry. In column (1) and (2), the dependent variable is R&D expense scaled by total asset. In column (3) and (4), the dependent variable is the natural logarithm of one plus a firm's total number of patents filed and eventually granted. In column (5) and (6), the dependent variable is the difference between the natural logarithm of one plus a firm's total number of patents in a year and the natural logarithm of one plus the total R&D expense in the past five years. *Treated* is a dummy variable indicating affected suppliers. *Treated* is zero for the matched control firms in the same SIC 2-digit industry as the affected suppliers *High growth* is one if the median value of the market to book ratio of the fraud customer industry is above the median value of this variable over all sample customer fraud events in the year prior to the revelation. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D		Dependent variable: Log(Patents)		Dependent variable: Risky R&D	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated*Post	-0.0000	0.0021	-0.0405	-0.0459	-0.1797**	-0.1651**
	(-0.01)	(0.51)	(-1.03)	(-1.21)	(-2.28)	(-2.09)
Treated*Post	-0.0211***	-0.0151**	-0.1202**	-0.1217**	-0.1620*	-0.1559*
*High growth	(-3.37)	(-2.67)	(-2.15)	(-2.34)	(-1.72)	(-1.69)
Post*High	-0.0021	-0.0035	-0.0018	-0.0031	-0.0027	-0.0007
growth	(-0.47)	(-0.36)	(-0.22)	(-0.38)	(-0.33)	(-0.07)
Controls	No	Yes	No	Yes	No	Yes
Firm*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	462,991	462,991	422,579	422,579	369,601	369,601
Adjusted R^2	0.679	0.751	0.850	0.852	0.911	0.913

Online Appendix Table OA6(iv): Innovation style and fraud customer industry growth opportunities (full sample)

This table reports the coefficients from the stacked DID regressions of the affected suppliers' innovation style on Treated*Post and its interactions with the high growth opportunities dummy for the fraud customer industry. The dependent variable in columns (1) and (2) is the number of exploitative patents divided by the number of patents of a firm in a fiscal year. The dependent variable in columns (3) and (4) is the number of explorative patents divided by the number of patents of a firm in a fiscal year. *Treated* is a dummy variable indicating affected suppliers. *High growth* is one if the median value of the market to book ratio of the fraud customer industry is above the median value of this variable over all sample customer fraud events in the year prior to the revelation. *Post* is an indicator variable equal to one for five years post fraud revelation and zero for five years before the fraud revelation. Firm-cohort and year-cohort fixed effects are included. The standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Exploitative	(2) Exploitative	(3) Explorative	(4) Explorative
Treated*Post	-0.0140*	-0.0153**	-0.0072	-0.0056
	(-1.95)	(-2.15)	(-0.28)	(-0.21)
Treated*Post *High growth	-0.0337**	-0.0348**	0.0577**	0.0579**
	(-2.18)	(-2.19)	(2.60)	(2.62)
Post*High growth	0.0068	0.0068	-0.0011	-0.0014
	(0.85)	(0.84)	(-0.09)	(-0.10)
Firm*Cohort FE	Yes	Yes	Yes	Yes
Year*Cohort FE	Yes	Yes	Yes	Yes
Observations	74,365	74,365	74,365	74,365
Adjusted R^2	0.370	0.371	0.383	0.385

Online Appendix Table OA7: Firm survival and explorative vs. exploitative innovation (Full sample)

This table presents the results from regressions of survival analysis on treated suppliers and their industry peers after the revelation of customers' fraud. Failure is an indicator variable which is one if a firm has performance-related stock market delisting, liquidation, and distressed merger (delisting codes 400-490 and 520-584). In panel A, we report the results of the matched sample. *CExploit* (*CExplore*) is the natural logarithm of one plus the percentage of the cumulative number of exploitative (explorative) patents after the revelation of customers' fraud. *P*-values are reported in parentheses. Standard errors are clustered by SIC 2-digit industry. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Survival Analysis		Failure (1/0)
	(1)	(2)	(3)
	Cox	Weibull	LPM
CExploit	1.1637	1.1262	0.0091
	(0.288)	(0.269)	(0.119)
CExplore	0.5284***	0.5161***	-0.0263***
	(0.000)	(0.000)	(0.000)
Treated	0.5425***	0.5339***	-0.0095***
	(0.000)	(0.000)	(0.000)
Size	0.7940***	0.7975***	-0.0097***
	(0.002)	(0.004)	(0.000)
Mtb	0.8816**	0.8820**	-0.0046***
	(0.018)	(0.015)	(0.000)
Leverage	1.0398***	1.0445***	0.0338***
	(0.000)	(0.000)	(0.000)
Roa	0.8347**	0.8206*	-0.0486***
	(0.029)	(0.064)	(0.000)
Capex	0.9238	0.9679	-0.0007
	(0.234)	(0.181)	(0.219)
Tangibility	1.1476	1.0674	-0.0288***
	(0.756)	(0.883)	(0.000)
Hindex	1.8488**	1.8891**	-0.0010
	(0.035)	(0.039)	(0.856)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	31,639	31,639	31,639