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Abstract

This dissertation consists of three essays in corporate finance. In the first essay, which is a joint work with Lilian Ng and Yelena Larkin, we investigate how short-term institutional investors gain informational advantage over other market participants. In particular, we examine the information transmitted along the supply chain to test whether short-term investors are better able to process public, yet slowly diffusing, information ahead of others. We find that greater supplier dependence on a few major customers is associated with larger holdings by short-term institutional investors, consistent with our hypothesis that short-term institutions value complex public information. Further substantiating our findings, we show that the relation is stronger when institutional investors have less alternative means of gaining informational advantages. The impact of customer concentration on short-term investment decisions is more pronounced for opaque firms and for periods following the passage of the Fair Disclosure Regulation. Our results offer an explanation to the apparent contradicting evidence that short-term institutions would prefer firms with more information disclosure even though these investors gain from trading on their informational advantage over others.

The second essay, coauthored with Rui Dai and Lilian Ng, examines the strategic bad news withholding of firms facing distinct dimensions of competition. We exploit the network of customer-supplier relationships to distinguish the competitive threats posed by existing rivals from those by potential competitors. In particular, suppliers of similar products are classified as existing rivals if they serve the same corporate customers and as potential rivals otherwise. Our analyses show that existing competition is positively related to stock price crash risk, a proxy for the accumulation of undisclosed unfavorable information. Further investigation finds that such relation is driven by increased proprietary costs of disclosing bad news to existing rivals, corporate customers, and investors. In contrast, we find a negative relation between potential competition and crash risk, indicating that firms facing threats from potential entrants disclose unfavorable information to deter entry.

In the third essay, using the 1977 amendment of the Clean Air Act nonattainment designations as an exogenous source of variations in county-wide environmental regulations, I find that regulatory effects differ across firms facing varying degrees of competition. Firms in more competitive product markets have stronger incentives to remain in regions with tightened regulations and seek competitive advantages through green innovation and product differentiation. Analyses in a triple-difference framework show that competition dampens regulatory effects on plant closure decisions and alleviates their adverse impact on firm operating performance. I also find that post-shock variations in firm performance are driven by increased green innovative output, greater product differentiation, and better customer attraction and retention for more competitive firms. My results show that competition plays an important role in firm responses to environmental regulations. It has significant implications for the policy design of environmental regulations.'

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1. Short-Term Institutional Investors and the Diffusion of Supply Chain Information

1.1 Introduction

The role of institutional investors in US financial markets has increased dramatically over the past three decades, receiving growing interests from researchers across different disciplines. Existing studies show that institutional investors play an important role in corporate governance, financial policies, as well as investment and management decisions of their portfolio firms through direct engagement, voting, and threats of exit (e.g., Aghion, van Reenen, and Zingales, 2013; Fich, Harford, and Tian, 2015; McCahery, Sautner, and Starks, 2016; Harford, Kecskès, and Mansi, 2017). Given the pivotal role of institutions in firm management, previous research has attempted to shed light on how institutions make their investment decisions. This literature has devoted particular attention to studying the information advantage of institutions (e.g., Bushee and Noe, 2000; Ke and Petroni, 2004; Yan and Zhang, 2009).

Interestingly, while the literature seems to be in agreement that long-term investors are good at gathering information about the fundamental value of a firm when making their investment decisions, there is no similar consensus regarding the informational advantage of short-term investors. On the one hand, Ke and Petroni and Yan and Zhang provide evidence that short-term institutions possess better information-processing skills at predicting future earnings than do long-term investors and hence, can achieve superior returns. On the other hand, Bushee and Noe show that compared to long-term investors with information-gathering capabilities, short-term institutions implement strategies that benefit from better disclosure of information. Thus, it remains unclear whether trading gains of short-term institutions are derived from implementing strategies that rely on enhanced transparency and more information disclosure, or from exploiting their information-processing advantage.

In this paper, we offer a way to reconcile these competing views in the literature by arguing that one key advantage of short-term institutional investors lies in their ability to process publicly disclosed, while potentially complex, information, but nevertheless is overlooked by the general public. The existing literature shows that relevant information that is complex to process, such as soft information (Engelberg, 2008), information on economically-related entities, including suppliers and customers (Cohen and Frazzini, 2008; Menzly and Ozbaz, 2010), subsidiary industries (Cohen and Lou, 2012), and foreign divisions (Huang, 2015) is incorporated into stock prices slowly and generates return predictability. If short-term investors are good at processing complex public information in advance of the less sophisticated market participants and then are able to act upon it, they can generate superior returns without the need to invest in costly collection of private information.

To empirically examine this question, we look at information transfers along customer-supplier links. Focusing on firms with large customers provides a particularly suitable laboratory to test our predictions. First, given that customers and suppliers are economically linked, knowledge of major customers is informative of the firms' future performance. At the same time, any customer-related information, although publicly available, is not transmitted through the supply chain instantaneously and is often overlooked by investors, especially the less informed ones (Cohen and Frazzini, 2008; Menzly and Ozbaz, 2010). Second, while customer-supplier relations tend to be persistent over time, changes in customer concentration are nevertheless more frequent than opening/closing of inter-industry and multinational divisions.[1] Third, as will be elaborated below, supply-chain information setting allows us to tease out changes in customer concentration that are plausibly exogenous to firm fundamentals, and therefore, address endogeneity concerns.

We conjecture that a firm's disclosure of its major customers should affect short-term investors more than long-term investors, and empirically test this prediction by examining whether customer clientele shapes a firm's short-term investor clientele. If short-term institutions value public, but difficult to process, information more compared to other market participants, cus-

[1] In untabulated analysis of our sample, we find that 52.49% of suppliers add or drop a customer in a given year. As opposed to that, only 22.89% of firms in the same sample add or drop an industry segment (defined based on 2-digit SIC) in a given year.

tomer concentration should attract short-term institutional investors. On the other hand, customer concentration should have little or no impact on long-term investors, who generally have more access to private information than short-term investors and are less interested in exploiting short-lived informational advantages (e.g., Porter, 1992; Bushee and Noe, 2000; Boone and White, 2015).

Our study begins by examining how customer clientele affects investor ownership structure on a sample of 46,099 firm-year observations for the 1980-2015 period. We identify firms that report major customers in Compustat Customer Segment Files and employ information of 13F institutional holdings to determine their investment horizon in these firms. Our baseline evidence shows that only short-term institutional investors are attracted to firms with large customer concentration, and that the relation is economically significant. An increase in customer concentration in the magnitude of its interquartile range (75th minus 25th percentile) attracts approximately 11% of additional institutional holdings relative to the median short-term institution ownership. At the same time, long-term investors do not exhibit any preference towards firms with high customer concentration. Both findings are robust to a battery of alternative definitions of customer concentration and alternative classifications of institutional investors.

It is possible that the baseline results are subject to endogeneity issues. For instance, the observed relationship may be attributed to omitted variables that are related to both customer concentration and institutional holdings. It is also likely that institutions actively affect managerial decisions, and that their intervention impacts customer concentration. To mitigate these concerns, we conduct three instrumental variable (IV) analyses. In our first approach, we construct an instrumental variable using M&A activity in the customer industry, following Campello and Gao (2017). High M&A activity increases the customer concentration for a given supplier, as suppliers face a more concentrated distribution of customers following the mergers. Since our specifications also include supplier industry-year fixed effects, this IV is orthogonal to the M&A activity of the supplier, and is unlikely to affect the institutional holdings of the supplier through alternative channels, such as propagation of merger waves across industries. In an alternative approach, we follow Gutierrez and Philippon (2017) and use the regulation index in the customer industry as an instrument. This approach relies on the notion that increased regulations generate barriers to entry and benefit larger firms, shifting the distribution of customer industry incumbents towards a small number of sizable firms. Once again, the inclusion of supplier industry-year fixed effects accounts for the possibility that some government regulations could affect supplier and customer industries simultaneously. In our final test, we follow Dhaliwal, Judd, Serfling, and Shaikh (2016) and instrument customer concentration using the lagged industry average concentration in the supplier's industry. We find that our IV results are consistent with the baseline evidence, primarily among short-term investors.

Next, we provide evidence in support of public information transfer as the channel through which customer concentration attracts institutional ownership. To gauge this channel, we start by evaluating the overall information environment in which institutions operate by considering the role of Fair Disclosure (FD) Regulation. FD Regulation, implemented in year 2000, prohibited selective disclosure of material information to a small group of investors (typically analysts and some institutions) without making it publicly available. Ke, Petroni, and Yu (2008) show that short-term investors are particularly affected by the reform and have changed their trading behavior. As a result, if the private information advantage of short-term institutions has declined following the reform, the information value of supply chains should, in turn, increase. Consistent with this conjecture, we find that the impact of customer concentration on short-term institutional holdings has become more pronounced following the FD Regulation.

To further substantiate the information channel, we examine whether the information environment of the concentrated firms affects institutional holdings decisions. If institutional preference for customer-concentrated firms is driven by the information transfer channel, we would expect this transfer to be slower among more opaque firms, generating better investment opportunities for short-term investors. To perform this analysis, we split the sample into transparent and opaque firms using the forecast error as a proxy for information asymmetry. We find that institutional investors are primarily attracted to firms with high customer concentration when information asymmetry is high, confirming our argument.

Our final test looks at short sellers – another type of sophisticated investors who have superior information processing skills (see, Reed, 2013). Short sellers can be viewed as a special type of short-term investors with a primary focus on short, rather than long positions, and whose trades are based on speculative motives and short-lived information advantage (Reed, 2013). We examine the intensity of short sellers' trading activities, as proxied by the fluctuations in the number of open short positions over time. We expect that, similar to short-term institutional investors with long positions, short sellers can also capitalize on the customer information before it is impounded into the supplier's stock price. Thus, if gradual transfer of public information is the channel underlying our main findings, we should find short sellers to trade more actively in firms with larger customer concentration. Our cross-sectional results, as well as the IV's, are consistent with the prediction that short interest dispersion is greater among firms with large customer concentration, further lending support to the information mechanism.

Finally, we address alternative explanations of our findings. The first explanation we consider is that short-term investors prefer firms with customer concentration due to their risk-return profile. Existing literature has shown that concentrated customer base improves operating efficiency, increases economies of scale, and enhances profitability (Patatoukas, 2012; Irvine, Park, and Yildizhan, 2016). At the same time, firms' dependence on a few major customers increases their risk profile, leading to higher costs of equity and debt capital (Dhaliwal et al., 2016; Campello and Gao, 2017). If short-term investors are less risk-averse than long-term institutions are, then they may be attracted to higher profitability of firms with customer concentration, and also be willing to bear additional risk, associated with such investment. We address this issue in two ways. First, we include controls for both risk and stock performance in all of our specifications. Second, we repeat our main analysis by looking at subsample of firms with government as the major customer. Dhaliwal et al. (2016) demonstrate that government suppliers are less risky, and at the same time, less profitable than corporate suppliers. If risk-return preference explanation is at work, we should find that short-term investors exhibit lower preference towards firms with government customers compared to suppliers of corporate customers. Our results indicate that this is not the case. The effect of government customer concentration on short-term holdings is statistically significant and is similar in magnitude to the impact of large corporate customer base. This finding reinforces the notion that short-term investors are attracted to the informational feature of concentrated firms, rather than their risk-return profile.

We also examine whether the positive effects of customer concentration on short-term institutional ownership are driven by cross-ownership in both the supplier and customer firms. Firms with stronger customer-supplier links may attract common ownership for non-informational reasons, and disentangling the motivations behind common investors can be challenging. To address this issue, we reestimate our baseline regression for supplier's shares owned by institutional investors that do not simultaneously own any of the linked customers. We find that the positive effects of customer concentration on short-term institutional ownership remain even after excluding institutional cross-ownership, indicating that other mechanisms, potentially driving the common ownership, cannot fully explain our main findings.

Overall, our research sheds light on the sources of trading strategies of short-term investors. Existing literature demonstrates that short-term investors value short-term investment strategies of firms (e.g., Krueger, Sautner, and Starks, 2018). However, there is still scant information about the selection process that short-term institutions implement in their decision-making beyond standard firm characteristics, such as size, book-to-market ratios, past stock performance and liquidity (Bushee and Noe, 2000; Bushee, 2001, 2004; Gompers and Metrick, 2001). Our work expands the extant literature by showing that product market characteristics play a crucial role in portfolio management decisions of short-term institutional investors. Motivated by this strand of research, our study explores whether institutions with different investment horizons are attracted to firms with concentrated customers.

Our work introduces a channel through which customer concentration affects investor clientele of supplier firms. Although the main purpose of the Statement of Financial Accounting System (SFAS) disclosure was to benefit and protect investors, little research has been done to examine whether a firm's improved information environment through disclosure of major customers has affected market participants to the same extent. Ellis, Fee, and Thomas (2012) demonstrate the downsides of customer voluntary disclosure due to strategic responses of competitors. In contrast, our research focuses on mandatory, rather than voluntary, disclosure of customer information and outlines the benefits of revealing such information to certain groups of investors.

The rest of our paper is structured as follows. Section 1.2 provides literature review hypothesis development; Section 1.3 describes the databases used in this study and summarizes the sample's descriptive statistics. Section 1.4 discusses the main results, and Section 1.5 addresses endogeneity tests. In Section 1.6, we offer evidence supporting the role of transparency as a potential mechanism, and Section 1.7 addresses alternative explanations, followed by the conclusion in the final section.

1.2 Related literature and key hypothesis

A large body of literature shows that institutions with different investment horizons differ in their abilities and resources to acquire private information. Prior studies mostly agree that long-term institutional investors, who hold large and stable ownership positions, have both the incentives and the abilities to invest in gathering private information about the firms they own (e.g., Porter, 1992; Bushee and Noe, 2000; Callen, Livnat, and Segal, 2006; Boone and White, 2015). Bushee and Noe examine the annual rankings of firm disclosure practices, as published by the Association for Investment and Management Research, and find little association between firm transparency levels and the long-term institutions' investment decisions. Their evidence lends support to the notion that long-term investors find public disclosures by firms less important for their monitoring and valuation purposes given their reliance on the private information. Complementary to the earlier study, Boone and White show that higher institutional ownership by long-term investors have no significant influence on the propensity for firms to provide voluntary disclosure via management forecasts and 8-K filings. Their study indicates that greater long-term institutional investor presence does not affect the demand for public information production. Instead of examining the relationship of long-term institutional ownership and a firm's overall level of transparency, Callen et al. investigate long-term investors' demand for public information in a more direct manner. The authors examine to what extent the long-term institutional investors would find public release of information via SEC filings relevant in revising their prior beliefs in firm performance. They find that these investors tend to gather private information prior to SEC filings, suggesting that such public disclosures are less value-relevant for them.

However, research on whether short-term investors exploit informational benefits in their investment strategies, provides mixed evidence. One strand of literature argues that short-term institutional investors possess superior private information and trade on it. For example, Ke and Petroni (2004) find abnormal stock selling by short-term investors can predict bad news earnings that follow a string of good news earnings. Hu, Ke, and Yu (2009) and Yan and Zhang (2009) also show that short-term institutions' trading forecasts future stock returns. Such predictive ability of the short-term institutional investors is consistent with the notion that these investors have access to and are able to exploit private pre-disclosed information. This argument is further accentuated by Ke et al., (2008) follow-up study and the work by Li, Radhakrishnan, Shin, and Zhang (2011). Ke et al. show that the ability for short-term investors to predict future bad news earnings diminishes after Reg-FD, a reform that restricts access of selected groups of market participants, such as analysts and institutions, to information that has yet released to the general public. Similarly, Li et al. provide evidence that short-term institutional investors sell stocks prior to the publicly announced financial restatements, but such abnormal selling decreases after Reg-FD. A more recent study by Maffett (2012) focuses on the relationship between institutional trading and firms' public information reporting, and argues that investors derive higher profits from private information in opaque information environment. He finds that short-term institutional investors trade more in firms with opaque public financial reporting, supporting the private information argument.

On the other hand, a different strand of research provides evidence that rebuts the private information trading argument in support of the notion that short-term institutional investors favor more transparent firms to minimize their information gathering efforts. First, Bushee and Goodman (2007) argue that the predictive ability of short-term investors to forecast future earnings does not necessarily imply trading on private information. The authors find that while trading by short-term investors is predictive of future firm performance, it is also positively related to the past and current performance. Such results are more consistent with momentum trading than trading on private information. Second, a number of prior studies show a positive association between short-term institutional ownership and firm transparency. Bushee and Noe (2000) and White (2013) suggest that short-term institutions prefer firms with more forthcoming disclosure practices and less accounting discretion. Short-term investors are also attracted to firms with less information asymmetry as characterized by greater analyst coverage and more accurate analyst earnings forecasts (Chan, Zhang, and Zhang, 2013; Mintchik, Wang, and Zhang, 2014). Moreover, greater presence of short-term investors is associated with increased propensity for firms to provide voluntary disclosure via more timely and precise management forecasts. Boone and White (2015) attribute this relationship to the investors' demand for greater firm transparency. Third, by documenting that the information content of SEC filings is more value-relevant for short-term investors, Callen et al. (2006) suggest that, compared to long-term investors, short-term investors are less likely to collect additional information to assess firm performance before the firms' SEC filings.

Given the mixed results from prior literature, to what extent the short-term institutional investors are informed remains an open question. On the one hand, these investors possess superior information about future firm performance. On the other hand, these investors appear to be attracted to firms with more publicly available information. Our study offers a way to reconcile some of the disagreement in the literature by suggesting that these two seemingly contradicting views are not always mutually exclusive. Aside from acquisition of private information, sophisticated investors can also gain informational advantage through superior ability to interpret the implications of public information (Kim and Verrecchia, 1994; Fischer and Verrecchia, 1999; Choi and Sias, 2012). We posit that short-term investors are one such type of sophisticated investors and can take advantage of the publicly available information that may be difficult to process by other market participants.

The supply chain information provides an appropriate setting to test our prediction. First, customers and suppliers are economically linked (e.g. Hertzel, Li, Officer, and Rodgers, 2008; Kolay, Lemmon, and Tashjian, 2016) so that public disclosure of a firm's customer base allows investors to evaluate the supplier's performance and inherent business risk. The stronger the economic link, the more information the customers reveal about the suppliers. Hence, firms with greater dependence on major customers should be more transparent. Second, while customer-related information is publicly available, it is not transmitted through the supply chain instantaneously and is often overlooked by investors. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) document significant cross-predictability of customer returns on future supplier returns. Thus, this setting captures the slow diffusion of public information, and investors with superior ability to learn from public signals should take advantage of it. We predict that short-term institutional investors prefer firms with greater dependence on its major customers. Short-term investors may be limited in resources and time to gather private information, but as sophisticated investors, they can process and exploit the customer-related information for temporary information advantage before such information is fully incorporated. Motivated by short-term trading strategies and high portfolio turnover, the short-term institutional investors would trade on their information advantage and realize such trading gains fairly quickly (Bushee and Noe, 2000). Although short-term institutional investors do not invest in gathering information about a firm in a way that long-term investors do, they nevertheless may take advantage of publicly-available information that may be difficult to process by other market participants.[2] Hence, this group of investors can benefit from trading on the slow incorporation of supply chain information into the firm's stock price. The greater the customer concentration, the greater is

[2]Existing studies have shown that information is not transmitted instantaneously along the supply chain and that customer returns have predictive power for supplier future returns (Cohen and Frazzini, 2008; Menzly and Ozbaz, 2010).

the potential informational advantage these investors can gain from leveraging on the customer information. In contrast, we expect that long-term institutional investors are not attracted to firms with higher customer concentration. Given their own private information-gathering capabilities, long-term investors would find public customer-related information a less important source of informational advantage. The above discussion leads to the following hypotheses:

HYPOTHESIS 1a: *The short-term institutional ownership is positively related to the firm's customer concentration.*

HYPOTHESIS 1b: *The long-term institutional ownership is not significantly related to the firm's customer concentration.*

1.3 Sample selection and empirical methodology

SFAS Nos. 14 and 131 of Financial Accounting Standards Board (FASB) require public firms to disclose sales derived from all major customers, who account for at least 10% of the firms' total revenue. We obtain this information from Compustat Customer Segment Files. Besides customer names and sales information, the database also provides information on whether a customer is a government entity or a corporation. For the purpose of our analysis, we focus on corporate customers only.[3] Information transfer channel posits that short-term institutions should pay attention to publicly available, rather than privately collected, information. Therefore, the channel is at work when investors know the identity of the customers and can obtain information about their performance. To ensure that we focus on information transfer of publicly available knowledge, we further restrict our analysis to those corporate customers whose names are disclosed and can be matched to Compustat. The database reports customer names without any unique identifiers, so we identify customers by manually matching each customer's name to a firm's name in Compustat Fundamentals Annual Files to obtain the customer's gvkey

[3] We exclude government customers from our main analysis as previous studies show that government-dependent suppliers are subject to stricter information requirements (Samuels, 2016) and exhibit different behaviors from otherwise similar firms (i.e., lower capital investment, R&D expenditure, and sales growth) (Cohen and Malloy, 2016). We examine the role of government customers separately in Section 6.

code.[4] While not required by the regulations, firms sometimes voluntarily report customers that account for less than 10% of their total sales. To reduce the self-selection bias associated with firms' decisions to disclose non-major customers, we restrict our sample to include only supplier firms that have at least one major corporate customer accounting for at least 10% of its supplier's total sales.

We construct our main sample by merging the suppliers that have concentrated customer base with the quarterly institutional holdings obtained from Thomson Reuters Institutional Holdings (13f) database, monthly stock returns from CRSP, and annual financial statement data from Compustat. We restrict our sample to firm-year observations with non-missing values for our main variables of interest and exclude all financial and regulated utility firms (SIC codes 4900-4999 and 6000-6999). This yields a final sample of 7,570 unique supplier firms and 46,099 firm-year observations for the 1980-2015 period.[5]

1.3.1 Measures of customer concentration

Firms across supply chains are economically linked; hence, a shock to major customers would have an economic impact on suppliers. As a result, customer concentration allows us to measure a firm's dependence on the business relationships with its major customers, thereby capturing the strength of such economic links. Following previous studies (Patatoukas, 2012; Irvine et al., 2016; Dhaliwal et al., 2016; Campello and Gao, 2017), we choose the following three measures to capture the extent of a firm's customer base concentration.

The first measure is the sum of sales to all major customers of a supplier, scaled by the total sales of the supplier.

$$\text{Customer Sales}_{i,t} = \sum_{c=1}^{k} \frac{Sales_{i,c,t}}{Sales_{i,t}}, \tag{1.1}$$

where $Sales_{i,t}$ represents the total sales of supplier i in year t, $Sales_{i,c,t}$ represents supplier i's sales to its major customer c in year t, and k is the number of major customers that supplier i

[4] We implement the Levenshtein distance and Phonetic matching algorithms for the name-matching process and manually check every matched pair to ensure accuracy.

[5] The sample period is bounded by the data availability of Thomson Reuters 13f database, which starts its coverage in 1980.

has in year t. The more the supplier sells to its major customers, the more concentrated is its customer base, so a higher Customer Sales captures a greater customer concentration.

The second measure is a modification of the Herfindahl-Hirschman Index (HHI), applied to the distribution of sales to major customers. It is defined as the sum of squared sales percentages to major customers.

$$\text{Customer HHI}_{i,t} = \sum_{c=1}^{k} \left(\frac{Sales_{i,c,t}}{Sales_{i,t}} \right)^2, \tag{1.2}$$

Compared to the first measure, Customer HHI puts more weight on the larger share of sales.

In the third measure, we focus on the largest share of total sales. It is the share of sales to the customer firm that represents the largest share of the supplier's total sales.

$$\text{Largest Customer}_{i,t} = \frac{\max_{c} \; Sales_{i,c,t}}{Sales_{i,t}}, \tag{1.3}$$

It is important to stress that the measures of customer concentration tend to exhibit little variation over time. The stability characteristic may, in turn, masks the effects of customer concentration when firm-fixed effects are incorporated into the model. As a result, we follow existing studies (e.g., Patatoukas, 2012; Irvine et al., 2016; Dwaliwal et al., 2016) by including industry-level fixed effects. However, we depart from these studies by including interacted industry-year fixed effects, as opposed to including just a vector of industry-fixed effects and a vector of year-fixed effects. This refined matrix of industry-time controls absorbs transient industry-specific shocks and eliminates a large number of alternative explanations. Nevertherless, we address the issues of endogeneity more rigorously in Section 1.4, where we perform a battery of IV tests.

1.3.2 Measures of institutional clientele

Following the discussion of the previous sections, we investigate the ownership decisions of short- and long-term institutional investors separately, because they exhibit different preferences for publicly disclosed information (Bushee and Noe, 2000). While long-term investors, who are better at gathering private information, find public information to be less important, we argue that short-term investors tend to invest more heavily in firms with public, but slow to disseminate, information to realize trading gains. Empirically, we define short-term and long-term institutional investors based on their portfolio turnover. Following Gaspar, Massa, and Matos (2005), for every institutional investor we calculate the quarterly churn rate to measure how frequently institutional investors rotate their portfolio stock holdings over a quarter. The churn rate is defined as follows:

$$\text{Churn}_{i,t} = \frac{\sum\limits_{j \in Q} |N_{i,j,t}P_{j,t} - N_{i,j,t-1}P_{j,t-1} - N_{i,j,t-1}\Delta P_{j,t}|}{\sum\limits_{j \in Q} (N_{i,j,t}P_{j,t} + N_{i,j,t-1}P_{j,t-1})/2}, \tag{1.4}$$

where Q is a set of stocks investor i held in quarter $t-1$ and t, $N_{i,j,t}$ is the number of shares of stock j held by investor i in quarter t, $P_{j,t}$ is the price of stock j in quarter t, and $\Delta P_{j,t}$ is the change in stock j's price from quarter $t-1$ to t.

Following Yan and Zhang (2009), we sort all institutions, in each quarter, into terciles based on their average equity portfolio churn rates over the last four quarters. Institutions in the top tercile are defined as short-term institutions, while those in the bottom tercile are defined as long-term institutions. We then match the horizon classification of institutions with institutional holdings at the end of the quarter to define institutional holdings by different institutional type. Quarterly short-term (long-term) ownership is the number of shares owned by all short-term (long-term) institutions divided by the number of shares outstanding. For all tests, we match all financial variables, including customer concentration, with the institutional ownership one quarter after the fiscal year-end to ensure that the most recent financial information is available to institutional investors.

Portfolio turnover features of each group of institutions are as follows. The short-term institutions (i.e., those in the top tercile), hold a stock in their portfolios for an average period of around 5 months, while their long-term counterparts (i.e., those in the bottom tercile) tend to hold a stock for an average period of over three years long (about 39 months). The large difference in the investment horizon becomes a desirable property when it comes to examining the information channel, as the heterogeneities in short-term and long-term investors allow us to capture how differently the two types of investors capitalize on the supply chain information.

1.3.3 Summary statistics

Table 1.1 presents the summary statistics of our main sample. On average, short-term institutional investors hold about 5% of the supplier's total shares outstanding, while long-term institutional investors hold about 17%; the remainder is driven by investors with intermediate investment horizon. Customer-concentrated suppliers, on average, have business relationships with two major customers, with an interquartile range from one to two major customers. The average percentage of sales to all major customers is 40% with about 29% attributed to the largest customer. Hence, for an average firm, the customer base is dominated by its largest customer. The average customer HHI index is approximately 0.14.

The suppliers have an average firm size, as measured by market capitalization, of \$117 million (log value of 4.8) and an interquartile range from \$24 million (log value of 3.18) to \$504 million (log value of 6.22). The average age is 12 years (log(12) = 2.50), with interquartile range from 7 (log value of 1.95) to 21 years (log value of 3.05). The Tobin's Q averages at 2.05, with interquartile range from 1.05 to 2.27. The suppliers' stocks are, on average, priced at \$7.30 (log value of 1.99) with dividend yield of about 1%, stock volatility of about 16%, and turnover of approximately 13%.

Table 1.2 reports pairwise correlations of firm-specific variables included in our analysis. Both short- and long-term institutional ownership across all investment horizons are positively correlated with firm size, age, stock price, and turnover, and are negatively correlated with stock volatility (columns 1-2), indicating that institutional investors share common preferences in some firm characteristics. However, long- and short-term investors also appear to have heterogeneous preferences for other characteristics, as suggested by their correlations with dividend yield, historical returns, and Tobin's Q. While short-term ownership has close to zero correlation with dividend yield and positive correlation with Tobin's Q and historical returns, long-term ownership is positively correlated with dividend and negatively correlated with Tobin's Q. Short-term institutional ownership is has overall positive, but economically low correlation with customer concentration, whereas long-term investors shy away from stocks with high customer concentration, as evident from negative correlation coefficients. Since customer concentration is also correlated with other firm characteristics, such as Tobin's Q, price and volatility, a multivariate analysis is required for a proper evaluation of links between institutional and customer clientele. We turn to regression analysis in the next section.

1.4 Customer concentration and investor clientele

1.4.1 Effects of customer concentration on investor clientele

To assess how customer concentration attracts institutional investors of different investment horizons, we estimate the following panel regression model:

$$\text{Inst\%}_{i,t} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \Sigma_{k=1}^{K} \beta_k X_{ki,t} + \epsilon_{i,t}, \tag{1.5}$$

where $\text{Inst\%}_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), and Customer $\text{Concentration}_{i,t}$ is one of the three measures for customer base concentration defined in Section 1.2 – Customer Sales, Customer HHI, and Largest Customer. $X_{ki,t}$ is a set of firm characteristics that have previously been shown to affect institutional ownership. Following Gompers and Metrick (2001) and Yan and Zhang (2009), we include Tobin's Q, firm size, age, dividend yield, stock volatility, stock turnover, the log of stock price, and historical stock returns over the previous year as our controls. All regressions include industry-year interacted fixed effects that control for unmodeled heterogeneity across industry-years. Standard errors are clustered by firm and year. A detailed definition of all variables is provided in Appendix Table A.1.

Table 1.3 presents results of the baseline model (1.5), where short- and long-term institutional ownership are separately regressed on each of three different measures of customer concentration, while controlling for firm-specific variables as well as industry-year fixed effects. We find that the coefficient of each customer concentration measure is positive and statistically significant at the 5% level. For example, an interquartile-range (from 25th to 75th percentile) increase in a firm's total sales to major customers yields an 11% increase in short-term institutional ownership relative to the sample median short-term holding (column (1)). At the same time, the impact of concentration on long-term ownership is statistically insignificant and economically small: an interquartile change in total sales is associated with only a 2% increase in long-term institutional ownership (column (2)) relative to the sample median. These results support our hypothesis that short-term institutional investors have strong preference for firms with concentrated customer base, potentially due to greater firm transparency brought by more precise information flow from customers to suppliers.

The coefficients on control variables are consistent with prior studies on institutional preference (Gompers and Metrick, 2001; Yan and Zhang, 2009). Institutional investors, both short- and long-term, exhibit preferences for stocks with larger market capitalization, higher turnover, higher price, lower volatility, lower Tobin's Q, as well as lower dividend yield (Grinstein and Michaely, 2005). However, we also observe that short- and long-term institutional investors have different preferences for some firm characteristics. For instance, short-term institutions tend to invest in younger firms, as suggested by the age coefficient of -0.003, while long-term institutions invest more in older firms with a larger and positive age coefficient of 0.033. The preferences for past stock returns are also different for the two groups of institutions. Short-term institutional investors are momentum traders and prefer stocks with high past returns, whereas long-term institutional investors seem to invest in underperforming firms, and hold stocks with low past returns.

Taken together, the results indicate that short-term institutional investors are more attracted to firms with higher customer concentration, whereas long-term institutions do not exhibit any preference towards such firms. This evidence is consistent with our main hypothesis that short-term institutional investors prefer firms that are more transparent due to disclosure of customer links.

1.4.2 Alternative investor ownership definitions

Our main analysis relies on the implicit assumption that institutional investors are completely unconstrained in their portfolio allocation decisions. However, many institutions hold a large portion of their investments in indexed positions that, in turn, limits their ability to make active investment decisions. Therefore, one concern for baseline analysis is that the relationship between customer concentration and institutional ownership may be driven by confounding variables that increase the probability of supplier firms to be included in the major stock indices, which would in turn also increase the holdings by passive institutions. To address this issue, our first robustness check examines whether our findings hold after excluding the passive investors.

Following Bushee (1998 and 2001), we classify investors into three groups: (i) the short-term-focused "transient" institutions, characterized as having high portfolio turnover and diversified portfolio holdings; (ii) the long-term-focused "dedicated" institutions, characterized as having extremely low portfolio turnover and more concentrated portfolio holdings; and (iii) "quasi-indexer" institutions, characterized as having passive portfolios that closely benchmark an index.[6] We exclude quasi-indexers from the sample of institutions, and re-estimate the main regressions using the percentage of ownership by the transient (dedicated) investors as an alternative proxy for short-term (long-term) institutional ownership as our dependent variables (variables Tran% and Dedi%, respectively).

Columns (7)-(12) of Table 1.3 present the regression results based on the alternative measures of short-term and long-term institutional ownership. Consistent with the results reported in columns (1)-(6), the coefficients on the short-term institutional ownership (Tran%) are all statistically and significantly positive at conventional levels, but the coefficients on the long-term ownership (Dedi%) are not. The Tran% coefficients are also economically significant. For example, in column (7), an increase in total sales to major customers by its interquartile range is associated with an 11% increase in transient institutional ownership relative to the sample

[6]We obtain Bushee's (1998 and 2001) institutional investor classification data from Brian Bushee's website. See http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html.

median. Overall, the implication is that firms with customer concentration base tend to attract short-term, but not long-term institutional ownership, and the evidence is not driven by the presence of passive investors.

1.5 Identification strategies

While our baseline results point to an economically and statistically significant relationship between a firm's customer concentration and its institutional ownership, causal inferences drawn from this relationship are subject to endogeneity concerns. For example, it is unclear whether firms with concentrated customer base attract institutional investors, or firms actively pursue large customers under the pressure of institutional shareholders. Moreover, there may be confounding variables that simultaneously affect both institutional ownership and customer concentration, hence driving the observed relationship. To alleviate these endogeneity concerns, we conduct three sets of instrumental variable (IV) analyses to exploit exogenous variations in customer base concentration.

1.5.1 Customer industry M&A intensity

In our first identification strategy, we follow Campello and Gao (2017) and use the intensity of merger and acquisition (M&A) activities in customer industries as a source of exogenous variation in customer concentration. M&A between two existing customers would mechanically increase the supplier's customer concentration through the consolidation of purchasing accountings. Furthermore, prior studies document that horizonal mergers of customers with other firms in the same industry lead to a more concentrated distribution of customers (e.g., Fee and Thomas, 2004; Bhattacharyya and Nain, 2011; Campello and Gao, 2017). Thus, the suppliers that retain the customers post-merger would gain significant growth in sales from the combined purchases of those customers and the firms they merged with, thereby increasing customer concentration. Campello and Gao (2017) find that the average sales of a supplier to an acquirer doubled the pre-merger level in five years after the merger. Therefore, we expect that higher M&A intensity in customer industries would induce a more concentrated customer base for suppliers, thereby satisfying the relevance condition.

We also expect the identification strategy to satisfy the exclusion restriction. Since the M&A activity of the customer's industry is likely independent of the corporate decisions of suppliers, it is reasonable to assert that such M&A activity should only affect the institutional ownership of the suppliers through its effects on customer concentration. One possible concern with the instrument is that merger waves could have contagion effects through customer and supplier networks, and that our IV implicitly captures the M&A activity in the supplier industry. While plausible, this argument of M&A propagation along the supply chain is less critical in our setting; Ahern and Harford (2014) show that the effect of supplier industry consolidation on customer M&A activity is much larger than the impact of customer consolidation on supplier industry. Nevertheless, to address all remaining concerns and to remove any unobserved industry-wide effect of the suppliers that may contaminate the exclusion restriction, we control for the suppliers' industry-year fixed effects in the IV analysis.

Our empirical procedure is based on a two-stage least-squares estimation. In the first stage, we regress a supplier's customer concentration on the M&A intensity of its customer's industry. The second stage tests the effect of instrumented customer concentration on institutional ownership. Formally, we estimate the following two-stage model:

$$\begin{aligned} \text{Customer Concentration}_{i,t} = &\quad \gamma_0 + \gamma_1 \text{Customer Industry M\&A}_{i,t} + \Sigma_{k=1}^{K} \lambda_k X_{ki,t} + \eta_{i,t} \\ \text{Inst\%}_{i,t} = &\quad \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \Sigma_{k=1}^{K} \beta_k X_{ki,t} + \epsilon_{i,t}, \end{aligned} \tag{1.6}$$

where Customer Industry M&A$_{i,t}$ represents the average industry M&A intensity across industries to which supplier i's major customers belong, and all other variables are defined above. We obtain the firm-level annual costs of M&A activity from Compustat (Item AQC). The industry M&A intensity in year t is measured as the aggregate M&A costs divided by the aggregate sales over all firms within an industry (2-digit SIC) in a year, and it is averaged over the last five years. For each supplier, the instrumental variable Customer Industry M&A is the weighted average customer industry M&A intensity over all the supplier's customers' industries, where the weights are determined by its sales percentages to customers.

Table 1.4 presents the two-stage least-squares estimates of institutional ownership on customer concentration. We report the first-stage regression results for Customer Concentration on Customer Industry M&A intensity in columns (1), (4), and (7). The coefficients on the weighted average customer industry M&A intensity are all positive and statistically significant for all three customer concentration measures, consistent with the notion that the supplier's customer base becomes more concentrated following intense M&A activity in its customer's industry. Specifically, the coefficient estimates on Customer Industry M&A lie between 13.17 (column (4)) and 16.33 (column (1)). The F-statistics from the first-stage regressions are well above 10, further indicating that the customer industry M&A intensity is a strong instrument that satisfies the relevance condition.

The second-stage estimates of institutional ownership on the instrumented customer concentration are shown in the next two columns following the first-stage results. The coefficients on customer concentration remain positive and statistically significant in models where the dependent variable is short-term institutional ownership (columns (2), (5) and (8)), consistent with our *prior* that short-term institutions prefer firms with concentrated customer base. For example, column (2) shows that the coefficient on the instrumented Customer Sales is 0.011 (significant at the 5% level), and the results are also significant when using alternative measures of concentration in columns (5) and (8). On the other hand, the instrumental variable coefficients for long-term institutional ownership are statistically insignificant (columns (3), (6), and (9)).

Taken together, the results provide evidence of a significant causal link between customer concentration and short-term investors, but not between customer concentration and long-term institutional ownership. The overall implication is that firms with more concentrated customer base are more likely to attract investments from short-term rather than from long-term institutional investors. The evidence offers the first indication of the information channel that will be formally tested in later sections. Long-term investors may rely less on public supply chain information given their own information-gathering capabilities and focus on firm performance over longer time horizon (Bushee and Noe, 2001). In contrast, short-term institutional investors may pursue firms with customer concentration to leverage on such public information and realize trading profits from the temporary information advantage.

1.5.2 Customer industry regulation

While the previous IV analysis alleviates the endogeneity concerns, it is difficult to completely rule out the possibility that there may be unobserved developments simultaneously attracting institutions to certain suppliers and triggering M&A activity among their customers. Thus, we exploit an alternative approach that relies on the aggregate regulation level of customers' industries to instrument for customer concentration. Gutierrez and Philippon (2017) argue that rising regulatory stringency generates large fixed cost components that benefit larger firms and introduces barriers to entry that are advantageous to incumbent firms. Hence, customer industries with increased regulation would exhibit shifts in the distribution of industry incumbents towards a small number of sizable firms, thereby increasing the customer concentration of their suppliers. One challenge to this approach is the possibility that some government regulations affect both the supplier and customer industries concurrently. As in the previous subsection, we control for supplier industry-year fixed effects to address this potential issue. By doing so, this IV approach, in essence, captures the difference in the level of regulatory stringency between the customer and supplier industries. Even if institutional preferences are affected by the overall amount of regulatory restrictions in the customers' industries, it is unlikely that the difference in the level of regulation across the supply chain is associated with the corporate decisions and the institutional ownership of the suppliers. Therefore, the industry-wide regulatory stringency should meet both the relevance and exclusion conditions.

Following Gutierrez and Philippon (2017), we employ the Regulation Index constructed by McLaughlin and Sherouse (2018) to proxy for the level of regulatory stringency in the customers' industries. Government regulations are typically implemented by many different agencies and apply to a wide range of industries. The RegData Project is McLaughlin and Sherouse's efforts to quantify the applicability of federal regulations to specific industries. This methodology relies on text analysis to count the number of regulatory restrictions affecting each 6-digit NAICS industry and, in turn, generate the Regulation Index using these results.[7]

For the first stage of our IV analysis, we average the natural logarithm of one-year-lagged Regulation Index across all customers of a supplier firm based on the weights determined by the firm's sales percentage to its customers. We then regress the supplier's major customer concentration on the weighted average customer Regulation Index to generate the instrumented customer concentration measures for the second stage analysis. Formally, we estimate the following two-stage model:

$$\begin{aligned} \text{Customer Concentration}_{i,t} = &\quad \gamma_0 + \gamma_1 \text{Customer Reg Index}_{i,t-1} + \Sigma_{k=1}^{K} \lambda_k X_{ki,t} + \eta_{i,t} \\ \text{Inst\%}_{i,t} = &\quad \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \Sigma_{k=1}^{K} \beta_k X_{ki,t} + \epsilon_{i,t}, \end{aligned} \tag{1.7}$$

where Customer Reg Index$_{i,t-1}$ represents the average of one-year-lagged Regulation Index in log form across all industries to which supplier i's major customers belong, and all other variables are as defined in Specifications (1) and (2). Results are reported in Table 1.5.

Columns (1), (4), and (7) indicate that the customers' weighted average Regulation Index satisfies the relevance condition. In particular, the coefficients on Customer Reg Index$_{i,t-1}$ lie within the 0.066-0.074 range across the three customer concentration measures and are all statistically significant at the 1% level. It is apparent that a firm's customer base becomes more concentrated as the customers' industries become more regulated. The large first-stage F-statistics further suggest that the instrumental variable passes the weak identification test.

The second-stage estimates of institutional ownership confirm our previous findings, and are consistent with the customer industry M&A IV analysis. Similar to the results of Table 1.4, customer concentration bears a positive and statistically significant effect on short-term

[7] The newest Regulation Index dataset is obtained from the RegData Project website https://quantgov.org/regdata/. See Al-Ubaydli and McLaughlin (2015) for more details about the Regulation Index measure.

institutional ownership but not on long-term ownership. For example, the coefficients on the instrumented customer concentration vary from 0.019 to 0.023 for short-term institutions, but once again, is insignificant for long-term investors. These results further support a causal effect of customer concentration on the short-term but not long-term institutional ownership.

1.5.3 Industry customer concentration

To provide additional evidence in support of our causal inferences, we use an alternative instrumental variable that does not depend on customer industry characteristics. Specifically, following Dhaliwal et al. (2016), we use the historical industry average customer concentration. For each of our three measures of customer concentration, we calculate the two-year lagged industry average in the supplier's industry based on its 2-digit SIC (excluding the supplier firm). The instrumental variable, which captures the customer base structure of a supplier's industry, should be highly correlated with that of the individual supplier; hence, we expect the industry average customer concentration to meet the relevance condition. Furthermore, it is unlikely that a firm's institutional ownership structure is driven by the historical industry average customer concentration except through its effects on the firm's customer base. The historical industry average customer concentration is also unlikely to be an outcome of future pressure from institutional investors. Thus, it is likely to also satisfy the exclusion restriction. Accordingly, we estimate the following two-stage model:

$$\begin{aligned} \text{Customer Concentration}_{i,t} &= \gamma_0 + \gamma_1 \text{Ind Customer Concentration}_{-i,k,t-2} + \Sigma_{k=1}^{K} \lambda_k X_{ki,t} + \eta_{i,t} \\ \text{Inst\%}_{i,t} &= \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \Sigma_{k=1}^{K} \beta_k X_{ki,t} + \epsilon_{i,t}, \end{aligned} \tag{1.8}$$

where Ind Customer Concentration$_{-i,k,t-2}$ represents the two-year lagged average customer concentration for the industry k to which supplier i belongs, excluding supplier i itself, and all other variables are previously defined above. We exclude the industry-year interacted fixed effects from this model since industry average customer concentration should already correct for the unobserved heterogeneity across industry-years. Standard errors are clustered by firm and year. The estimates of model (1.8) are shown in Table 1.6.

Similar to those of Tables 1.4 and 1.5, the results of Table 1.6 further reinforce the baseline evidence. The instrumented customer concentration has a positive and statistically significant effect on short-term institutional ownership, while non-robust impact on long-term institutions

Taken together, our IV regression results establish a causal relationship between customer concentration and institutional ownership, suggesting that customer clientele is shaped by investor clientele, especially short-term investors. The robustness of our main findings to various IV approaches collectively suggests that short-term institutions value concentrated customer clientele, rather than some omitted supplier characteristics that determine both its customer distribution and institutional ownership. When a firm experiences shock that consolidates its customer base, short-term investor clientele increases.

1.6 The information channel

So far, our findings have demonstrated that the larger a supplier's customer-concentration base, the greater the short-term investor ownership of the supplier's stock. In this section, we explore whether the information transfer channel could explain this relationship. Public information about a firm's customer base allows investors to evaluate its performance and inherent business risk. For example, investors who are attentive to information about the identity and performance of a supplier's customers would be able to better assess the supplier's own performance. We therefore hypothesize that short-term institutional investors, who are sophisticated market players with superior information processing skills, exploit information about the customer-supplier link when investing in firms with higher customer concentration, compared with other market participants. Specifically, we examine the information role by (i) investigating how institutional investors make their investment decisions under different information environments, and (ii) analyzing how customer concentration affects another type of sophisticated investors – the short sellers.

1.6.1 *Effects of fair disclosure regulation*

To empirically test the information channel, we first investigate whether the relationship between short-term institutional investors and customer concentration changes when the overall information environment in which the institutions operate undergoes an exogeneous change. In particular, we consider the role of Fair Disclosure Regulation (Reg FD), which was implemented by the SEC in October 2000. Reg FD prohibits selective disclosure of material non-public information to a small subset of market participants (e.g., analysts and institutional investors) without concurrently making it publicly available. Previous literature (e.g., Eleswarapu, Thomson, and Venkataraman, 2004; Chiyachantana, Jiang, Taechapiroontong, and Wood, 2004) provides evidence that Reg FD has reduced information asymmetries among different groups of investors. This regulation has severely affected institutions as they could no longer access any selective disclosure and benefit from private information. Moreover, Ke et al., (2008) focus on short-term investors and demonstrate that after the reform implementation, transient, or short-horizon, institutions no longer exhibit abnormal selling of stocks in the quarter before a bad news break. These results further suggest that the reform has changed private information advantage of short-term investors, and therefore, has potentially increased the benefits of slowly-transferred public information. We conjecture that if institutional preferences are driven by a firm's customer information disclosure, short-term institutional investors would be more sensitive to the firm's customer base structure post-Reg FD. Long-term investors, on the other hand, are less inclined to trade on public information for short-term gains. As long-term investors tend to use supply-chain information for monitoring purposes, they would not necessarily find such information to be more important post-Reg FD. To test our hypothesis, we re-estimate our baseline model (1.5) across two subperiods. The first, pre-Reg FD, subperiod is based on the 1980-1999 period, whereas the second period spans the time period following the introduction of the reform in October 2000.

The results, reported in Table 1.7, reveal the heterogeneous effects of customer concentration on short- and long-term investors under the changing information environment. The coefficient on all three customer concentration variables is positive and significant at the 1% level during the PostFD subsample, but insignificant and negligible in magnitude before the reform implementation. At the same time, the impact of concentration is not significantly different from zero in the case of LT% as the dependent variable. Thus, during years following Reg FD, customer concentration becomes valuable to short-term investors only, but not to long-term investors. The cross-institutional differences are consistent with the idea that institutional preferences towards customer-concentrated firms are driven by the information flow within the customer-supplier network.

To summarize, the evidence using a quasi-natural experiment around the Reg FD reform is supportive of the public information transfer channel. The findings suggest that short-term institutions start relying more on slowly disseminated public information when potential sources of profit due to private information exploitation becomes less available.

1.6.2 Effects of firm information environment

The evidence using a quasi-natural experiment around the Reg FD reform relies on a shock to regulatory environment that improves the benefits of trading based on public information. However, the shock is common to all stocks. Therefore, we further consider the role of information transfer channel by exploiting differences in information environments across firms. Specifically, we ask whether the link between customer concentration and short-term investor positions strengthens when a firm's information diffusion is more gradual. Existing literature demonstrates that news is incorporated into stock prices slower when information asymmetry and opinion divergence are high (e.g., Zhang, 2006; Garfinkel and Sokobin, 2006). The slow speed of information transfer, in turn, should provide short-term investors with more opportunities to establish positions in a stock based on public information regarding the firm's customers before the rest of market participants react to the news. As a result, short-term investors should be able to realize higher trading profits when information asymmetry is high. The higher gain potential should, in turn, increase the preference of short-term investors towards firms with high customer concentration.

To empirically test this idea, we use a forecast error as a proxy for information environment and opinion divergence. The forecast error is defined as the absolute value of the difference between the reported earnings for the contemporary fiscal quarter and the median of analyst forecasts (measured at the closest to the earnings announcement date), scaled by the stock price at the beginning of the fiscal quarter. We split the overall sample into two subsamples based on high versus low forecast error. To form the two groups, we calculate the median forecast error for every industry-year, and divide firms into low forecast error group if their forecast error is below industry-year median, and into high forecast error group if the error is equal to or higher than the median. We then estimate the main regressions separately for each subsample, and compare the customer concentration coefficients between high and low forecast error groups, and well as between short and long-term investors.

The results, reported in Table 1.8, are consistent with our information channel hypothesis. The link between customer concentration and institutional holdings continues to be significant only for short-term investors, but not for their long-term peers. More importantly, the impact of concentrated customer base is positive and significant at the 1% level only within the high forecast error group subsample, and is insignificant and small in magnitude among the subsample of firms with low forecast error. The cross-sectional differences across supplier firms with major customers further support the idea that institutional preferences towards customer-concentrated firms are driven by the information flow within the customer-supplier network. The slower diffusion of supply chain information provides more opportunities for short-term investors to implement short-horizon trading strategies ahead of other investors and thus, realize higher gains.

1.6.3 Short-selling activity

As an alternative way to test the validity of the information channel in shaping the decisions of short-term investors, we turn to analyzing another group of short-term informed investors

– the short sellers. Short sellers sell borrowed stocks in the hope to profit from a decrease in the stock price when they reverse their position at a later time. Since these strategies are usually implemented for a period of several months only, short sellers can be viewed as one type of short-term investors. Existing literature also shows that short sellers possess superior information processing skill (e.g., Diamond and Verrecchia, 1987; Dechow, Hutton, Maelbroek, and Sloan, 2001; Desai, Ramesh, Thiagarajan, and Balachandran, 2002; and Boehmer, Jones, and Zhang, 2008). As a result, we predict that short sellers can also capitalize on the slowly diffusing public supply chain information before such information gets impounded into the stock price. Thus, if information is the underlying mechanism of our main findings, then concentrated customer-base should also encourage more trading by short sellers in response to better access to value-relevant information. To address the issue, we examine the intensity of short sellers' trading activity. As more short sellers actively trade in a firm's stock, the number of open short positions for the firm should experience greater fluctuations. We measure open short positions by constructing monthly short interest, defined as the number of shares shorted on the 15th business day of each month (obtained from Compustat) scaled by the total number of shares outstanding at the end of the month. We then compute the standard deviation of the monthly short interest over the past 12 months and use it as a proxy for the fluctuation of short positions. A positive association between customer concentration and the dispersion of short interest is in line with the information channel.

To assess the relationship between customer concentration and the intensity of short-selling activity, we estimate the following panel regression,

$$\text{Disp Short Interest}_{i,t+1} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \Sigma_{k=1}^{K} \beta_k X_{ki,t} + \epsilon_{i,t}. \tag{1.9}$$

In Eq. (1.9), Disp Short Interest$_{i,t+1}$ is measured using the standard deviation of monthly short interests over year $t+1$. Similar to our preceding analysis, we estimate the effect of customer concentration on short sellers using both OLS and three IV approaches. Results are reported in Table 1.9. For brevity, the table only reports the second-stage regression estimates of the three IV regressions in columns (4)-(12), using customer industry M&As, customer regulation index, and industry average customer concentration as the respective instruments.

The table produces robustly significant and positive effects of customer concentration on short-sellers' activity using both the OLS and the IV approaches. The results suggest that short sellers become more active in trading in firms with larger customer concentration. The findings regarding the positive relation between the short interest positions of short-term investors and customer clientele complements our previous findings, which establish the link between long positions of short-term investors, as reported in the 13F database, and customer concentration. Taken together, these findings are consistent with the notion that information about the customer base increases the likelihood of a firm to become a target of short-lived investment strategies, whether through long or short positions in the stock.

1.7 Alternative explanations

The previous section has provided direct evidence in support of the information channel. In this section, we further strengthen our argument by considering alternative explanations that could potentially produce similar results. First, we ask whether institutional preferences towards customer-concentrated firms are driven by changes in the risk-return profile of firms. Second, we focus on the role of cross-ownership, and ask whether common holdings of both customer and supplier firms can potentially explain our results.

1.7.1 Risk-Return Profile of Customer-Concentrated Firms

Perhaps the most intuitive alternative explanation of the link between customer concentration and short-term clientele is the risk-return profile of concentrated firms. One strand of the existing literature highlights the benefits of operating efficiency among firms with concentrated customers due to lower selling expenses and higher asset turnover rates. These costs savings, in turn, translate into higher profit margins and better returns (Patatoukas, 2012; Irvine et al., 2016). At the same time, another group of researchers shows that reliance on a limited group of customers increases the risk profile of a firm, leading to more frequent loan failures, and higher systematic and idiosyncratic risk (Campello and Gao, 2017; Dhaliwal et al., 2016). As a result, a portfolio of customer concentrated firms may generate higher return and greater risk, which, in turn, attracts return-seeking and risk tolerant investors. If short-term investors are able to bear more risk so they can generate better performance, it is possible that they are attracted to higher profitability of firms with customer concentration, while also willing to bear additional risk associated with such investments.

We address this argument in several ways. First, all our regressions include measures of past performance and risk, which should account for potentially different profiles of firms with various levels of customer concentration. Second, it is worth noting that changes in risk-return profiles induced by customer concentration do not explain our cross-sectional findings well. For example, while Reg FD has changed the information environment of firms with customer concentration, it is unlikely that the reform has also made firms with customer concentration more profitable or risky, as it should not have any bearing on customer distribution of supplier firms.

To further mitigate the validity of the risk-return explanation, we examine the institutional clientele of firms with government as major customer. Although the focus of our paper is on the relation between a concentrated base of corporate customers and institutions, a supplier can also be highly dependent on revenues from the U.S. federal government. Dhaliwal et al. (2016) demonstrate that federal government customers are safer, as they are much less likely to default or declare bankruptcy, and also operate based on longer-term procurement contracts. The lower risk, in turn, translates into lower risk premium of government suppliers compared to corporate suppliers. Hence, focusing on government customers provides a suitable laboratory that allows us to disentangle the information transfer mechanism from the risk-return profile channel. Since information on government initiatives and budget is, to a large extent, publicly available knowledge, we expect that the public transfer mechanism should be at play, shaping short-term investors' preference towards firms with higher government customer concentration. However, if the risk-return profile is the dominating explanation, we should find that short-term investors exhibit significantly lower sensitivity towards government suppliers, as investment in these firms provide a lower return for a given unit of risk.

To test this prediction, we use the Compustat segment files to identify suppliers that report a US federal government customer as accounting for at least 10% of the total annual revenues of the supplier firm. Based on this data, we re-construct our three measures of customer concentration. For example, Corporate Customer Sales is the total share of sales of a supplier firm to all major government suppliers. We then re-estimate the main specification (1) after augmenting it with the proxies of government concentration. The results, reported in Table 1.10, show that our measures of corporate customers concentration remain significant and similar in magnitude to the main regressions. More importantly, the impact of government concentration is also positive and statistically significant in all three specifications with short-term holdings as the dependent variable. The F-test, reported at the bottom of the table, provides a formal comparison of the two magnitudes. Low p-values across all specifications indicate that we cannot reject the null hypothesis that the two coefficients are equal. Similar to the results of our earlier estimations, neither corporate nor government concentration has a significant impact on long-term holdings, further supporting our main argument, and indicating that these institutions may employ different investment strategies and focus on collecting private information. Thus, we conclude that the significance of our results among government suppliers mitigates the concern that short-term investors may choose those firms due the attractiveness of their risk-return profile.

1.7.2 Institutional cross-ownership

Another concern is that the observed relationship between customer concentration and institutional ownership is the result of increased joint institutional ownership in firms with stronger economic links. Institutional investors may own stocks of both customer and supplier firms for several reasons. Cross-ownership can be information driven, as it would allow institutions to become more informed about the trading firms and extract valuable information from the supplier-customer relationships, especially if the link becomes stronger. Such motivation is consistent with the information channel, but could be driven by both private and public information transfer. Moreover, cross-ownership can also be a result of the institutions' intention to gain control rights over both the customer and supplier so that they can pressure firms into undertaking joint-value maximizing actions that may not necessarily be firm value maximizing (Hansen and Lott, 1996). For example, institutional investors of customers may decide to own shares of the supplier's stock to encourage more stable cooperation between the firms, or to pressure the supplier to provide more relationship-specific investments that would benefit the customer they own. Hence, firms with stronger customer-supplier links may attract common ownership for non-informational reasons.

Thus, although common ownership per se does not contradict our hypothesis, it may nevertheless be driven by private information benefits, as well as other incentives, such as pressure for disclosure, activism, and corporate governance. Since disentangling these explanations can be empirically challenging, we exclude all the cases of cross-ownership from our analysis. Specifically, we repeat the baseline regression analysis for the percentage of supplier's shares owned by institutional investors that do not simultaneously own any of the linked customers. This analysis tests against the alternative explanation that our findings are driven by common institutional investors, who potentially make ownership decisions for purposes other than utilizing information advantage. If public information transfer explains our key finding, we would expect the positive effect on institutional ownership to remain after excluding institutional cross-ownership. To test this effect, we rerun Eq. (1.5) by using non-cross institutional ownership as the dependent variable.

$$\text{NCross Inst\%}_{i,t} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \Sigma_{k=1}^{K} \beta_k X_{ki,t} + \epsilon_{i,t}, \qquad (1.10)$$

where NCross Inst$\%_{i,t}$ is non-cross short-term (NCross ST%) or long-term institutional ownership (NCross LT%). Results are reported in Table 1.11. Except for those in columns (1)-(2), customer concentration exhibits strongly significant and positive effects on non-cross institutional ownership. For instance, the coefficients on Customer HHI and Largest Customer are 0.005 and 0.006, respectively, for non-cross short-term ownership (columns (3) and (5)) and 0.019 and 0.027 (columns (4) and (6)) for non-cross long-term ownership. These results reinforce our key evidence that other mechanisms, potentially driving the common institutional holdings, cannot fully explain our main findings.

1.8 Conclusion

All publicly-listed US firms are required to disclose the amount of sales derived from all major customers that account for at least 10% of their total sales. Such disclosure improves the information environment of the firms and can be critical to investor decision making. Yet, not all investors are equally able to process this information, which, in turn, slows information diffusion and creates return predictability. This study examines whether concentrated customer clientele also shapes the investor clientele of the supplier firm by creating information processing benefits to some groups of investors. Based on a large sample of 46,099 firm-year observations for the 1980-2015 period, we find that short-term institutional investors exhibit preference for firms with large customer concentration, and that the relation is economically significant. At the same time, we find no evidence that long-term institutions exhibit the same preference. Our baseline finding is robust to a multitude of alternative definitions of customer concentration, alternative classifications of institutional investors, and to the possible endogeneity issues.

We next establish the channel of public information transfer as the key mechanism behind the relationship between firms with concentrated customer base and institutional clientele. Our results show that the link between the customer and short-term investor clientele is stronger following the passage of Fair Disclosure regulation, which prohibits selective disclosure to small investor groups. The relationship between the two clienteles is also more pronounced in the environment of asymmetric information, when slower information diffusion helps short-term investors establish positions in a stock ahead of less sophisticated market participants.

Our results have significant implications for disclosure policies of customer information. Prior studies suggest that a firm's stock price does not promptly incorporate its customers' news (e.g., Cohen and Frazzini, 2008; Menzly and Ozbaz, 2010). Our study suggests that a firm with concentrated customer base attracts institutional investors who can, through active trading, potentially improve the firm's stock price informativeness and thus, reduce such information inefficiencies.

Table 1.1: Descriptive Statistics

This table presents the descriptive statistics for our main variables. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015. A major customer is defined as a customer that accounts for at least 10% of its supplier's total sales. All variables are winsorized within 1st and 99th percentiles. See Table A.1 for variable definitions.

	N	Mean	Median	Std	P25	P75
ST%	46,099	0.049	0.060	0.002	0.027	0.076
LT %	46,099	0.167	0.164	0.027	0.115	0.270
Total Customer Sales	46,099	0.404	0.249	0.190	0.350	0.570
Customer HHI	46,099	0.138	0.169	0.030	0.073	0.172
Largest Customer	46,099	0.289	0.184	0.152	0.230	0.360
Number of Customers	46,099	1.726	0.918	1.000	1.000	2.000
Log Age	46,099	2.503	0.725	1.946	2.485	3.045
Tobin's Q	46,099	2.054	1.910	1.047	1.438	2.268
Size	46,099	4.765	2.164	3.182	4.639	6.223
Div. Yield	46,099	0.007	0.019	0.000	0.000	0.000
Log Price	46,099	1.991	1.329	1.163	2.122	2.968
Turnover	46,099	0.128	0.157	0.031	0.074	0.161
Volatility	46,099	0.162	0.095	0.097	0.139	0.200
$Return_{-3,0}$	46,099	0.022	0.314	-0.162	0.000	0.164
$Return_{-12,-3}$	46,099	0.112	0.601	-0.263	0.005	0.319

Table 1.2: Correlation Matrix

This table presents the pairwise correlation coefficients for our main variables. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015. A major customer is defined as a customer that accounts for at least 10% of its supplier's total sales. All variables are winsorized within 1st and 99th percentiles. See Table A.1 for variable definitions.

	ST%	LT%	Customer Sales	Customer HHI	Largest Customer	Log Age	Tobin's Q	Size	Div. Yield	Log Price	Turnover	Volatility	$Return_{-3,0}$
LT%	0.37												
Total Customer Sales	0.13	0.18											
Customer HHI	0.11	0.13	0.83										
Largest Customer	0.09	0.10	0.80	0.94									
Log Age	0.11	0.39	0.06	0.03	0.01								
Tobin's Q	0.05	-0.03	0.06	0.08	0.09	-0.16							
Size	0.43	0.65	0.19	0.13	0.10	0.31	0.17						
Div. Yield	-0.02	0.10	-0.02	-0.03	-0.04	0.18	-0.12	0.19					
Log Price	0.37	0.57	0.04	0.01	-0.01	0.30	0.16	0.79	0.20				
Turnover	0.34	0.23	0.13	0.11	0.09	-0.02	0.18	0.35	-0.06	0.23			
Volatility	-0.14	-0.33	0.00	0.02	0.03	-0.30	0.16	-0.36	-0.24	-0.45	0.19		
$Return_{-3,0}$	0.10	0.04	0.01	0.00	0.00	0.02	0.20	0.15	-0.05	0.23	0.10	0.09	
$Return_{-12,-3}$	0.08	-0.01	-0.01	0.00	0.00	0.01	0.24	0.12	-0.03	0.23	0.11	0.14	0.02

Table 1.3: Investor Clientele and Customer Concentration

This table presents results from our baseline OLS regression, as given below.

$$\text{Inst\%}_{i,t} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},$$

where $\text{Inst\%}_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), or transient (Tran%) or dedicated institutional ownership (Dedi%), $\text{Customer Concentration}_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. In all specifications, we include industry-year fixed effects. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

	Measure of Institutional Ownership Using Churn Rates						Bushee's (1998) Measure of Investor Clientele					
	ST% (1)	LT% (2)	ST% (3)	LT% (4)	ST% (5)	LT% (6)	Tran% (7)	Dedi% (8)	Tran% (9)	Dedi% (10)	Tran% (11)	Dedi% (12)
Customer Sales	0.008***	0.006					0.012***	0.007				
	(4.27)	(1.31)					(3.68)	(1.13)				
Customer HHI			0.010***	0.004					0.013***	0.004		
			(3.89)	(0.55)					(2.93)	(0.48)		
Largest Customer					0.007***	0.003					0.009**	0.001
					(3.21)	(0.44)					(2.45)	(0.17)
Age	-0.003**	0.030***	-0.003**	0.030***	-0.003**	0.030***	-0.009***	0.030***	-0.009***	0.030***	-0.009***	0.030***
	(-2.16)	(11.91)	(-2.23)	(11.86)	(-2.27)	(11.86)	(-4.58)	(9.82)	(-4.65)	(9.72)	(-4.66)	(9.70)
Tobin's Q	-0.002***	-0.007***	-0.002***	-0.007***	-0.002***	-0.007***	-0.002***	-0.013***	-0.002***	-0.013***	-0.002***	-0.013***
	(-11.62)	(-8.53)	(-11.52)	(-8.49)	(-11.32)	(-8.48)	(-4.01)	(-13.57)	(-3.97)	(-13.54)	(-3.89)	(-13.51)
Size	0.008***	0.033***	0.008***	0.033***	0.008***	0.033***	0.016***	0.051***	0.015***	0.051***	0.015***	0.051***
	(13.56)	(20.97)	(13.49)	(20.92)	(13.44)	(20.90)	(19.31)	(25.40)	(19.20)	(25.42)	(19.14)	(25.37)
Div. Yield	-0.235***	-0.510***	-0.236***	-0.510***	-0.235***	-0.510***	-0.554***	-0.919***	-0.554***	-0.919***	-0.554***	-0.918***
	(-7.59)	(-4.96)	(-7.61)	(-4.95)	(-7.60)	(-4.95)	(-10.35)	(-5.78)	(-10.36)	(-5.77)	(-10.35)	(-5.76)
Price	0.005***	0.025***	0.005***	0.025***	0.005***	0.025***	0.011***	0.036***	0.011***	0.036***	0.011***	0.036***
	(5.83)	(7.31)	(5.82)	(7.30)	(5.80)	(7.30)	(5.83)	(7.71)	(5.81)	(7.70)	(5.80)	(7.70)
Turnover	0.080***	0.053***	0.080***	0.053***	0.080***	0.053***	0.166***	0.097***	0.166***	0.097***	0.166***	0.097***
	(13.00)	(5.08)	(13.07)	(5.10)	(13.07)	(5.10)	(16.90)	(6.68)	(16.97)	(6.70)	(16.96)	(6.70)
Volatility	-0.027***	-0.050***	-0.028***	-0.050***	-0.027***	-0.050***	-0.049***	-0.095***	-0.049***	-0.094***	-0.049***	-0.094***
	(-4.50)	(-3.18)	(-4.50)	(-3.17)	(-4.48)	(-3.17)	(-6.17)	(-4.31)	(-6.16)	(-4.30)	(-6.13)	(-4.30)
$Return_{-3,0}$	0.004*	-0.034***	0.004*	-0.034***	0.004*	-0.034***	0.007***	-0.047***	0.007***	-0.047***	0.007***	-0.047***
	(1.97)	(-7.25)	(1.98)	(-7.25)	(1.98)	(-7.25)	(2.91)	(-7.24)	(2.92)	(-7.24)	(2.91)	(-7.24)
$Return_{-12,-3}$	0.003***	-0.025***	0.003***	-0.025***	0.003***	-0.025***	0.009***	-0.032***	0.009***	-0.032***	0.009***	-0.032***
	(2.93)	(-10.72)	(2.95)	(-10.72)	(2.95)	(-10.72)	(6.30)	(-10.89)	(6.34)	(-10.89)	(6.34)	(-10.89)
N	46,099	46,099	46,099	46,099	46,099	46,099	42,539	42,539	42,539	42,539	42,539	42,539
$\bar{R}^2$	0.30	0.54	0.30	0.54	0.30	0.54	0.46	0.59	0.46	0.59	0.46	0.59
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.4: Instrumental Variables Regressions: Customer Industry M&As

This table presents results from two-stage instrumental variables regressions, as follows:

$$\begin{aligned}\text{Customer Concentration}_{i,t} &= \gamma_0 + \gamma_1 \text{Customer Industry M\&A}_{i,t} + \sum_{k=1}^{K} \lambda_k X_{k\,i,t} + \eta_{i,t}, \\ \text{Inst\%}_{i,t} &= \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},\end{aligned}$$

where Inst$\%_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. Customer Industry M&A$_{i,t}$ represents the weighted average industry M&A intensity across industries to which supplier i's major customers belong. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

		Second-Stage			Second-Stage			Second-Stage	
	First-Stage	ST%	LT%	First-Stage	ST%	LT%	First-Stage	ST%	LT%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Customer Industry M&A	16.327***			13.165***			13.896***		
	(20.32)			(21.31)			(19.87)		
Customer Sales		0.011**	-0.008						
		(2.12)	(-0.50)						
Customer HHI					0.014**	-0.010			
					(2.09)	(-0.49)			
Largest Customer								0.013**	-0.010
								(2.09)	(-0.50)
N	18,546	18,546	18,546	18,546	18,546	18,546	18,546	18,546	18,546
$\bar{R}^2$	0.35	0.28	0.54	0.42	0.28	0.54	0.39	0.28	0.54
First-stage F-test	412.8		454.0			394.7			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.5: Instrumental Variables Regressions: Customer Regulation Index

This table presents results from two-stage instrumental variables regressions, as follows:

$$\begin{aligned} \text{Customer Concentration}_{i,t} &= \gamma_0 + \gamma_1 \text{Customer Reg Index}_{i,t-1} + \sum_{k=1}^{K} \lambda_k X_{k\,i,t} + \eta_{i,t}, \\ \text{Inst\%}_{i,t} &= \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t}, \end{aligned}$$

where Inst%$_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, Customer Reg Index$_{i,t-1}$ is the one-year lagged weighted average Regulation Index across all industries to which supplier$i$'s major customers belong, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield, Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

		Second-Stage			Second-Stage			Second-Stage	
	First-Stage	ST%	LT%	First-Stage	ST%	LT%	First-Stage	ST%	LT%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Customer Reg Index	0.074***			0.062***			0.066***		
	(32.40)			(30.12)			(25.84)		
Customer Sales		0.019***	0.014						
		(3.10)	(0.93)						
Customer HHI					0.023***	0.017			
					(3.07)	(0.93)			
Largest Customer								0.022***	0.016
								(3.07)	(0.93)
N	12,569	12,569	12,569	12,569	12,569	12,569	12,569	12,569	12,569
$\bar{R}^2$	0.46	0.27	0.54	0.60	0.27	0.54	0.57	0.27	0.54
First-stage F-test	1049.0			907.5			667.5		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 1.6: Instrumental Variables Regressions: Industry Average Customer Concentration

This table presents results from two-stage instrumental variables regressions, as follows:

$$\text{Customer Concentration}_{i,t} = \gamma_0 + \gamma_1 \text{Ind Customer Concentration}_{i,t-2} + \sum_{k=1}^{K} \lambda_k X_{k\,i,t} + \eta_{i,t},$$

$$\text{Inst\%}_{i,t} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},$$

where Inst$\%_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, Ind Customer Concentration$_{i,t-2}$ is the two-year lagged average customer concentration measure in the supplier's 2-digit SIC industry with supplier i itself excluded, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

		Second-Stage			Second-Stage			Second-Stage	
	First-Stage	ST%	LT%	First-Stage	ST%	LT%	First-Stage	ST%	LT%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry Customer Concentration	0.656***			1.109***			0.445***		
	(0.050)			(0.077)			(0.060)		
Customer Sales		0.039**	0.139**						
		(2.67)	(2.71)						
Customer HHI					0.055***	0.091			
					(3.17)	(1.37)			
Largest Customer								0.079**	0.225*
								(2.57)	(1.85)
N	46,020	46,020	46,020	46,020	46,020	46,020	46,020	46,020	46,020
$\bar{R}^2$	0.08	0.25	0.45	0.09	0.25	0.48	0.06	0.22	0.43
First-stage F-test	174.0			207.4			54.1		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No	No	No	No	No	No

Table 1.7: Regulation Fair Disclosure, Investor Clientele, and Customer Concentration

This table presents OLS regression results of firms during the pre- and post-Regulation (Reg) Fair Disclosure periods. We estimate the following model:

$$\text{Inst\%}_{i,t} \quad = \quad \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},$$

where Inst$\%_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. In all specifications, we include industry-year fixed effects. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

Panel A: Customer Clientele Effects on Investor Clientele

	Short-Term Inst Ownership (ST%)						Long-Term Inst Ownership (LT%)					
	Pre-Reg Fair Disclosure			Post-Reg Fair Disclosure			Pre-Reg Fair Disclosure			Post-Reg Fair Disclosure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Customer Sales	0.002			0.012***			0.001			0.016*		
	(1.41)			(4.37)			(0.16)			(2.01)		
Customer HHI		0.002			0.015***			-0.002			0.020	
		(0.95)			(3.91)			(-0.28)			(1.73)	
Largest Customer			0.001			0.012***			-0.004			0.019*
			(0.34)			(3.40)			(-0.65)			(1.77)
N	24,539	24,539	24,539	21,560	21,560	21,560	24,539	24,539	24,539	21,560	21,560	21,560
$\bar{R}^2$	0.258	0.258	0.258	0.251	0.250	0.250	0.456	0.456	0.456	0.477	0.477	0.477
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Test of the Difference in Customer Clientele Effects between Pre- and Post-Reg Fair Disclosure Periods

	Short-Term Inst Ownership (ST%)			Long-Term Inst Ownership (LT%)		
	Customer Sales	Customer HHI	Largest Customer	Customer Sales	Customer HHI	Largest Customer
F-Statistics	10.05	9.41	8.96	3.20	3.04	3.85
(P-Value)	(0.00)	(0.00)	(0.01)	(0.08)	(0.09)	(0.06)

Table 1.8: Forecast Errors, Investor Clientele, and Customer Concentration

This table presents results of the following OLS regression on subsamples of firms formed based on forecast errors, where those above the median are classified as firms with high forecast errors, and those at or below are low. We estimate the following model:

$$\text{Inst\%}_{i,t} \quad = \quad \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},$$

where Inst$\%_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. In all specifications, we include industry-year fixed effects. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

Panel A: Customer Clientele Effects on Forecast Errors

	Short-Term Inst Ownership (ST%)						Long-Term Inst Ownership (LT%)					
	Low Forecast Error			High Forecast Error			Low Forecast Error			High Forecast Error		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Customer Sales	0.002			0.012***			0.001			0.013*		
	(0.71)			(4.79)			(0.07)			(1.82)		
Customer HHI		0.002			0.015***			0.009			0.016	
		(0.58)			(3.97)			(0.72)			(1.55)	
Largest Customer			0.001			0.013***			0.011			0.013
			(0.22)			(3.67)			(1.05)			(1.41)
N	13,311	13,311	13,311	12,840	12,840	12,840	13,311	13,311	13,311	12,840	12,840	12,840
$\bar{R}^2$	0.18	0.18	0.18	0.24	0.24	0.24	0.45	0.45	0.45	0.45	0.45	0.45
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Test of the Difference in Customer Clientele Effects between Low and High Forecast Errors Groups of Firms

	Short-Term Inst Ownership (ST%)			Long-Term Inst Ownership (LT%)		
	Customer Sales	Customer HHI	Largest Customer	Customer Sales	Customer HHI	Largest Customer
F-Statistics	10.05	9.41	8.96	3.20	3.04	3.85
(P-Value)	(0.00)	(0.00)	(0.01)	(0.08)	(0.09)	(0.06)

Table 1.9: Short Selling Activity and Customer Concentration

This table presents results from regressing one-year-ahead short interest dispersion on customer concentration. Columns (1)-(3) show estimates of the following model,

$$\text{Disp Short Interest}_{i,t+1} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t}.$$

Disp Short $\text{Interest}_{i,t}$ is measured by the standard deviation of the monthly short interests over year $t+1$; Customer $\text{Concentration}_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. Columns (4)-(12) show the second-stage estimates of IV regressions using Customer Industry M&A, Customer Reg Index, and Industry Average Customer Concentration as instruments. All variables are defined in Table A.1. With the exception of columns (10)-(12), we include industry-year fixed effects. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major customer reported in Compustat Customer Segment Files from 1980 to 2015.

	OLS			IV - Customer Industry M&A			IV - Customer Reg Index			IV - Industry Customer Con		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Customer Sales	0.002***			0.004***			0.003*			0.011***		
	(4.38)			(2.79)			(1.86)			(3.11)		
Customer HHI		0.003***			0.005***			0.004*			0.018***	
		(3.99)			(2.72)			(1.86)			(3.58)	
Largest Customer			0.002***			0.004***			0.004*			0.031**
			(3.85)			(2.74)			(1.86)			(2.60)
N	23,447	23,447	23,447	9,966	9,966	9,966	7,100	7,100	7,100	23,702	23,702	23,702
$\bar{R}^2$	0.30	0.30	0.30	0.27	0.27	0.27	0.26	0.26	0.26	0.26	0.25	0.14
First-stage F-test				494.7	582.2	620.1	718.7	745.0	663.5	73.7	95.1	18.3
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No

Table 1.10: Investor Clientele and Corporate/Government Customers

This table presents results from our baseline OLS regression, as given below.

$$\text{Inst}\%_{i,t} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},$$

where Inst$\%_{i,t}$ is short-term (ST%) or long-term institutional ownership (LT%), Corporate and Government Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. In all specifications, we include industry-year fixed effects. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

Panel A: Effects of Corporate and Government Sales on Institutional Investors

	ST% (1)	LT% (2)	ST% (3)	LT% (4)	ST% (5)	LT% (6)
Corporate Customer Sales	0.007***	0.005				
	(4.11)	(1.09)				
Government Customer Sales	0.005**	-0.002				
	(2.49)	(-0.24)				
Corporate Customer HHI			0.009***	0.003		
			(3.76)	(0.49)		
Government Customer HHI			0.006*	-0.004		
			(1.80)	(-0.34)		
Corporate Largest Customer					0.007***	0.002
					(3.09)	(0.28)
Government Largest Customer					0.006**	-0.005
					(2.38)	(-0.62)
N	50,760	50,760	50,760	50,760	50,760	50,760
$\bar{R}^2$	0.301	0.544	0.301	0.544	0.301	0.544
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Test of the Difference in Corporate vs. Government Effects on Institutional Ownership

	ST%	LT%	ST%	LT%	ST%	LT%
F-Statistics	0.622	0.607	0.490	0.285	0.179	0.443
(P-Value)	(0.435)	(0.441)	(0.489)	(0.597)	(0.675)	(0.510)

Table 1.11: Non-Cross Institutional Ownership and Customer Concentration

This table repeats our baseline OLS regression by replacing using non-cross institutional ownership as the dependent variable in a following way.

$$\text{NCross Inst\%}_{i,t} = \alpha_0 + \alpha_1 \text{Customer Concentration}_{i,t} + \sum_{k=1}^{K} \beta_k X_{k\,i,t} + \epsilon_{i,t},$$

where NCross Inst$\%_{i,t}$ is either non-cross short-term (NCross ST%) or long-term institutional ownership (NCross LT%) of the supplier and its customers, Customer Concentration$_{i,t}$ is measured using total Customer Sales, Customer HHI (Herfindahl Index), and Largest Customer, and $X_{k\,i,t}$ is a set of firm characteristics: Tobin's q, Size, Age, Div. Yield , Volatility, Turnover, Price, and Returns. All variables are winsorized at 1st and 99th percentiles and their definitions are contained in Table A.1. In all specifications, we include industry-year fixed effects. Industry classifications are based on 2-digit SIC. Standard errors are clustered by firm and year. The sample includes all firms that have at least one major corporate customer reported in Compustat Customer Segment Files from 1980 to 2015.

	NCross ST% (1)	NCross LT% (2)	NCross ST% (3)	NCross LT% (4)	NCross ST% (5)	NCross LT% (6)
Customer Sales	-0.004**	-0.041***				
	(-2.68)	(-7.30)				
Customer HHI			0.006***	-0.004		
			(2.75)	(-0.50)		
Largest Customer					0.006***	0.007
					(2.86)	(0.98)
N	46,099	46,099	46,099	46,099	46,099	46,099
$\bar{R}^2$	0.21	0.28	0.21	0.28	0.21	0.28
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

2. Withholding Bad News When Competing Peers Have Common Customers

2.1 Introduction

Theoretical research suggests that different sources of competition have distinct effects on firms' disclosure choices. One strand of literature (e.g., Verrecchia 1983; Clinch and Verrecchia 1997) argues that competition from existing rivals increases the proprietary cost of private information and, in turn, inhibits disclosure. Another strand (e.g., Darrough and Stoughton 1990; Wagenhofer 1990; Feltham and Xie 1992), on the other hand, predicts that competition from potential entrants encourages information disclosure to deter entry. These seemingly conflicting effects underscore the importance of distinguishing two sources of competition: threats from existing rivals and threats from potential entrants. Yet there is still little research that incorporates these distinct dimensions of competition, and this probably contributes to the mixed empirical evidence on the relationship between competition and disclosures.[8] In this study, we exploit a newly available database on supply chains that allows us to disentangle competitive threats posed by existing rivals from other sources of competition and to examine whether and how existing rivals influence a firm's strategic disclosure of unfavorable information. We also investigate how major stakeholders in financial and product markets – competitors, customers, and investors – each play a role in inducing this relationship.

Our study focuses on the corporate customer-supplier network and utilizes firms' shared relationships with common corporate customers as a basis for distinguishing existing competition from potential competition. Firms in the same product space, as defined by Hoberg and Phillips's (2010, 2016) Text-based Network Industry Classifications (TNIC), are classified as either existing rivals if they supply to the same corporate customers (customer-connected peers/suppliers) or potential competitors if they do not (non-connected peers/suppliers). Using common customers as a market boundary to identify existing competitors, among others, enables us to capture

[8] For example, Bamber and Cheon (1998), Botosan and Stanford (2005), and Ali, Klasa, and Yeung (2014) find that firms in competitive industries are more forthcoming with their disclosure. In contrast, Verrecchia and Weber (2006) and Li and Zhan (2018) find a positive association between competition and information withholding.

the essential distinguishing characteristic of existing competition adequately. First, customer-connected peers are good representations of rival firms whose entry costs are sunk costs as they have already made relationship-specific investments to serve the same market. Thus, connected peers are expected to compete closely against one another for continued businesses with their common customers and are immediate threats to each other. Second, customers may find it easier to switch between their current suppliers (i.e., customer-connected suppliers) than to new suppliers with no prior relationship (i.e., non-connected suppliers). Customers in an attempt to establish new trading relationships may face frictions such as a higher level of information asymmetry between them and their potential suppliers and fewer customer-tailored products offered by these potential suppliers.[9] Hence, the primary concern of a firm over its customer-connected peers would be how the peers' strategic moves jeopardize its position in existing trading relationships with common customers. The firm's main concern over non-connected peers, however, would be their potential access to the common customers rather than how they compete within their own existing market.

We contend that competitive threats from customer-connected peers would induce negative news hoarding. As suggested by the "proprietory cost of disclosure" theory (Verrecchia 1983), a firm facing competitive threats from existing rivals would be concerned over how these rivals might use negative information in a manner that disadvantages the firm in the product market. Intense existing competition would incentivize a firm to withhold such information from its competitors (competitor-induced motives). There may also be increased concerns over customers' responses in light of disclosed information. To the extent that competition from connected peers reflects a lower switching cost for the common customers, a firm under competitive pressure would face a higher risk of losing its position in future contractual arrangements with the customers. Such a firm would, in turn, have a stronger incentive to manage the customers' perceptions about its business prospects and hoard any negative information that

[9] Our univariate analysis finds that customer-connected peers are, on average, located closer to their common customers than their non-connected peers, suggesting that these customers may have better access to information on connected than non-connected suppliers. Results also indicate that products offered by connected peers have a higher degree of similarity than those provided by non-connected ones, pointing to the connected peers' efforts in supplying tailored products to common customers in comparison with non-connected peers.

would hamper such perceptions (customer-induced motives). Furthermore, the proprietary cost of the disclosure may provide an opportunity for managers to conceal bad news from investors. Investors expect firms that face competition from existing rivals to hide both favorable and unfavorable information from competitors and hence would not interpret withholding information as unambiguously negative and discount firm values as such (Verrecchia 1983). The existence of proprietary cost in a competitive environment, thus, would enable a firm with more negative than positive information to take advantage of such expectations of investors and conceal negative information without being adequately penalized (investor-induced motives).

To construct measures of existing competition, we exploit the recently available information on customer-supplier relationships from the Factset Revere database and Compustat Customer Segment files.[10] More specifically, competition from existing rivals are proxied by the number of customer-connected peers (Peer Count), their sales to the common customers (Peer Sales), and the similarity between their products and the focal firm's (Peer Similarity). Competition from potential entrants is similarly estimated by the number of non-connected peers (Non-Linked Peer Count) and the extent of their product similarity with the focal supplier's (Non-Linked Peer Similarity). We employ the formation of a stock price crash as a measure of unfavorable information withholding, following the extant literature (e.g., Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009). It is argued that bad news withheld by managers accumulates over an extended period until it reaches a tipping point beyond which the cost of concealing the news exceeds the benefit. The managers would then be forced to release the accumulated news at once, causing the stock price to crash. The three measures of crash risk include the negative skewness of firm-specific weekly stock returns (NCSKEW), the asymmetric volatility of negative versus positive returns (DUVOL), and the number of extremely negative returns (Crash Count).

Using a sample of 28,598 firm-year observations from 4,436 unique supplier firms over the 1996-2015 period, we find that stock price crash risk is significantly higher for firms facing greater

[10]See Dai, Liang, and Ng (2020) for a more detailed description of the Factset Revere database.

competition from connected peers, consistent with our prediction that existing competition inhibits the disclosure of unfavorable information. The results are strong and robust to controlling for potential as well as overall competition. In contrast, we find a negative association between competitive threats from non-connected peers and crash risk, indicating that potential competition encourages the disclosure of negative information. Combined, these findings highlight the offsetting effects of existing and potential competition on disclosure decisions and provide validation for our new constructs in capturing the different dimensions of competition. Additional analyses using other proxies of adverse news disclosure further substantiate our information hoarding interpretation of crash risk, contrary to the alternative explanation that crash risk is capturing firm fundamentals such as operating risk rather than consequences of withholding negative news.

While we have established that existing competition increases the likelihood of a firm withholding adverse information, our causal inferences of this link may be subject to endogeneity concerns. To alleviate such concerns, we exploit three different quasi-natural experiments to capture large exogenous shocks to customer-connected peers. First, we employ the intensity of mergers and acquisitions (M&A) activities of customers as a source of an exogenous increase in the number of peers supplying to the customers, and thus, the supplier's heightened existing rivalry. The acquiring customers would mechanically gain new trading partners through consolidation of purchasing accounts, which in turn would add new customer-connected peers to the existing customer-supplier network. Next, we examine an exogenous reduction in competition due to the bankruptcies of customer-connected peers. Customers tend to lose confidence in bankrupt firms and would seek for safer alternatives (Altman 1984; Opler and Titman 1994; Cheng and McDonald 1996). Thus, we expect that when a connected peer files for bankruptcy, the common customers would rely less on the filing peer for inputs, if not switching away completely. Finally, we explore exogenous shocks related to major natural disasters that disrupt the domestic operations of customer-connected peers. Such disruptions in local plant and establishment operations would reduce the competitive positions of customer-connected peers in the short-run, thereby temporarily relieving the focal firm from some of the competitive and predatory threats from existing rivals. The findings from all three quasi-natural experiments suggest that our baseline results are robust to potential endogeneity issues and that they capture a causal effect of existing competition on a firm's stock price crash risk.

Next, we investigate whether the positive association between existing competition and bad news hoarding is driven, in part, by each of the three major participants in product and financial markets – competitors, customers, and investors. First, we test competitor-induced motives by examining whether less aggressive competition and more information sharing between the focal firm and its connected peers reduce the need as well as the ability for a firm to hide bad news from these competitors. Consistent with our conjecture, we find that establishing business alliances with existing rivals weakens the impact of existing competition on crash risk while reducing hostility and information asymmetry between the parties.[11] Second, we examine customer-induced motives by evaluating whether the positive impact from existing competition would be less pronounced when customers have a lower propensity to switch away and/or are better informed about the firm. Analyses on business alliances and trade credits with customers provide supportive evidence on this motive. Finally, we investigate investor-induced motives by testing whether investor informedness would have any moderating effects on the baseline relationship. Using institutional ownership breadth, analyst forecast dispersion, and news coverage as proxies for information asymmetry between a firm and its investors, we show that investor informedness dampens the link between competition and crash risk. These findings lend support to our *prior* that the more informed are the investors about the content of withheld information, the fewer opportunities a firm may have in withholding adverse news without being fully penalized.

Closely related to our work is the study by Li (2010), who has also constructed variables to capture existing competition and potential competition separately. More specifically, she uses industry concentration as a proxy for competitive threats from existing rivals and industry-average

[11]To the extent that operating conditions of customer-connected peers affect their competitiveness, the identification tests using peer bankruptcy and natural disaster incidences also indicate the significant role such peers have in influencing a firm's disclosure behavior.

capital and R&D expenditures to measure threats from potential entrants. These measures are, however, criticized for simultaneously reflecting both types of competitive threats (Karuna 2010). For instance, it is arguable that capital and R&D spending may both deter prospective entrants and discourage existing rivals by altering production levels. In a similar vein, a low industry concentration reflecting more intense competition among the incumbent firms may also deter entrants. In contrast, our study constructs measures of existing and potential competitors directly based on their product similarity and the customers they serve. Our measures, therefore, allow us to distinguish between threats from existing competitors and those from potential competitors.

Our study makes several significant contributions to the disclosure literature. First, prior research on the relationship between competition and disclosure primarily considers the costs of disclosing information to competitors as the key underlying mechanism (e.g., Botosan and Stanford 2005; Verrecchia and Weber 2006; Berger and Hann 2007; Li 2010; Ali et al. 2014; Li and Zhan 2019). They make relatively little efforts to find direct evidence supporting this competitor-induced motive and largely overlook motives associated with other market participants. We fill the gap in the literature by incorporating two additional mechanisms, the costs of disclosing information to customers and the benefits of withholding information from investors, into our analysis, and by providing empirical support to all three motives behind firms' disclosure decisions in competitive scenarios.

Second, our study contributes to the growing crash risk literature by documenting the effects of trading relationships on a firm's information withholding behavior. Two recent papers (Chen, Hu, Yao, and Zhao 2018; Kim, Lee, and Song 2018) are closely related. They extract information from the corporate customer-supplier network and examine whether crash risk is associated with corporate customer concentration. Both studies reach the same conclusion that customer concentration, which proxies for a firm's dependence on a few large customers, increases crash risk. Unlike these papers, we employ the identities of both the customers and suppliers to determine each customer's network of suppliers. Such detailed information allows us to focus on a pool of suppliers connected through common customers and investigate how their relationships in the product market affect crash risk beyond that of customer concentration.

Finally, we validate stock price crashes as a measure of negative news hoarding. Extant research on agency theory-based arguments of managerial incentives for hoarding information (e.g., Kim, Li, and Zhang 2011a,b; Kim, Li, and Li 2014; Kim, Wang, and Zhang 2016) relies heavily on the prior work by Jin and Myers (2006), Bleck and Liu (2007), and Hutton, Marcus, and Tehranian (2009) to motivate the use of crash risk measures as proxies for adverse information withholding. However, stock price crashes can be driven by many other factors such as heterogeneity in investors' beliefs (Hong and Stein 2003) and the nature of firm operations, among others (Habib, Hasan, and Jiang 2017). By showing that an effect on crash risk coincides with a similar effect on other measures of negative news hoarding, we complement earlier work and confirm the information hoarding interpretation of stock price crash risk.

The remainder of the paper is organized as follows. Section 2.2 develops testable hypotheses. Section 2.3 describes data sources, sample construction, and variable definitions. Section 2.4 examines the impact of existing competition on adverse information withholding. Section 2.5 establishes the causal relationship between existing competition and crash risk. Section 2.6 investigates the underlying mechanisms driving the baseline relationship, and Section 2.7 concludes.

2.2 Hypothesis Development

Theories suggest that more intense competition from existing rivals inhibits disclosure of unfavorable information. For instance, Verrecchia (1983) models a post-entry game in which incumbent firms in a product market compete among themselves. He argues that disclosure decisions are determined by the trade-offs between countervailing incentives from product and financial markets. On the one hand, a firm is concerned over the costs associated with disclosing proprietary information to its competitors. Existing rivals may use the revealed information to strategize competitive actions against the disclosing firm. Thus, the high cost of releasing proprietary information discourages the firm from divulging any of its negative information. On the other hand, a firm is also concerned about uninformed investors rationally discounting firm value to the extent that they expect the non-disclosed information withheld to contain bad news. The investors' conjecture about the content of such information may be so unfavorable that the firm is better off disclosing the adverse news. Such concerns from the capital market encourage disclosure.[12] However, as competitive pressure from existing rivals mounts, both forces provide more incentives for a firm to withhold information. First, the proprietary cost of disclosure increases with the competition, as incumbents are more likely to take aggressive actions in response to the disclosed information. Second, investors adjust their inferences to account for changes in proprietary costs. They expect that firms with higher proprietary costs are more likely to conceal both favorable and unfavorable information and hence would not interpret withheld information as unambiguously negative and discount firm values accordingly.

Clinch and Verrecchia (1997) similarly predict a positive association between existing competition and detrimental news withholding. In a post-entry duopoly game, the incumbents competing in a product market each have private information about the aggregate future demand for a product. Since knowledge of aggregate demand affects the level of production, firms are inclined to withhold extremely damaging information, such as dismal future demand, to exploit incorrect production decisions made by their rivals. As competition between firms intensifies, so are their incentives for concealing low demand information. Hence, both the amount of information disclosed and the likelihood of information being released decrease as the level of existing competition increases.

The above arguments give rise to the following hypothesis:

H1a: *Competitive threats from existing rivals are positively associated with bad news withholding.*

In contrast, theoretical evidence suggests that threats from potential entrants encourage in-

[12]In addition to a value discount, firms may also be concerned about stockholder litigation and reputational costs when investors are surprised by material negative information. Hence, firms would be inclined to make preemptive bad news disclosures to avoid the accumulation of unfavorable information (Skinner 1994; 1997).

cumbent firms' disclosure of unfavorable information to reduce the attractiveness of the product market (e.g., Darrough and Stoughton 1990; Wagenhofer 1990; Feltham and Xie 1992). Unlike in the post-entry game, disclosure could still affect the probability of entry for potential competitors in an entry game model. In this context, prospective entrants would only enter the product market if their expected return exceeds the cost of entry, and unfavorable information from incumbents reduces such expected return. Thus, incumbent firms facing threats from potential entrants are inclined to reveal negative information as a way to deter entry. Accordingly, we expect existing and potential competition to have offsetting effects on information hoarding behavior. This argument leads to the following hypothesis:

H1b: *Competitive threats from potential rivals are negatively associated with adverse news withholding.*

We then explore the mechanisms behind the positive association between existing competition and bad news hoarding. As suggested by Verrecchia (1983), one such mechanism is the increased cost associated with disclosing information to competitors. As competition intensifies, existing rivals are more likely to use the disclosed information in devising competitive strategies against the disclosing firm. Negative information, in particular, may additionally encourage predatory actions by rivals. Engaging predation can be costly, so predatory actions would only be taken when there is sufficient information to suggest reasonable costs and the probability of success associated with them (Bernard 2016). Disclosure of unfavorable information helps the competitors in resolving these uncertainties and informing them of the target firm's lower ability to withstand and survive aggressive actions. While firms with increasing concerns over rivals' competitive efforts are more inclined to hoard information, they could also mitigate such concerns by forming alliances with rivals. We contend that establishing business alliances with rival firms would lead to less hostility but more information sharing between a firm and its competitors, thereby reducing the need or incentive for the firm to hide adverse information from these competitors. We test this competitor-induced motive in the following hypothesis:

H2: *The positive association between competitive threats from existing rivals and bad news withholding is less pronounced when business alliances are formed between the focal firm and its rival(s).*

Firms may also have customer-induced motives for withholding adverse news in a competitive environment. As the competition among existing rivals increases, firms become increasingly concerned over maintaining stable relationships with their customers. When customers have more alternative suppliers to choose from, they face lower switching costs and gain bargaining power over their suppliers. The latter, in turn, face higher risks of losing their positions in future contracts with the former. To the extent that existing competition captures such risk of a supplier firm, it provides incentives for the firm to manage customers' perceptions about its business prospects and hide any negative information that would hamper such perceptions. One testable implication of such motives is that the effect of existing competition on bad news hoarding would become weaker when the firm builds a cooperative relationship with its customers through forming business alliances and providing trade credits. We posit that in the presence of customer-induced motives, a lower propensity to switch away would reduce the need for the firm to influence the customers' perceptions, and a lower degree of information asymmetry between them would limit the firm's ability to conceal information. We formally test the customer-induced motive hypotheses as follows:

H3a: *The positive association between competitive threats from existing rivals and bad news withholding is less pronounced when business alliances are formed between the focal firm and its corporate customers.*

H3b: *The positive association between competitive threats from existing rivals and bad news withholding is less pronounced when the focal firm offers trade credits to its corporate customers.*

Finally, competitive threats from existing rivals may give rise to investor-induced motives for information hoarding behavior. As argued above, higher proprietary costs of disclosure induced by intense competition provide an opportunity for firms to conceal negative information from investors. Investors' conjecture about the content of the withheld information depends on the firm's motivation for withholding it (Verrecchia 1983). When proprietary costs of the disclosure are low, investors expect that information hoarding behavior is possibly driven by capital market concerns and hence anticipate the information withheld to be likely bad news. As proprietary costs increase, however, investors expect the behavior to be more likely motivated by product market threats, thereby anticipating the information withheld to consist of both good and bad news. With a broader range of possible interpretations of withheld information, investors discount the withholding of negative information less heavily. Therefore, more competitive pressure (and higher proprietary costs) allows a firm with more negative than positive news to take advantage of investors' rational expectations and hide negative information without being adequately penalized. One important testable implication of the investor-induced motive is that the more informed the investors are about the content of withheld information, the fewer opportunities firms would have in withholding negative information even in a competitive environment where proprietary costs are higher. Formally, the investor-induced motive hypothesis is stated as follows:

H4: *The positive association between competitive threats from existing rivals and bad news withholding is less pronounced for firms with greater investor informedness.*

2.3 Data and Sample Construction

We construct our sample from several data sources: (i) supplier-customer relationship data from both the Factset Revere and Compustat's Customer Segments data, available through the Wharton Research Data Services (WRDS); (ii) stock return data from the Center for Research in Security Prices (CRSP); (iii) product market classification and firm relatedness information developed in Hoberg and Phillips (2010, 2016), which is made available via Hoberg and Phillips's data library; (iv) information on M&A deals from the SDC Platinum; (v) Chapter 11 bankruptcy filings data from Ma, Tong, and Wang (2019);[13] (vi) county-level disaster data from Federal Emergency Management Agency (FEMA); (vii) firm employment data by establishment from Dun and Bradstreet via Mergent; (viii) firm disclosure events from Capital IQ Key Development; (ix) the SEC comment letter and restatement records from Audit Analytics; (x) institutional holdings data from Thomson Reuters Institutional Holdings (13f); (xi) financial analyst forecast information from the Institutional Brokers Estimate System (IBES); (xii) firm-specific press articles from Ravenpack full package; and (xiii) financial statement data from Compustat. Our primary sample intersects these databases with non-missing values for our main variables of interest. We exclude financial and regulated utility firms (SIC codes 4900-4999 and 6000-6900). This merging of databases yields a final sample of 28,598 firm-year observations, consisting of 4,436 unique supplier firms over the period between 1996 and 2015. The sample period is bounded by the availability of Hoberg and Phillips' industry classification and firm product relatedness data; their coverage ranges from 1996 to 2015. The actual number of observations varies across analyses, given different data availability. The definitions of all the key variables are depicted in Table A.2.

2.3.1 Customer-supplier networks

We use both the Revere and Customer Segments data to identify customer-supplier relationships. Under SEC Regulation S-K Item 101, all public firms in the United States are required to disclose the existence and identities of major customers representing more than 10% of their sales, while suppliers can also voluntarily disclose minor customers that account for less than 10% of the revenues. The Customer Segments data rely on such regulation to obtain supply chain information from suppliers' annual 10-K filings and hence contain mainly information on firms' major customers. A critical shortcoming of this database is that it does not assign unique company identities (GVKEYs) to publicly-listed customer firms, whose names are as reported in the original filing and are abbreviations or even subsidiary names. To circumvent these data challenges, we strictly follow Banerjee, Dasgupta, and Kim (2008) and Cen, Maydew, Zhang,

[13] We thank Wei Wang for generously sharing the bankruptcy data with us.

and Zuo (2017) in manually matching the customer names with their unique GVKEYs that would allow us to link customer information with other databases.[14] Unlike Customer Segments data, Revere gathers information from multiple sources, including corporate quarterly and annual filings (e.g., 8-K, 10-Q, and 10-K), investor presentations, websites, and press releases. The database identifies customer-supplier relationships based on both direct disclosure by the reporting company and indirect disclosure by companies doing business with the reporting company. It thus offers a more comprehensive supply chain information consisting of both major and minor customers. No manual matching is necessary given that Revere data provide GVKEYs for publicly-listed customers. We complement Revere data, which start coverage from 2003, with Customer Segments data to obtain corporate customer-supplier pairs over our 1996-2015 sample period. For illustration purposes, we show in Figure 2.1 a portion of the 2014 supply chain network containing Texas Instruments Inc. The figure depicts the linkages between Texas Instruments, its customers, and other firms in the same product space supplying to its customers. Leveraging such comprehensive information, we construct our measures of existing and potential competition based on the connectivity among suppliers through common customers.

2.3.2 Measures of competition

To construct measures of competition, we first identify competing peers for each supplier firm S_i. Specifically, peers are defined as firms within the same product space as S_i, based on Hoberg and Phillips' (2010; 2016) Text-based Network Industry Classifications (TNIC). Such a classification system allows us to identify competitors based on their product similarity. To the extent that firms offering similar products can replace one another, this approach reasonably captures substitutability relationships in which S_i faces competitive pressure from its peers rather than complementarity relationships in which the firms are supplying different components of a final product.[15] We then classify the peers as existing rivals if they have at least one common corpo-

[14] We thank Ling Cen for providing us his matched Customer Segments data for calibration purposes.

[15] While one may still be concerned that the minimum similarity threshold required by TNIC is not sufficient to tease out all complementary peers, we further address this issue by explicitly constructing competition measures based on product similarity scores as discussed later in this section.

rate customer as S_i (customer-connected peers/suppliers) and potential competitors otherwise (customer-connected peers/suppliers).

As an example, suppose supplier firms S_1, S_2, S_3, and S_4 produce similar products. S_1 and S_2 supply to customer C_1, whereas S_3 and S_4 supply to customer C_2. While all four suppliers are in the same product space, only S_2 shares a common customer with S_1 and is, thus, considered as S_1's existing competitor. S_3 and S_4 are considered as potential rivals of S_1 who may establish new relationships with C_1 in the future. This approach enables us to highlight two key distinguishing characteristics of competition among existing rivals. First, customer-connected peers are good representations of rival firms that have already incurred costs associated with market entry. For instance, an existing relationship between S_2 and C_1 suggests that S_2 has already made considerable relationship-specific investments in supplying to the same customer as S_1. Hence, S_1 is competing with an existing rival that is committed to optimizing its position in the same product market. It is in clear contrast to competing with the potential entrants S_3 and S_4 that have not invested in establishing relationships with C_1. Second, the classification suggests a lower switching cost associated with existing rivals than with potential competitors. A common customer such as C_1 that maintains simultaneous relationships with both S_1 and S_2 may find it easier to switch between the two existing suppliers than to other potential suppliers. Consequently, any strategic moves by S_2 would jeopardize S_1's position in its relationship with C_1. In contrast, a customer may incur significant costs when switching to new suppliers due to frictions such as information asymmetry between the parties and a lack of customer-tailored products offered by the potential suppliers. Thus, C_2 would be considered as a different market by S_1, and the main concern S_1 has over S_3 and S_4 would be their potential access to C_1 rather than how they compete within their own market for C_2.

Focusing on the customer-connected peers, we construct three measures of existing competition. These proxies capture the extent to which S_i's corporate customers are simultaneously dependent on alternate suppliers offering similar products as S_i. Intuitively, the more relationships that customers are concurrently maintaining with other sources of supply, the greater the competitive pressure that S_i would face in maintaining its current positions and seizing future contractual opportunities with the common customers. For our first measure, Peer Count, we count the number of customer-connected peers that S_i obtains in year t through each of its customers C_j and take the log average of the counts across the all customers as shown in Eq. (2.1) below.[16] The other competition measures are averaged in the same fashion.

$$\text{Peer Count}_i = \ln\left(\frac{\sum_j^{n_i} m_j}{n_i}\right), \tag{2.1}$$

where supplier S_i has n_i customers in year t, and each customer C_j has m_j alternate suppliers other than S_i in the same TNIC industry. The intuition behind Peer Count is illustrated in Figure 2.2, which exemplifies a scenario where supplier S_1 is, on average, competing with four other industry peers through each of the customers, whereas supplier S_2 is only competing against two other suppliers. Hence, a higher value of Peer Count corresponds to a more significant competitive threat from the customer-connected peers.

Our second measure, Peer Sales, similarly captures C_j's existing relationships with the customer-connected peers of S_i, but further accounts for the extent to which C_j depends on those alternate suppliers by taking the sum of the peers' sales to C_j as a percentage of C_j's costs of goods sold. The more reliant is C_j on the peers for inputs, the higher is the competitive pressure for S_i.

$$\text{Peer Sales}_i = \sum_j^{n_i}\left(\frac{\sum_k^{m_i} Sales_{j,k}}{COGS_j}\right) \Big/ n_i \tag{2.2}$$

where $Sales_{j,k}$ is the percentage of peer firm P_k's sales attributed to each customer C_j of supplier S_i in year t, and $COGS_j$ is C_j's cost of good sold.

For our third measure of existing competition, we consider the scarcity of S_i's products relative to those of the existing rivals. More specifically, we take the average of the product similarity scores between S_i and its customer-connected peers, where the scores measure the relatedness of two firms based on their product descriptions in 10-K filings. The higher the

[16]Over 70% of the customer-supplier pair observations have missing sales distribution information. We work with equally-weighted average measures instead of sales-weighted averages to avoid eliminating a large portion of the sample.

average score, the more substitutable are S_i's products, and the less dependent C_j would be upon S_i.

$$\text{Peer Similarity}_i = \sum_{j}^{n_i} \left(\frac{\sum_k^{m_i} Similarity_{i,k}}{m_j} \right) \Big/ n_i \tag{2.3}$$

where Peer Similarity$_{i,k}$ is the product similarity score between S_i and its connected peer P_k in year t. Using product similarity, and hence substitutability, to measure competitive threats, this proxy alleviates the concern that our measures may be capturing non-competitive relationships among firms who produce complementary products.

In addition, we construct two measures of potential competition to capture the threats from non-connected peers who may potentially establish new trading relationships with S_i's customers and reduce S_i's profits. In particular, we define Non-Linked Peer Count as the log number of non-connected peers S_i has in year t and Non-Linked Peer Similarity as the average product similarity scores between S_i and its non-connected peers.[17]

2.3.3 Measures of bad news withholding

Following the existing literature (Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; and Kim, Li, and Zhang 2011a, b), we employ three firm-specific measures of stock price crash risk for each firm-year as proxies for bad news withholding. To construct the measures, we first run the following regression for each firm-year using weekly returns during the 12 months ending three months after the supplier's fiscal year-end. The three-month lag is used to ensure that financial information is available to investors and is, in turn, incorporated into stock prices at the time of measurement.

$$r_{i,\tau} = \alpha_i + \beta_{1,i} r_{m,\tau-2} + \beta_{2,i} r_{m,\tau-1} + \beta_{3,i} r_{m,\tau} + \beta_{4,i} r_{m,\tau+1} + \beta_{5,i} r_{m,\tau+2} + \epsilon_{i,\tau}, \tag{2.4}$$

where $r_{i,\tau}$ is the return on stock i in week τ, $r_{m,\tau}$ is the return on CRSP value-weighted market index in week τ, and $\epsilon_{i,\tau}$ is the firm-specific residual return in week τ after removing the impact of

[17] One may be concerned that the TNIC classification is insufficient to ensure a high degree of product similarity between non-connected peers and S_i, and as a result, these peers may contain a subset of unrelated firms who have little incentive to enter into S_i's product market. To address this issue, we further require the non-connected peers to share at least one common product-based Revere Industry classification code with S_i.

market fluctuations. The lead and lag market returns are included to account for nonsynchronous trading (Dimson 1979). We calculate the firm-specific weekly return for supplier i in week τ as the natural logarithm of one plus residual return ($W_{i,\tau} = ln(1 + \epsilon_{i,\tau})$) from Eq. (2.4).

The first measure of crash risk is the negative skewness of firm-specific weekly returns (NCSKEW). It is defined as the negative of the ratio of the third moment to the standard deviation cubed of $W_{i,\tau}$ for each firm-year. A higher value of NCSKEW corresponds to a more left-skewed distribution of supplier i's weekly returns, indicating a higher incidence of a crash. Explicitly, NCSKEW of supplier i's stock returns in year t is computed as:

$$\text{NCSKEW}_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,\tau}^{3}\right] \bigg/ \left[(n-1)(n-2)\left(\sum W_{i,\tau}^{2}\right)^{3/2}\right] \tag{2.5}$$

where n is the number of observations of $W_{i,\tau}$ during year t.

The second measure is the down-to-up volatility measure (DUVOL). For each firm-year, we separate all weeks into two groups based on whether the weekly returns are above or below the annual mean. Those returns above the mean are grouped into up weeks, and those below are categorized into down weeks. We then compute DUVOL as the log ratio of the standard deviation of $W_{i,\tau}$ of the down weeks to that of the up weeks as illustrated in Eq. (2.6). Similar to NCSKEW, a higher value of DUVOL corresponds to a more left-skewed distribution of $W_{i,\tau}$, indicating a higher crash risk.

$$\text{DUVOL}_{i,t} = \ln\left[\frac{(n_u - 1)\sum_{Down} W_{i,\tau}^{2}}{(n_d - 1)\sum_{Up} W_{i,\tau}^{2}}\right] \tag{2.6}$$

where n_d is the number of down weeks for supplier i in year t, and n_u is the number of up weeks.

The third measure is based on the number of firm-specific weekly returns $W_{i,\tau}$ exceeding 3.09 standard deviations above and below the mean weekly return over the entire fiscal year for each supplier i. The 3.09 standard deviation is chosen so that the crash incidents account for 0.1% of frequency in the normal distribution. The measure Crash Count is defined as the difference of downside and upside counts (Callen and Fang, 2015, 2017), so a higher value corresponds to a higher frequency of crashes.

2.3.4 Control variables

We also follow the above-mentioned prior studies to identify control variables that affect stock price crash risk. Specifically, our analyses control for firm-specific variables, including firm size (Size), market-to-book ratio of equity (MB), leverage ratio (Leverage), profitability (ROA), and cumulative discretionary accrual (AbAccr). These studies show that the likelihood of future stock price crashes tends to be positively correlated with Size, MB, and AbAccr and negatively associated with Leverage. While the existing literature documents a significant ROA effect on crash risk, the direction of its effect is unclear. For example, Hutton, Marcus, and Tehranian (2009) and Kim, Li, and Zhang (2011a, b) find a negative relationship between ROA and crash risk, whereas Kim and Zhang (2016) and Li and Zhan (2019) document a positive relationship. We also control for stock-specific characteristics, including the change in stock turnover (ΔTurnover) computed as the average of the monthly turnover within a fiscal year minus its counterpart in the previous year, firm-specific average weekly return within a fiscal year (Return), firm-specific weekly return volatility computed within a fiscal year (Sigma), and one-year-lagged negative skewness measure (NCSKEW). We expect crash risk to be higher for stocks with greater heterogeneity in investor opinions and higher past returns, past stock volatility, and past return skewness. The detailed definitions of the control variables are provided in Appendix Table A.2.

2.3.5 Summary statistics

Table 2.1 presents the summary statistics for the key variables used in our analysis; Panels A, B, and C report the distributions for the existing competition measures, stock price crash risk, and control variables, respectively. The mean value of Peer Count is 1.015, indicating that a firm's customers are, on average, also trading with about two of its existing rivals simultaneously (i.e., $\ln(1 + 1.760) = 1.015$). The mean value of Peer Sales, as expressed in percentage of inputs, suggests that, on average, the customers rely on these rivals to produce about 1.6% of their inputs. A supplier has an average product similarity score, Peer Similarity, of 0.022 with its customer-connected peers, and the interquartile range is between zero and 0.033.

The table also reveals that at least 25% of the sample has a zero value for both Peer Count and Peer Similarity, where a zero value indicates that the focal firm has no other competing peers supplying to its customers. Over 50% of the sample has a zero value for *Peer Sales*, since many suppliers do not disclose their sales figures by individual customers. While we include observations with zero values in our main analyses, unreported results suggest that our findings are robust to excluding those observations from the three existing competition measures. Moreover, it is important to stress that the competition measures are persistent over time, so incorporating firm fixed effects into the regression models may mask the effects of competition given a much smaller within-firm variation than between-firm variation. For these considerations and consistency with existing studies, only industry and year fixed effects are reported in all tables throughout this paper.

The mean values of NCSKEW and DUVOL are 0.057 and 0.042, respectively. The positive values indicate that, on average, a supplier's weekly returns are left-skewed. The mean value of Crash Count is -0.008, suggesting that a supplier firm has, on average, 0.008 more upside weeks than downside crash weeks during a year. All control variables are within reasonable ranges and are comparable with the statistics reported in the prior studies mentioned earlier.

2.4 Competitive Threats and Bad News Hoarding

In this section, we test whether existing competition compels a supplier to withhold negative information by examining the relationship between competitive threats from connected peers and stock price crash risk. Next, we investigate whether competition from potential entrants would have an offsetting effect on such information hoarding behavior. We also conduct a multitude of empirical tests on other measures of managerial disclosure practices to further substantiate our information hoarding interpretation of the crash risk measures.

2.4.1 Baseline evidence

To empirically examine the relationship between existing competition and supplier stock-price crash risk, we regress each crash risk measure on a competition measure constructed from customer-connected peers, firm-level controls, and year and industry fixed effects as follows:

$$\text{Crash Risk}_{i,t+1} \quad = \quad \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t}, \quad (2.7)$$

where Crash $\text{Risk}_{i,t+1}$ is a measure of one-year-ahead crash incidences of supplier i (i.e., NCSKEW, DUVOL, or Crash Count); Connected Peer $\text{Threat}_{i,t}$ is one of the proxies for competitive threats from customer-connected peers (i.e., Peer Count, Peer Sales, or Peer Similarity) faced by supplier i in year t; $X_{ki,t}$ is a vector of firm-specific control variables defined earlier, measured in year t. We also control for industry, defined by two-digit SIC classification, and year fixed effects (FE) in all regressions to account for unmodeled heterogeneity across industries and years.[18] Standard errors are clustered at the firm level.

Results from our baseline model Eq. (2.7) are reported in Table 2.2. The dependent variables are $\text{NCSKEW}_{i,t+1}$ in Columns (1)-(3), $\text{DUVOL}_{i,t+1}$ in Columns (4)-(6), and Crash $\text{Count}_{i,t+1}$ in Columns (7)-(9). Consistent with H1a, all three measures of Connected Peer Threat generate statistically significant and positive coefficients for each of the crash risk measures. For instance, the coefficient on Peer Count is 0.029 for NCSKEW, corresponding to an increase in the negative skewness of supplier returns by 0.029 for each one-standard-deviation increase in Peer Count. This magnitude is large compared to the mean NCSKEW of 0.057. The coefficients on Peer Sales and Peer Similarity are 0.417 and 1.151, respectively, corresponding to increases in NCSKEW by 0.016 and 0.031 (i.e., 27.8% and 54.5% of the NCSKEW mean) for a one-standard-deviation change in the competition variables. The effects on DUVOL and Crash Count are also sizable and economically significant. For example, a one-standard-deviation change in Peer Count, Peer Sales, and Peer Similarity leads to 36.3%, 21.8%, and 40.0% increases in DUVOL relative to

[18] Habib, Hasan, and Jiang (2017) suggest that some industries may potentially be more prone to crashes than others due to the fundamental nature of their operations. Industry fixed effects are used to control for such heterogeneities.

the sample mean. These findings indicate that firms are more inclined to withhold unfavorable information as competition from existing rivals intensifies.

The control variables yield the same signs and similar coefficients as those reported in the previous studies mentioned in the earlier section. Specifically, the coefficients on Size, MB, ΔTurnover, AbAccr, NCSKEW, Sigma, ROA, and Return are all positive and significant. The coefficients on Leverage are negative, but they are statistically insignificant in all regressions.

2.4.2 Potential competition and other sources of competitive threats

To test whether threats from existing rivals have distinct effects from other sources of competitive threats, we add each measure of potential and overall competition, one at a time, to our regression model (2.7). Panels A and B of Table 2.3 show regression results that include each measure of non-connected peers proxying for potential competition (i.e., Non-Linked Peer Count and Non-Linked Peer Similarity), whereas Panels C and D of the same table present the results that include, respectively, measures of the overall competition, namely, Hoberg, Phillips, and Prabhala's (2014) Fluidity and the traditional Herfindahl Index (HHI). Fluidity captures the extent to which firms with similar product vocabulary as supplier i's are changing their product descriptions. A higher value corresponds to increased product market instabilities arising from competitor actions and hence more intense competition. Incorporating these measures into our model enables us to examine the effects from distinct sources of competition separately and to alleviate the concern that Connected Peer Threat measures may potentially capture competition of other dimensions than existing rivalry.

The overall results further substantiate our *prior* stated in H1a that the positive association between existing competition and crash risk is not subsumed by other dimensions of competitive threats. The coefficients on the three Connected Peer Threat proxies remain positive and statistically significant for all crash risk measures. Another important observation from the table is that competition from potential rivals, as proxied by Non-Linked Peer Count and Non-Linked Peer Similarity, appears to have a negative effect on crash risk. The coefficients on Non-Linked

Peer Count are negative across all nine sets of regressions and are statistically significant in six of them. Results for Non-Linked Peer Similarity are considerably weaker, but the signs of the coefficients remain negative for most of the regressions. These findings are consistent with H1b and lend support to validating our new competition constructs.

We observe that the coefficients of Connected Peer Threat remain materially unaffected after adding HHI to the model and are somewhat weaker for the Crash Count estimations after factoring in Fluidity. Importantly, none of the coefficients on HHI and Fluidity are statistically significant, suggesting that no other dimensions of competition have incremental effects in inducing the bad news hoarding behavior beyond that already captured by the Connected Peer Threat measures.

In summary, the results indicate that competition from customer-connected peers is the primary motive for firms to avoid bad news disclosure, and that they are consistent with the notion that competition from existing and potential rivals have distinct effects on disclosure decisions.

2.4.3 Managerial strategic disclosure behavior

While we have established the effects of existing competition on crash risk, one may criticize that crash risk is but an indirect measure of negative information hoarding subject to alternative interpretations. For instance, price crashes can be driven by the fundamental nature of a firm's operations, irrespective of whether negative information about the firm is withheld. In addressing such skepticism, we construct other proxies for managerial strategic disclosure behavior and examine their relationships with existing competition.

First, we exploit *firm-specific* corporate disclosure events, including conference presentations, earnings calls, earnings announcements, client announcements, product-related announcements, and corporate guidance, to construct three measures capturing managers' tendencies to releasing bad news. Each of these events is classified as a positive-news (negative-news) disclosure event if the cumulative abnormal return CAR(-1,1) during the 3-day window surrounding the event is positive (negative). All News, defined as the ratio of the number of firm-specific negative-news events to the number of firm-specific positive-news events, gauges firm managers' overall propensity to release negative information, incorporating both material and immaterial information. In contrast, 5% Significant News and 10% Significant News are intended to only capture the propensity of disclosing material news that results in significantly large investor reactions. Specifically, 5% Significant News (10% Significant News) is the ratio of the number of firm-specific negative-news events with CAR(-1,1) less than -5% (-10%) to positive-news events with CAR(-1,1) more than 5% (10%). We replicate our baseline analysis using these three proxies measured one year ahead as the outcome variables and report the results in Panel A of Table 2.4.

The panel reveals some distinct findings. The coefficients on All News, as shown in Columns (1)-(3), are negative and statistically significant across all connected peer competition measures, indicating that firms facing intense competition from existing rivals tend to release less negative news in general. In contrast, the coefficients on extreme news ratios tend to be positive, suggesting that intense competition is associated with more material information disclosure. Columns (4)-(9) show that the coefficients are mostly statistically significant. For example, the coefficient on Peer Count is 0.017 (t = 3.20) for 5% Significant News estimation and 0.020 (t = 4.16) for 10% Significant News estimation. The results are consistent with the notion that firms under competitive pressure stockpile negative news until it becomes material information; at which point, it is disclosed at the cost of stronger negative investor reactions.

Second, we examine whether managers are urged to make bad reporting choices in their mandatory filings to conceal adverse information about their firms. One *ex post* identification of company filing deficiencies is the comment letters sent by SEC. The SEC's Division of Corporation Finance has an oversight role of financial reporting through its review of company filings (e.g., Form 10-Ks, Form 10-Qs, Form S-1s, and DEF 14A) to ensure compliance with "the applicable disclosure and accounting requirements." The Division conducts three levels of reviews: (i) a complete review of all of a firm's filings; (ii) a financial statement review that involves financial statements, notes, and related disclosure such as the management discussion and analysis or MD&A; or (iii) a targeted review examining particular issues in a filing. If a report flags potential deficiencies, the SEC sends a comment letter to the firm requesting clarification, additional information, or disclosure adjustments in the filing or future filings. Due to limited time and resources, the Division only conducts reviews on a chosen subset of firms registered with the SEC. We exploit these comment letters to evaluate the quality of a firm's mandatory financial reporting in response to competitive threats. If existing competition incites detrimental information withholding, then the required financial filings may lack clarity and, in turn, trigger SEC feedback.

The comment letters are obtained from the Audit Analytics for the 2005-2015 period, from which we define the number of SEC comment letters as the number of different corporate filings from a firm that triggered a comment letter. Firm-year observations not receiving any comment letters would have a value of zero. We conduct two sets of regressions using the same specifications as Eq. (2.7) and report the results in Columns (1)-(6), Panel B of Table 2.4. The first set analyzes the full sample, whereas the second set focuses on only the sample of firm-years reviewed by the SEC. The coefficients on all three measures constructed from customer-connected peers are positive and strongly significant at the 1% level, consistent with our prediction that competitive pressure from existing rivals motivates the strategic disclosure of bad news.

Finally, we examine the material restatements of a firm's financial reporting as another *ex post* measure of deliberate information hoarding behavior. Effective 2004, all firms are required to disclose restatements of any SEC filing via Item 4.02 in Form 8-K. Compared to those in other filings (also known as stealth restatements), restatements disclosed in 8-Ks are associated with significant adverse market reactions, indicating the materiality of such information (Irani and Xu 2011). Using these restatements available in Audit Analytics, we conduct logit regressions with a dependent variable indicating the occurrence of material restatements. Columns (7)-(9) of Panel B report our findings. The positive and statistically significant coefficients indicate increased withholding of information, which ultimately precipitates financial restatements.

The overall evidence validates the bad news hoarding interpretation of stock price crash risk and confirms our prediction stated in H1a. While these constructs have the advantage of directly measuring disclosure behavior over the crash risk proxies, they suffer essential drawbacks. For instance, the disclosure events with significant adverse investor reactions are rare in occurrence, and the likelihood of identifying them is highly dependent on the overall number of disclosure events held by a firm. Firms exhibit considerable heterogeneity in a number of these events, and the decisions of holding them may be endogenously determined, potentially confounding our causal inferences of the relationship. Similarly, SEC reviews, let alone comment letters, are rarely found in our sample, and SEC's decisions to review may be endogenous. Furthermore, material restatements also capture extreme practices of disclosure that cannot be observed regularly. To circumvent any potential issues that arise from extreme observations and endogeneity, our study uses these disclosure proxies only for validation purposes and focuses on crash risk hereafter.

2.4.4 Other robustness tests

We conduct additional analyses to exhaust alternative interpretations of the baseline findings. Results are reported in Appendix Tables A.3 and A.4. First, one may argue that the customer-connected peer competition measures potentially capture the customer concentration of a firm (Chen, Hu, Yao, and Zhao 2018; Kim, Si, Xia, and Zhang 2018). However, we contend that such issues are not critical since (i) we examine all customer-supplier relationships irrespective of whether the customers are major or minor; and (ii) our proxies do not depend on a firm's number of major customers nor do they rely on the percentage of sales attributed to these customers. Nonetheless, we test against these possibilities by controlling for the sum of squared sales percentages to a firm's major corporate customers, a measure of firm dependence on major customers. Panel A of Table A.3 shows that the coefficients on Customer Concentration are positive and statistically significant in Columns (1)-(6), but not in Columns (7)-(9). More importantly, the coefficients on all three measures of connected peer threats remain robust to the additional control variable.

Second, we test whether our findings are driven by difficult times when the likelihood of relationship termination is higher. For instance, Cen, Maydew, Zhang, and Zuo (2017) argue that when facing a greater risk of losing its customers, a firm is more inclined to manage detrimental news disclosure. In addressing this concern, we exclude financial crisis years (2008-2009) from the sample to remove the influences of extreme economic conditions. As shown in Panel B, the coefficients on all three existing competition measures remain statistically significant.[19]

Additionally, we perform tests to rule out the possibility that our key results are driven by firms that are more prone to stock price crashes due to the fundamental nature of their operations. We construct three proxies to capture operating and business risks, namely, (i) the price-cost margin scaled by sales as a measure of market power; (ii) the annual standard deviation of operating income before depreciation over total assets as a measure of operating risk; and (iii) the contemporaneous operating performance defined as the number of negative news articles net of positive news articles available in Ravenpack on topics related to a firm's demand guidance, demand, production outlook, supply guidance, supply, market guidance, and market share. We repeat our analysis of Eq. (2.7), while controlling for the three constructs separately. Results shown in Table A.4 suggest that our main evidence is not driven by operating risks.

2.5 Identification strategies

Thus far, the results underscore a strong positive association between existing competition and stock price crash risk. However, our causal inferences of this relationship may be subject to endogeneity concerns such as reverse causality and confounding factors. To alleviate these concerns, we exploit three quasi-natural experiments to capture large exogenous shocks to customer-connected peers.

[19] We also replicate Li and Zhan's (2019) study by constructing a sample similar to theirs and find that their evidence based on Fluidity as a measure of product market competition is specific to their time period employed, but that Fluidity becomes statistically insignificant when the crisis period is removed from the sample.

2.5.1 Customer M&A intensity

Our first identification strategy uses the intensity of customer M&A activities as an exogenous source of an increase in the number of customer-connected peers and, thus, the focal supplier's existing competition. Through the consolidation of purchasing accounts, the acquiring customers would mechanically gain new trading partners, which in turn would add new customer-connected peers to the existing customer-supplier network. Hence, intense customer M&A activities should correspond to an increase in the competitive pressure from customer-connected peers. Such an instrumental variable (IV) of existing competition satisfies not only the relevance condition but also the exclusion restrictions. First, customer M&A activities are as good as randomly assigned across suppliers since they are likely independent of suppliers' corporate decisions. There may be a concern that customers undertake M&As to counteract the monopoly power of their suppliers, which is, in part, determined by the suppliers' product market competition (Galbraith 1952). However, it can be alleviated by excluding all vertical M&As, which can potentially be motivated by customers' responses to the market power of upstream firms (Spengler 1950). Second, it is reasonable to assert that customer M&A activities would only affect the suppliers' crash risk through their effects on the suppliers' competitive pressure. One possible concern is that merger waves could have contagion effects through customer industries to supplier industries and, in turn, capture the impact of supplier M&As on crash risk. While plausible, this argument of M&A propagation along the supply chain industries is less critical in our setting. Ahern and Harford (2014) show that the effect of customer consolidation on the supplier industry is much less than the impact of supplier industry consolidation on customer M&A activity. Nevertheless, we control for the supplier industry fixed effects in the IV analyses to address all remaining concerns and to remove any unobserved industry-wide effect that may contaminate the exclusion restriction.

Our empirical procedure is based on a two-stage least-squares (2SLS) estimation. In the first stage, we regress a supplier's existing competition proxy on the customer M&A intensity measure. The second stage tests the effect of instrumented competitive threats on the stock price crash risk. Formally, we estimate the following two-stage model:

$$\begin{aligned}\text{Connected Peer Threat}_{i,t} = &\quad \gamma_0 + \gamma_1 \text{Instrumental Variable}_{i,t} + \sum_{k=1}^{K} \lambda_k X_{ki,t} + \text{FE} + \eta_{i,t} \\ \text{Crash Risk}_{i,t+1} = &\quad \alpha_0 + \alpha_1 \widehat{\text{Connected Peer}} \text{ Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t},\end{aligned} \tag{2.8}$$

where Instrumental Variable$_{i,t}$ is the average M&A intensity across all customers of firm i, and all other variables are defined as above. To construct the M&A intensity measure, we first obtain M&A deals from the SDC database and apply the following restrictions for each transaction: (i) the deal must be completed; (ii) the acquirer purchases at least 50% of the target and owns at least 90% after the transaction; (iii) the transaction value is no less than $1 million; (iv) for each customer-supplier pair, the target of the acquiring customer must be in a different 2-digit SIC industry from the focal supplier.[20] We then exclude all firm-year observations where the suppliers are in the same industry as the customers. Taking a similar approach as Campello and Gao (2017), the M&A intensity for each customer is measured as the aggregate M&A transaction values scaled by the customer's total sales in a year and averaged over the last five years.[21] For each supplier, the IV Customer M&A Intensity is defined as the weighted-average M&A intensity across all its customers, where the supplier's sales percentage determines the weights to each customer. The results are shown in Table 2.5.

Panels A, B, and C of the table present 2SLS regression results based on each Connected Peer Threat proxy. In Columns (1), (3), and (5), the first-stage results show positive and statistically significant coefficients on the average customer M&A intensity, consistent with the notion of increased competitive pressure following intense customer M&A activity. The first-stage regressions' F-statistics are well above 10, further indicating that the instrument satisfies the relevance condition. In Columns (2), (4), and (6), the second-stage estimates show that the predicted competitive threat measures measures have positive and significant effects on the

[20] Restriction (iv) may result in the exclusion of an M&A deal in some customer-supplier pairs but the inclusion of it in other customer-supplier pairs, depending on the 2-digit SIC industry of each supplier firm.

[21] To properly exclude the effects of vertical M&As from each firm-year observation, we consider a customer M&A as vertical if the target firm is in the same 2-digit SIC industry as the supplier, as long as the supplier-customer relationship is established within the next 5 years of the merger deal.

crash risk measures.

Overall, the customer M&A intensity IV approach corroborates our earlier findings and lends support to a causal interpretation of a positive relationship between the competitive threats that a firm faces and its bad news hoarding behavior.

2.5.2 Peer firm bankruptcy

Our second identification strategy exploits an exogenous reduction in existing competition due to the bankruptcies of customer-connected peers. Customers tend to lose confidence in bankrupt firms and would seek for safer alternatives (Altman 1984; Opler and Titman 1994; Cheng and McDonald 1996). Thus, we expect that when a connected peer files for bankruptcy, the common customers would rely less on it for inputs, if not switching away completely, given concerns over the peer's ability to fulfill its commitments. Competition among existing rivals would, in turn, decline considerably due to reductions in the common customers' dependence on those peers who file for bankruptcy. We use such exogenous shocks to connected peer threats in a difference-in-differences framework and expect to find a negative treatment effect on crash risk.

One might argue that corporate bankruptcies are endogenous to product market competition. However, to the extent that bankruptcies of connected peers are driven by the intense competition they face, these shocks also suggest fierce competition for the focal supplier that is in the same product space as those peers. Thus, a shock reflecting intense competition would work against us finding negative treatment effects on the crash risk measures. Another potential concern is confounding factors. For instance, peer bankruptcy may reflect adverse conditions within the industry (Warner 1977) and hence coincide with a higher crash risk for the focal firm. Such a concern is less critical in our setting, because it would also lead to an underestimation of the negative treatment effect. Alternatively, firms with bankrupt connected peers may benefit from increases in customer demand. Thus, a negative association between the shocks and stock price crashes may reflect a positive effect on the focal firm's operational performance rather than a negative effect on the incentives to withhold negative information. To account for such factors, we control for the focal firm's market share in the year its peers have filed for bankruptcy.

The Chapter 11 bankruptcy filings data are from Ma, Tong, and Wang (2019) that cover all U.S. public firms from 1980 to 2016. We define our treated group as suppliers whose customer-connected peers have filed for Chapter 11 bankruptcy in year $t+1$, where the customer-connected peers are those linked to the suppliers in year t. Our sample of Chapter 11 cases is not confined to any particular type of bankruptcy outcomes, such as liquidation, acquisition, or reorganization. We anticipate that irrespective of the final court decision, all bankruptcies would have almost immediate adverse effects on the firm's ability to compete in the product market. All other suppliers with no bankrupt peers are considered as our control group. The treatment period is defined as the year during which bankruptcies are filed, allowing us to test the immediate effect of the shock on the focal firm's competitive threats. Formally, we estimate the following regression model:

$$\begin{aligned}\text{Crash Risk}_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_{t+1} + \alpha_3 Treat_i \times Post_{t+1} + \text{Additional Controls} \\ & + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned} \tag{2.9}$$

where $Treat_i$ is a dummy variable indicating whether firm i's connected peers have filed for bankruptcy; $Post_{t+1}$ is a dummy variable covering the year during which the bankruptcies are filed;[22]; $X_{ki,t}$ includes the same set of firm-level controls as that in Eq. (2.7); and Additional Controls include $\text{Bankruptcy}_{i,t+1}$ and $\text{MktShare}_{i,t+1}$. Detailed definitions of these variables are provided in Appendix Table A.2.

In Table 2.6, the estimation results of (2.9) show that $\text{Bankruptcy}_{i,t+1}$ and $\text{MktShare}_{i,t+1}$ bear the expected signs, suggesting that a firm's own bankruptcy filing has positive effects on crash risk, whereas its market share has negative effects. Furthermore, the resulting coefficients on the interaction term, $Treat \times Post$, are negative and statistically significant across all crash risk measures. The negative treatment effect of peer bankruptcy lends further support to our *prior* that firms are more inclined to withhold negative information in response to competitive

[22]The variable $Post$ is dropped from the actual regression estimation due to its perfect collinearity with the year fixed effect dummies.

threats from existing rivals.

2.5.3 Peer firm disruptions by natural disasters

Our third approach explores the effects of major natural disasters on the operations of customer-connected peers. Similar to bankruptcies, natural disasters cause disruptions to a firm's production if they occur in locations where the firm's plants and establishments reside. However, we expect such disruptive events to differ from bankruptcies in a vital way – disruptions of a firm's operations caused by natural disasters tend to be temporary and hence would have, if any, short-term effects on the relationship with its customers. Thus, it is unlikely for disaster events to induce a sizeable shift in customer dependence to alternate suppliers as would be for bankruptcies.[23] We contend that, instead of affecting the three connected peer threat measures, peer disaster events would capture temporary reductions in the peers' competitiveness through adverse effects on their operating performance and disruptions in their competitive actions against others. Specifically, for any given level of customer dependence on the connected peers, the competitive threats posed by the troubled peers are expected to decline considerably following the events. Hence, our approach is to examine whether the competition-crash risk relationship weakens when connected peers are suffering from natural disasters. Our analysis has the same spirit as a difference-in-differences model. However, to emphasize the key feature that the treatment does not directly affect the existing competition variables but instead captures the nonlinearity in their impact, we interact the treatment indicator with the connected peer threat measures.

We obtain information on all federally declared disasters from the Federal Emergency Management Agency (FEMA). The database includes information on the incident start and end dates as well as the Federal Information Processing Standards (FIPS) code for all affected counties. Following Barrot and Saugvanat (2016) and He (2018), we focus on major disasters lasting

[23] Barrot and Saugvanat (2016) provide evidence supporting this argument. The authors find that the disaster-induced disruptions of a supplier do not result in increases in the sales growth of other suppliers servicing the same customer.

less than 30 days with total estimated damages above \$1 billion.[24] The resulting 28 major disaster events include hurricanes, blizzards, floods, and wildfires. Crucial to our analysis is the identification of affected firms by the disasters. We first collect plant- and establishment-level data from the Mergent Data Explr database, which is an annual snapshot data available in Dun and Bradstreet. Data Explr contains yearly information on employment and location by plant and establishment for all U.S. firms from 1985 to 2017. We then match the FEMA and Data Explr datasets by the location of each firm and measure the impact of natural disasters on the firm based on the percentage of its employees in the event area. Specifically, we consider a firm's operations to be disrupted by an event if at least 20% of the firm's total employees reside in the affected county.

We test the differential effects of existing competition when the customer-connected peers are affected by natural disasters as follows:

$$\begin{aligned}\text{Crash Risk}_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} \times \text{Peer Disaster}_{i,t+1} + \alpha_2 \text{Connected} \\ & \text{Peer Threat}_{i,t} + \alpha_3 \text{Peer Disaster}_{i,t+1} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \qquad (2.10)\end{aligned}$$

where Peer Disaster$_{i,t+1}$ is a binary indicator that takes the value of one for firm i in year $t+1$ if its connected peers are affected by a disaster occurred in $t+1$. In addition to the previously employed control variables, we also include a dummy variable indicating whether firm i itself is affected by a disaster in $t+1$ (Disaster$_{i,t+1}$). It accounts for the possibility that firm i is located close to its peers and hence is affected by the same disaster.

Results, as reported in Table 2.7, reveal the heterogeneous effects of existing competition. The coefficients on all three connected peer threat measures are positive and significant, indicating that competitive effects remain strong and robust for firms with peers unaffected by disasters. In contrast, the coefficients on the interaction term are significantly negative, producing a less pronounced competitive effect when peer operations are disrupted by natural disasters. Hence, exogenous disruptions to supplier peers' operations weaken their competitive threats to

[24]Major events are identified by manually matching the FEMA data with the list of major disasters provided in the two studies by Barrot and Saugvanat (2016) and He (2018).

the extent that they reduce the supplier's crash risk, consistent with our prediction that firms are more inclined to disclose negative news when facing less competitive threats from existing rivals.

Overall, the evidence from all three quasi-natural experiments suggests that our baseline results are robust to potential endogeneity concerns and that existing competition has causal effects on a firm's crash risk.

2.6 Bad News Withholding and Underlying Motives

We now investigate the mechanisms behind the bad news hoarding behavior of a firm facing competitive pressure from existing competitors. In particular, we examine how existing competitors, customers, and investors each play a role in motivating the strategic disclosure of negative information.

2.6.1 Competitor-induced motives

As stated in Section 2.2, we posit that a firm under competitive pressure is increasingly concerned about the proprietary costs of disclosing unfavorable information to existing competitors and is, thus, more inclined to hide bad news from its competitors. To test such competitor-induced motives, we examine whether the impact of existing competition on information hoarding behavior would be attenuated by less hostility and more information exchange between a firm and its competitors, as proxied by business alliances formed between them. We construct three new measures of connected peer threats that have formed at least one type of business alliance with the focal firm (hereafter CompAl), including research collaboration, integrated product offering, joint venture, cross-ownership in equity stakes, products, patents, and intellectual property licensing, and the use of each other's manufacturing, marketing, and distribution services.[25] We

[25]The identification of *CompAl* peers is based on the relationship information obtained from the Revere database.

then run the following panel regression.

$$\begin{aligned}\text{Crash Risk}_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 \text{Connected Peer Threat (CompAl)}_{i,t} + \alpha_2 \text{Connected Peer} \\ & \text{Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned} \tag{2.11}$$

where Connected Peer Threat (CompAl) is a subsample of our earlier defined Connected Peer Threat, except peers in the former have formed business alliances with firm i. In (2.11), Connected Peer Threat (CompAl) captures the incremental effects of CompAl peers relative to all other connected peers.

As reported in Table 2.8, the coefficients on all Connected Peer Threat proxies remain positive and statistically significant, suggesting that competitive threats from non-CompAl connected peers motivate negative information withholding. In contrast, the coefficients on all Connected Peer Threat (CompAl) measures are negative and statistically significant for Peer Count (CompAl) and Peer Similarity (CompAl). These findings indicate that firm-peer business alliances have moderating effects on the positive relationship between existing competition and crash risk, consistent with our H2 prediction.

2.6.2 Customer-induced motives

We also contend that a firm under competitive pressure is less willing to share negative information with its customers due to increased concerns over the latter's response to such adverse information. To test the customer-induced motives of information hoarding, we examine whether the effects of existing competition on crash risk are less pronounced for firms establishing cooperative relationships with their customers through forming business alliances and offering trade credits.

We construct three new measures of connected peer threats based solely on common customers who have formed at least one type of business alliances with the focal supplier (hereafter CusAl). We then re-estimate Eq. (2.11) with Connected Peer Treat (CustAl) replacing Connected Peer Threat (CompAl) and report our findings in Table 2.9. The coefficients on

Competitive Peer Threat (CusAl) measures are negative and statistically significant for all but one regression. The results are consistent with H3a that competitive pressure from CusAl peers dampens the overall competitive effects on crash risk.

We next construct AccRec, defined as log of one plus accounts receivable, to proxy for the credits extended by a firm to its customers and regress the following model:

$$\begin{aligned}\text{Crash Risk}_{i,t+1} \quad = \quad & \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} \times \text{AccRec}_{i,t} + \alpha_2 \text{Connected Peer} \\ & \text{Threat}_{i,t} + \alpha_3 \text{AccRec}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}, \end{aligned} \tag{2.12}$$

The regression results, as shown in Table 2.10, are consistent with H3b that AccRec has a dampening effect on the positive association between existing competition and stock price crash risk. The coefficients on the interaction term, α_1, are negative and mostly statistically significant.

2.6.3 Investor-induced motives

We now investigate the investor-induced motives of withholding adverse news by examining the cross-sectional impact of investor informedness on the link between existing competition and stock price crash risk.

Prior work demonstrates that institutional owners trade on superior information and, in turn, accelerate the incorporation of such information into stock prices (El-Gazzar 1998; Jiambalvo, Rajgopal, and Venkatachalam 2002; Piotroski and Roulstone 2004). Thus, a greater institutional presence should reflect a higher investor informedness about the true content of withheld information and, in turn, limit the ability for a firm to conceal bad news without being discounted for it. We test our prediction by rerunning Eq. (2.12) using institutional ownership breadth ($\#\ \text{Inst}_{i,t}$), defined as the log number of institutions holding firm i's shares in year t, as a proxy for institutional presence in firm i in place of AccRec. Results reported in Panel A of Table 2.11 show that connected peer threats continue to exhibit a positive impact on crash risk for firms with low institutional presence. But, consistent with H4, the positive effect is weakened for firms with a higher level of institutional breadth, as revealed by the negative and statistically significant coefficients on the interaction term across different model specifications.

Firm opacity impairs the ability for analysts to interpret the currently available information and reach a consensus on their predictions of a firm's future performance. Hence, more dispersed analyst opinions suggest a higher information asymmetry between the covered firm and its investors. Using the IBES data, we compute analyst forecast dispersion as the standard deviation of annual earnings per share (EPS) forecasts for a fiscal year t, scaled by the stock price at the beginning of the fiscal year. Following Lang and Lundholm (1996) and Gu and Wang (2005), we take the one-year-ahead consensus forecasts six months before the fiscal year-end to ensure that all analysts have access to the financial information from the previous fiscal year and have the same forecast horizon. We then define a binary variable High Dispersion to capture firms with forecast dispersion above the fourth quartile of all firms in the same industry-year. We re-estimate Eq. (2.12) with High Dispersion in place of AccRec and present the results in Panel B. The variable of interest is the interaction term, and its coefficients are all statistically significant and positive. When facing intense competition, opaque firms are more motivated to hoard unfavorable information than do their transparent peers.

Bushee, Core, Guay, and Hamm (2010) find that greater news coverage reduces the information asymmetry of a firm. Through the timely dissemination of firm-initiated information as well as the packaging of information from multiple sources, the business press provides information to investors incremental to firm disclosures and other information intermediaries. Thus, news coverage is another appropriate proxy for investor informedness. We obtain data on press articles from Ravenpack full package, which includes articles from over 150,000 press releases, regulatory disclosures, web aggregators, and blog sites. We utilize the log number of unique Ravenpack news sources covering each firm over its fiscal year as a proxy for news coverage breadth, Media Coverage. Panel C presents results from the estimation of Eq. (2.12) and corroborates the attenuating effects of investor informedness on the baseline relationship.

2.7 Conclusion

We exploit the network of supplier-customer links to provide insights on the strategic bad news disclosure behavior of firms facing intense competition from rivals producing similar products and supplying to common corporate customers. Our study employs a newly available database on detailed firm-level information of customer-supplier relationships that enables us to construct firm-specific competition measures that distinguish between competition from existing rivals (i.e., customer-connected peers) and competition from potential rivals (i.e., non-linked peers). We find that competitive threats from customer-connected peers play an essential role in a firm's stock price crash risk, a proxy for the accumulation of unfavorable information. This evidence suggests that firms strategize to withhold adverse news that has detrimental effects on their stock prices, and that such effects are further supported by three quasi-natural experiments that capture large exogenous shocks to linked peers. Our analyses also show that potential competitors, or non-customer-connected peers, exhibit a negative, while considerably weaker, influence on managers' behavior to withhold or delay bad news disclosure, implying that firms facing intense threats from potential entrants are likely to disclose adverse news as a means to deter entry. Finally, the findings suggest that firms' bad-news disclosure decisions are driven by their stakeholders, namely, customers, customer-connected peers, and investors.

Figure 2.1: A Snapshot of Texas Instruments, Inc's Network of Suppliers

This graph illustrates a portion of the supply-chain network of Texas Instruments, Inc in 2014. It includes corporate customers and peer suppliers of those customers that could be identified by Revere and Compustat data. We restrict all the firms in this graph to be a part of CRSP and Compustat universe. The red node indicates Texas Instruments Inc; the blue nodes represent the corporate customers of Texas Instruments Inc; and the orange nodes represent the customer-connected peers in the same industry as Texas Instruments, Inc according to Hoberg and Phillips's (2010; 2016) TNIC classification. In addition, the figure combines other peers that are not in the same industry into groups to reduce the number of nodes.

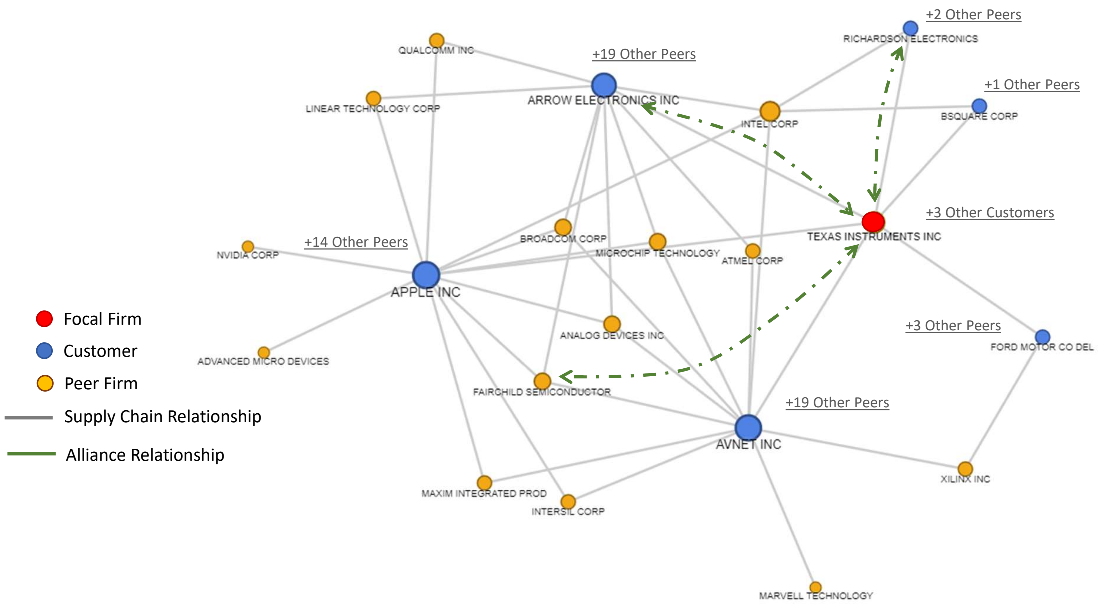

Figure 2.2: A Supplier's Customer Network and Peer Firms

Firm (S_i) has n_i customers; each customer (C_j) has m_j suppliers, including S_i and S_i's industry peer P_k, where industry is defined in Hoberg and Phillips (2010; 2016).

$$Peer\ Count_i = ln\left(\frac{\sum_{j=1}^{n_i} m_j}{n_i}\right) \qquad Peer\ Sales_i = \sum_{j=1}^{n_i}\left(\sum_{k=1}^{m_j}\frac{Sales_{j,k}}{COGS_j}\right)\Big/ n_i \qquad Peer\ Similarity_i = \sum_{j=1}^{n_i}\left(\sum_{k=1}^{m_j}\frac{Similarity_{i,k}}{m_j}\right)\Big/ n_i$$

where $Sales_{j,k}$ is the sales from P_k to C_j, $COGS_j$ is the cost of goods sold of C_j, and $Similarity_{i,k}$ is Hoberg-Phillips industry similarity between S_i and P_k.

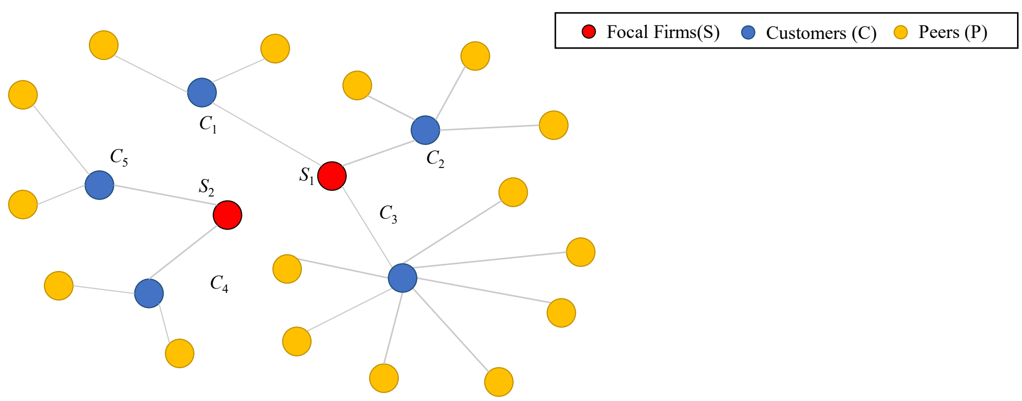

Table 2.1: Summary Statistics

This table reports the number of observations (NObs), the mean and standard deviation of the variable, as well as the distribution in different percentiles of 5%, 25%, 50% (median), 75%, and 95%. Panel A contains summary statistics of the three proxies for existing competition, namely (1) the log average number of customer-connected peers in the same product market based on TNIC classification (Peer Count); (2) the ratio of a supplier's sales to customer's cost of goods sold, summed across all customer-connected peers (Peer Sales); (3) the average product similarity score with the customer-connected peers (Peer Similarity). Panel B shows summary statistics of three measures of stock price crash risk: (1) the negative conditional skewness of stock returns (NCSKEW); (2) the log of the standard deviation of down weekly returns divided by the standard deviation of up weekly returns (DUVOL); (3) the number of firm-specific weekly returns exceeding 3.09 standard deviation below the mean firm-specific weekly return over the fiscal year (Crash Count). Panel C contains summary statistics of firm-specific control variables, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), and past stock return. The construction of the variables is presented in Appendix Table A.2. The sample period is from 1996 to 2015.

				Percentiles				
Variable	NObs	Mean	Std Dev	5%	25%	Median	75%	95%
Panel A: Connected Peer Threats								
Peer Count$_t$	28,598	1.015	1.015	0.000	0.000	0.693	1.792	2.952
Peer Sales$_t$	27,136	0.016	0.038	0.000	0.000	0.000	0.014	0.086
Peer Similarity$_t$	28,598	0.022	0.027	0.000	0.000	0.013	0.033	0.079
Panel B: Measures of Stock Price Crash Risk								
NCSKEW$_{t+1}$	28,585	0.057	0.849	-1.294	-0.426	0.019	0.480	1.589
DUVOL$_{t+1}$	28,585	0.042	0.542	-0.840	-0.320	0.024	0.380	0.982
Crash Count$_{t+1}$	28,598	-0.008	0.656	-1.000	0.000	0.000	0.000	1.000
Panel C: Control Variables								
Size$_t$	28,598	6.551	2.176	3.074	4.981	6.452	8.022	10.398
MB$_t$	28,598	3.307	3.983	0.676	1.338	2.168	3.649	9.371
Leverage$_t$	28,598	0.153	0.164	0.000	0.000	0.109	0.257	0.480
ROA$_t$	28,598	-0.003	0.167	-0.338	-0.018	0.038	0.078	0.159
ΔTurnover$_t$	28,598	-0.003	0.070	-0.116	-0.038	-0.005	0.029	0.122
AbAccr$_t$	28,598	0.216	0.184	0.038	0.090	0.160	0.277	0.604
Sigma$_t$	28,598	0.057	0.031	0.020	0.034	0.049	0.071	0.119
Return$_t$	28,598	-0.205	0.249	-0.702	-0.249	-0.118	-0.055	-0.020

Table 2.2: Existing Competition and Supplier Negative News Hoarding

This table reports results from regressing supplier stock price crash risk on each measure of connected peer threats and firm-specific controls as follows:

$$\text{Crash Risk}_{i,t+1} = \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t}.$$

where $X_{ki,t}$ is a vector of controls, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). The three proxies for existing competition include Peer Count, Peer Sales, and Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm-level. The number of observations (NObs) and adjusted R^2 are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count_t	0.029***			0.015***			0.019***		
	(5.45)			(4.28)			(4.64)		
Peer Sales_t		0.417***			0.241***			0.197*	
		(2.92)			(2.72)			(1.87)	
Peer Similarity_t			1.151***			0.622***			0.562***
			(5.61)			(4.83)			(3.57)
Size_t	0.039***	0.039***	0.038***	0.023***	0.023***	0.023***	0.027***	0.027***	0.027***
	(11.25)	(11.03)	(11.10)	(10.58)	(10.36)	(10.43)	(10.25)	(10.13)	(10.24)
MB_t	0.005***	0.004***	0.005***	0.004***	0.004***	0.004***	0.002*	0.002	0.002*
	(3.24)	(2.95)	(3.23)	(3.90)	(3.76)	(3.89)	(1.80)	(1.58)	(1.81)
Leverage_t	-0.032	-0.028	-0.042	-0.019	-0.019	-0.024	-0.012	-0.009	-0.018
	(-0.91)	(-0.78)	(-1.19)	(-0.85)	(-0.82)	(-1.08)	(-0.46)	(-0.34)	(-0.67)
ROA_t	0.267***	0.255***	0.272***	0.153***	0.145***	0.156***	0.193***	0.185***	0.193***
	(7.38)	(6.92)	(7.56)	(6.70)	(6.27)	(6.87)	(7.20)	(6.76)	(7.21)
$\Delta\text{Turnover}_t$	0.500***	0.540***	0.506***	0.308***	0.328***	0.311***	0.326***	0.359***	0.329***
	(5.78)	(6.19)	(5.85)	(5.66)	(5.95)	(5.72)	(4.87)	(5.33)	(4.92)
AbAccr_t	0.079**	0.096***	0.079**	0.056***	0.065***	0.056***	0.049**	0.057**	0.050**
	(2.48)	(2.97)	(2.49)	(2.82)	(3.24)	(2.82)	(1.99)	(2.26)	(2.05)
NCSKEW_t	0.013*	0.017**	0.013*	0.005	0.008*	0.005	0.014***	0.016***	0.014***
	(1.84)	(2.45)	(1.90)	(1.18)	(1.76)	(1.23)	(2.63)	(3.00)	(2.70)
Sigma_t	5.347***	5.475***	5.317***	3.012***	3.049***	2.985***	2.872***	3.076***	2.908***
	(7.99)	(7.99)	(7.93)	(7.12)	(7.02)	(7.05)	(5.58)	(5.81)	(5.64)
Return_t	0.611***	0.622***	0.610***	0.332***	0.333***	0.331***	0.369***	0.390***	0.373***
	(8.19)	(8.20)	(8.16)	(6.95)	(6.84)	(6.91)	(6.40)	(6.59)	(6.47)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.3: Existing Competition vs. Other Competitive Threats

This table reports results from regressing supplier stock price crash risk on each proxy for existing competition as well as a proxy for other source of competition, as follows:

$$\text{Crash Risk}_{i,t+1} = \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} + \alpha_2 \text{Other Competitive Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t},$$

where $X_{ki,t}$ is a vector of controls, such as size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). Panels A-D replicate the analysis as Table 2 in the presence of a proxy for other sources of competition, namely, non-linked peer count, non-linked peer similarity, HHI, and fluidity, respecitively. The three proxies for the existing competition include Peer Count; Peer Sales; and Peer Similarity, whereas the three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and R-squared (R^2) are reported. Construction of the variables is presented in Appendix Table A.2.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Proxy for Potential Competition: Non-Linked Peer Count									
Non-Linked Peer Count_t	-0.031***	-0.013	-0.028***	-0.022***	-0.013**	-0.021***	-0.017**	-0.005	-0.012
	(-2.85)	(-1.17)	(-2.63)	(-3.25)	(-2.02)	(-3.15)	(-2.06)	(-0.56)	(-1.44)
Peer Count_t	0.034***			0.018***			0.022***		
	(6.04)			(5.04)			(5.02)		
Peer Sales_t		0.449***			0.275***			0.208*	
		(3.07)			(3.05)			(1.93)	
Peer Similarity_t			1.317***			0.745***			0.635***
			(6.20)			(5.58)			(3.84)
NObs	28,546	27,084	28,546	28,546	27,084	28,546	28,546	27,084	28,546
R^2	0.025	0.024	0.025	0.027	0.026	0.028	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.3: Existing Competition vs. Other Competitive Threats – Continued

	$NCSKEW_{t+1}$			$DUVOL_{t+1}$			Crash $Count_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Proxy for Potential Competition: Non-Linked Peer Similarity									
Non-Linked Peer $Similarity_t$	-0.030	-0.084	-0.073	-0.068	-0.021	-0.103	-0.015	0.068	-0.011
	(-0.22)	(0.59)	(-0.52)	(-0.77)	(-0.24)	(-1.15)	(-0.14)	(0.64)	(0.11)
Peer $Count_t$	0.028***			0.015***			0.019***		
	(5.05)			(4.14)			(4.30)		
Peer $Sales_t$		0.402***			0.248***			0.184*	
		(2.75)			(2.74)			(1.71)	
Peer $Similarity_t$			1.125***			0.644***			0.529***
			(5.25)			(4.75)			(3.14)
NObs	28,555	27,093	28,555	28,555	27,093	28,555	28,555	27,093	28,555
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Proxy for Other Competitive Threats: Fluidity									
$Fluidity_t$	0.002	0.003	0.001	0.001	0.002	0.000	0.001	0.002	0.001
	(0.77)	(1.34)	(0.51)	(0.54)	(1.12)	(0.20)	(0.63)	(1.14)	(0.81)
Peer $Count_t$	0.018***			0.009**			0.011**		
	(2.76)			(2.04)			(2.22)		
Peer $Sales_t$		0.289*			0.169*			0.104	
		(1.92)			(1.80)			(0.94)	
Peer $Similarity_t$			0.814***			0.457***			0.274
			(3.46)			(3.09)			(1.51)
NObs	24,111	22,664	24,111	24,111	22,664	24,111	24,121	22,674	24,121
R^2	0.027	0.027	0.028	0.030	0.029	0.030	0.020	0.020	0.020
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel D: Proxy for Other Competitive Threats: HHI									
Supplier Industry HHI	0.239	0.204	0.226	0.193	0.189	0.188	0.259	0.234	0.241
	(0.90)	(0.75)	(0.85)	(1.15)	(1.09)	(1.12)	(1.35)	(1.18)	(1.25)
Peer $Count_t$	0.030***			0.015***			0.020***		
	(5.48)			(4.32)			(4.69)		
Peer $Sales_t$		0.421***			0.245***			0.202*	
		(2.94)			(2.76)			(1.91)	
Peer $Similarity_t$			1.157***			0.627***			0.569***
			(5.63)			(4.86)			(3.60)
NObs	28,582	27,120	28,582	28,582	27,120	28,582	28,595	27,133	28,595
R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4: Negative News, SEC Comment Letters, and Restatements

Panel A of this table reports results from regressing the ratio of the number of negative-news events to the number of positive-news events on each proxy for existing competition. All News accounts for all events with positive and negative CAR(-1,1), where CAR(-1,1) is a 3-day cumulative return in market reaction to news of management-involved events in year $t+1$. Number of 5% (10%) Significant News counts only key events with $|CAR(-1,1)| > 5\%(10\%)$. Panel B reports results from regressing the number of SEC comment letters on mandatory disclosures including annual and quarterly financial reports (Form 10-Ks, Form 10-Qs), material news disclosures (Form 8-Ks), registration and prospectus filings (e.g., Form S-1), and proxy filings (e.g., Def 14A), or the occurrence of material restatements of the different filings submitted by a supplier in year $t+1$ on each proxy for existing competition. In all regressions, we control for firm-specific variables, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). The three measures of existing competition include Peer Count, Peer Sales, and Peer Similarity. In Columns (1)-(6), the analysis is based on a sample period from 2004 to 2015, because SEC comment letters are available starting in 2005. $t-$statistics are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R^2† (adj R^2 in Columns (1)-(6) and pseudo-R^2 in Columns (7)-(9)) are reported. The construction of the variables is presented in Appendix Table A.2.

	All News$_{t+1}$			5% Significant News$_{t+1}$			10% Significant News$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Negative-Over-Positive Management Disclosure at $t+1$									
Peer Count$_t$	-0.022***			0.017***			0.020***		
	(-4.60)			(3.20)			(4.16)		
Peer Sales$_t$		-0.393***			0.219			0.201*	
		(-3.18)			(1.58)			(1.74)	
Peer Similarity$_t$			-0.439**			0.754***			0.674***
			(-2.17)			(3.54)			(3.69)
NObs	23,556	22,216	23,556	23,556	22,216	23,556	23,556	22,216	23,556
R^2	0.016	0.017	0.016	0.050	0.050	0.050	0.108	0.107	0.108
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Full Sample			Firms with Comment Letters			Occurrence of Restatements$_{t+1}$		
Panel B: Comment Letters and Material Restatements $t+1$									
Peer Count$_t$	0.053***			0.067***			0.007***		
	(6.27)			(6.36)			(4.97)		
Peer Sales$_t$		0.870***			0.907***			0.105***	
		(3.86)			(3.46)			(2.86)	
Peer Similarity$_t$			1.804***			2.121***			0.242***
			(5.52)			(5.36)			(3.75)
NObs	19,055	17,941	19,055	8,757	8,283	8,757	23,154	21,816	23,154
Adj-R^2†	0.063	0.060	0.063	0.098	0.094	0.097	0.026	0.025	0.025
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.5: Customer M&A and Supplier Stock Price Crash Risk

The table conducts two-stage least squares analysis using M&A as an instrumental variable, and reports a weak ID $F-$test. Similarly that of Table 2, each measure of the supplier stock price crash risk is regressed on a proxy for existing competition, while controlling for firm-specific variables, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned}\text{Connected Peer Threat}_{i,t} &= \gamma_0 + \gamma_1 \text{Instrumental Variable}_{i,t} + \sum_{k=1}^{K} \lambda_k X_{ki,t} + \text{FE} + \eta_{i,t}, \\ \text{Crash Risk}_{i,t+1} &= \alpha_0 + \alpha_1 \widehat{\text{Connected Peer}} \text{ Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}.\end{aligned}$$

The three measures of connected peer threats are Peer Count, Peer Sales, and Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and weak ID $F-$statistics are reported. Construction of the variables is presented in Appendix Table A.2.

	First-Stage	NCSKEW$_{t+1}$	First-Stage	DUVOL$_{t+1}$	First-Stage	Crash Count$_{t+1}$
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Peer Count						
Customer M&A Intensity$_t$	1.355***		1.355***		1.359***	
	(6.23)		(6.23)		(6.25)	
Peer Count$_t$		0.288***		0.158**		0.139*
		(2.81)		(2.49)		(1.84)
NObs	25,089	25,089	25,089	25,089	25,100	25,100
Weak ID F-stat		38.87		38.87		39.01
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Peer Sales						
Customer M&A Intensity$_t$	0.042***		0.042***		0.042***	
	(5.53)		(5.53)		(5.53)	
Peer Sales$_t$		9.117***		4.950**		4.481*
		(2.64)		(2.36)		(1.75)
NObs	23,901	23,901	23,901	23,901	23,912	23,912
Weak ID F-stat		30.53		30.53		30.60
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Peer Similarity						
Customer M&A Intensity$_t$	0.020***		0.020***		0.021***	
	(4.15)		(4.15)		(4.16)	
Peer Similarity$_t$		19.097**		10.474**		9.170*
		(2.51)		(2.27)		(1.74)
NObs	25,089	25,089	25,089	25,089	25,100	25,100
Weak ID F-stat		17.24		17.24		17.34
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.6: Difference-in-Differences Analysis: Peer Bankruptcy

The table presents a difference-in-differences analysis of supplier stock price crash risk based on peer bankruptcy shocks. The independent variables are Post, Treat, Bankruptcy, MktShare, as well as firm-specific controls.

$$\begin{aligned}\text{Crash Risk}_{i,t+1} &= \alpha_0 + \alpha_1 Treat_i + \alpha_2 Post_{t+1} + \alpha_3 Treat_i \times Post_{t+1} \\ &\quad + \text{Additional Controls} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}.\end{aligned}$$

Treat$_i$ is an indicator equal to one if any of the supplier i's peers files for Chapter 11 bankruptcy, and 0 if otherwise. Post$_{t+1}$ is an indicator that equals one during the year in which the peer files for bankruptcy, and 0 if otherwise. Bankruptcy$_{t+1}$ is an indicator that equals one if the firm files bankruptcy in $t+1$ and 0 if otherwise. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. Firm-specific variables include size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R-squared (R^2) are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW$_{t+1}$	DUVOL$_{t+1}$	Crash Count$_{t+1}$
Variable	(1)	(2)	(3)
Post$_{i,t+1}$ × Treat$_i$	-0.155***	-0.132***	-0.096**
	(-2.91)	(-3.38)	(-2.40)
Treat$_i$	0.027	0.019	0.023
	(1.10)	(1.18)	(1.23)
Bankruptcy$_{i,t+1}$	0.843***	0.508***	0.445***
	(3.40)	(2.84)	(2.66)
MktShare$_{i,t+1}$	-0.644***	-0.408***	-0.403***
	(-3.68)	(-3.72)	(-3.12)
NObs	19,222	19,222	19,227
Adj-R^2	0.022	0.027	0.014
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 2.7: Peer Disaster and Supplier Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for existing competition, Peer Disaster indicator, and the interaction between the latter two variables, while controlling for firm-specific variables ($X_{ki,t}$), including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE), as follows.

$$\begin{aligned}\text{Crash Risk}_{i,t+1} &= \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} \times \text{Peer Disaster}_{i,t+1} + \alpha_2 \text{Connected Peer Threat}_{i,t} \\ &\quad + \alpha_3 PeerDisaster_{i,t+1} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t},\end{aligned}$$

The three measures of connected peer threats include Peer Count, Peer Sales, Peer Similarity. The Peer Disaster indicator takes the value of one if a major disaster occurred in the county where the firm's peers had at least 20% of their employees and zero if otherwise. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R-squared (R^2) are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count$_t$ × Peer Disaster$_{t+1}$	-0.045**			-0.024*			-0.028*		
	(-2.00)			(-1.65)			(-1.70)		
Peer Count$_t$	0.033***			0.020***			0.022***		
	(3.63)			(3.36)			(3.11)		
Peer Sales$_t$ × Peer Disaster$_{t+1}$		-0.588*			-0.388*			-0.396*	
		(-1.81)			(-1.82)			(-1.71)	
Peer Sales$_t$		0.455**			0.315***			0.205	
		(2.53)			(2.75)			(1.57)	
Peer Similarity$_t$ × Peer Disaster$_{t+1}$			-1.051*			-0.283			-0.955**
			(-1.69)			(-0.71)			(-2.10)
Peer Similarity$_t$			1.061***			0.603***			0.436**
			(3.91)			(3.56)			(2.13)
Peer Disaster$_{t+1}$	0.073	0.014	0.034	0.032	0.005	0.002	0.043	0.009	0.034
	(1.42)	(0.64)	(1.15)	(1.00)	(0.37)	(0.12)	(1.13)	(0.55)	(1.50)
Disaster$_{t+1}$	0.018	0.014	0.019	0.014	0.008	0.014	0.014	0.012	0.013
	(0.67)	(0.49)	(0.68)	(0.83)	(0.43)	(0.84)	(0.67)	(0.56)	(0.63)
NObs	19,230	17,768	19,230	19,230	17,768	19,230	19,235	17,773	19,235
Adj-R^2	0.022	0.020	0.022	0.026	0.024	0.026	0.014	0.013	0.014
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.8: Peer Alliances and Supplier Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for competition among existing rivals who formed business alliances with the supplier, while controlling for general existing competition and firm-specific variables, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\text{Crash Risk}_{i,t+1} = \alpha_0 + \alpha_1 \text{Connected Peer Threat (CompAl)}_{i,t} + \alpha_2 \text{Connected Peer Threat}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}$$

The three measures of connected peer threats among rivals with business alliances include Peer Count (CompAl), Peer Sales (CompAl), and Peer Similarity (CompAl). The three measures of general connected peer thrats include Peer Count, Peer Sales, Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R-squared (R^2) are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count (CompAl)$_t$	-0.120**			-0.077**			-0.112***		
	(-2.46)			(-2.57)			(-2.91)		
Peer Count$_t$	0.033***			0.016***			0.024***		
	(5.20)			(4.06)			(4.98)		
Peer Sales (CompAl)$_t$		-0.031			-0.041			-0.034	
		(-0.49)			(-0.99)			(-0.59)	
Peer Sales$_t$		0.416***			0.239**			0.238**	
		(2.59)			(2.36)			(2.00)	
Peer Similarity (CompAl)$_t$			-1.653***			-1.079***			-1.461***
			(-2.58)			(-2.69)			(-2.97)
Peer Similarity$_t$			1.290***			0.738***			0.683***
			(5.31)			(4.85)			(3.68)
NObs	22,904	21,554	22,904	22,904	21,554	22,904	22,915	21,565	22,915
Adj-R^2	0.018	0.017	0.018	0.021	0.020	0.021	0.012	0.011	0.012
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.9: Customer Alliances and Supplier Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for existing competition formed based on common customers who formed business alliances with the supplier, while controlling for general connected peer threats and firm-specific variables, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned}\text{Crash Risk}_{i,t+1} &= \alpha_0 + \alpha_1 \text{Connected Peer Threat (CusAl)}_{i,t} + \alpha_2 \text{Connected Peer Threat}_{i,t} \\ &+ \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t}\end{aligned}$$

The three measures of connected peer threats from common customers who formed alliances include Peer Count (CusAl), Peer Sales (CusAl), and Peer Similarity (CusAl). The three measures of general connected peer thrats include Peer Count, Peer Sales, Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R-squared (R^2) are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Count(CusAl)$_t$	-0.018**			-0.012**			-0.013**		
	(-2.51)			(-2.50)			(-2.32)		
Peer Count$_t$	0.038***			0.020***			0.025***		
	(6.13)			(5.06)			(5.28)		
Peer Sales(CusAl)$_t$		-0.060**			-0.054***			-0.023	
		(-2.35)			(-3.11)			(-1.02)	
Peer Sales$_t$		0.454***			0.275***			0.211**	
		(3.14)			(3.06)			(1.98)	
Peer Similarity(CusAl)$_t$			-0.471*			-0.353**			-0.312*
			(-1.95)			(-2.30)			(-1.67)
Peer Similarity$_t$			1.370***			0.786***			0.708***
			(6.05)			(5.56)			(3.99)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.10: Customer Trade Credit and Supplier Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for existing competition, customer trade credit (*AccRec*), and the interaction between the two variables, while controlling for firm-specific variables ($X_{ki,t}$), including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE), as follows.

$$\begin{aligned}\text{Crash Risk}_{i,t+1} &= \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} \times \text{AccRec}_{i,t} + \alpha_2 \text{Connected Peer Threat}_{i,t} \\ &\quad + \alpha_3 \text{AccRec}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t},\end{aligned}$$

AccRec_t is defined as ln(1+ RecTr), where RecTr is the accounts receivable at year t. The three measures of connected peer threats include Peer Count, Peer Sales, Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R-squared (R^2) are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Peer\ Count_t \times AccRec_t$	-0.006**			-0.003			-0.004*		
	(-2.34)			(-1.58)			(-1.91)		
$Peer\ Count_t$	0.048***			0.024***			0.031***		
	(4.20)			(3.12)			(3.56)		
$Peer\ Sales_t \times AccRec_t$		-0.170**			-0.090**			-0.094*	
		(-2.55)			(-2.10)			(-1.91)	
$Peer\ Sales_t$		1.103***			0.604***			0.604**	
		(3.38)			(2.91)			(2.51)	
$Peer\ Similarity_t \times AccRec_t$			-0.248***			-0.109*			-0.175**
			(-2.75)			(-1.88)			(-2.57)
$Peer\ Similarity_t$			1.983***			1.003***			1.154***
			(4.50)			(3.60)			(3.53)
$AccRec_t$	-0.013***	-0.018***	-0.012**	-0.007**	-0.010***	-0.006**	-0.008**	-0.012***	-0.008**
	(-2.71)	(-4.03)	(-2.52)	(-2.14)	(-3.24)	(-2.00)	(-2.17)	(-3.47)	(-2.09)
NObs	26,379	24,936	26,379	26,379	24,936	26,379	26,392	24,949	26,392
Adj-R^2	0.023	0.022	0.023	0.026	0.025	0.026	0.015	0.015	0.015
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.11: Investor Informedness and Supplier Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for existing competition, investor informedness, and the interaction between the two variables, while controlling for firm-specific variables, including size, market-to-book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE).

$$\begin{aligned}\text{Crash Risk}_{i,t+1} &= \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} \times \text{Investor Informedness}_{i,t} + \alpha_2 \text{Connected Peer Threat}_{i,t} \\ &\quad + \alpha_3 \text{Investor Informedness}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE} + \epsilon_{i,t},\end{aligned}$$

The three measures of connected peer threats include Peer Count, Peer Sales, Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. The proxies for investor informedness include # Inst, which captures the log number of institutional investors; High Dispersion, taking a value of one if the dispersion of analyst forecast is above 75% percentile of firms in the same industry-year and zero otherwise; the media coverage, which measures the log number of news articules covering the supplier in year t. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R-squared (R^2) are reported. The construction of the variables is presented in Appendix Table A.2.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Breadth of Institutional Ownership									
Peer Count$_t$ × # Inst$_t$	-0.014***			-0.006**			-0.009***		
	(-3.42)			(-2.34)			(-3.07)		
Peer Count$_t$	0.080***			0.037***			0.053***		
	(4.41)			(3.08)			(3.78)		
Peer Sales$_t$ × # Inst$_t$		-0.403***			-0.222**			-0.211**	
		(-3.00)			(-2.51)			(-2.15)	
Peer Sales$_t$		2.203***			1.230***			1.103**	
		(3.36)			(2.83)			(2.32)	
Peer Similarity$_t$ × # Inst$_t$			-0.521***			-0.221**			-0.409***
			(-3.30)			(-2.14)			(-3.32)
Peer Similarity$_t$			3.175***			1.456***			2.145***
			(4.35)			(3.05)			(3.76)
# Inst$_t$	0.051***	0.049***	0.050***	0.026***	0.026***	0.025***	0.038***	0.037***	0.040***
	(7.65)	(7.84)	(7.75)	(6.16)	(6.61)	(6.19)	(7.51)	(7.82)	(8.04)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-R^2	0.027	0.026	0.027	0.028	0.027	0.028	0.019	0.019	0.019
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.11: Investor Informedness and Supplier Stock Price Crash Risk – Continued

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Dispersion in Analyst Forecasts									
Peer Count$_t$ × High Dispersion$_t$	0.025**			0.015**			0.016		
	(2.25)			(2.35)			(1.49)		
Peer Count$_t$	0.007			0.001			-0.001		
	(0.60)			(0.19)			(-0.05)		
Peer Sales$_t$ × High Dispersion$_t$		0.861**			0.463*			0.509**	
		(2.65)			(2.03)			(2.12)	
Peer Sales$_t$		-0.030			-0.059			-0.101	
		(-0.11)			(-0.34)			(-0.45)	
Peer Similarity$_t$ × High Dispersion$_t$			0.591*			0.358*			0.145
			(1.81)			(2.07)			(0.42)
Peer Similarity$_t$			0.496			0.195			0.184
			(1.58)			(1.17)			(0.65)
High Dispersion$_t$	-0.050*	-0.037	-0.039*	-0.020	-0.010	-0.014	-0.031	-0.020	-0.019
	(-1.87)	(-1.69)	(-1.76)	(-1.09)	(-0.64)	(-0.96)	(-1.53)	(-1.23)	(-1.05)
NObs	10,685	10,106	10,685	10,685	10,106	10,685	10,687	10,108	10,687
Adj-R^2	0.017	0.015	0.017	0.020	0.020	0.020	0.011	0.010	0.011
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Media Coverage									
Peer Count$_t$ × Media Coverage$_t$	-0.006**			-0.003			-0.006**		
	(-2.08)			(-1.33)			(-2.50)		
Peer Count$_t$	0.048***			0.023***			0.036***		
	(4.93)			(3.58)			(4.69)		
Peer Sales$_t$ × Media Coverage$_t$		-0.187**			-0.079			-0.107*	
		(-2.28)			(-1.56)			(-1.74)	
Peer Sales$_t$		0.973***			0.479***			0.514**	
		(3.36)			(2.69)			(2.41)	
Peer Similarity$_t$ × Media Coverage$_t$			-0.214**			-0.065			-0.252***
			(-2.17)			(-1.02)			(-3.21)
Peer Similarity$_t$			1.782***			0.821***			1.292***
			(5.17)			(3.70)			(4.69)
Media Coverage$_t$	-0.004	-0.002	-0.003	-0.005	-0.003	-0.005	0.002	0.003	0.003
	(-0.57)	(-0.28)	(-0.49)	(-1.18)	(-0.76)	(-1.23)	(0.33)	(0.53)	(0.60)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3. Do Environmental Regulations Do More Harm Than Good? Evidence from Competition and Innovation

"Today, 63% of U.S. adults say stricter environmental regulations are "worth the cost," while 30% say such regulations "cost too many jobs and hurt the economy.""

The February 2019 Survey by Pew Research Center[26]

3.1 Introduction

Do environmental regulations do more harm or good? The above quote from the 2019 survey conducted by Pew Research Center shows that a majority of Americans say stricter environmental laws and regulations are "worth the cost." While the survey suggests that most Americans consider environmental regulations to do more good than harm, the question remains one of the most controversial political issues that society faces today as combating climate change becomes a growing global concern. U.S. leaders and policy makers have different views on the economic impact of environmental regulations. Some fear that environmental policies would threaten the competitiveness of business sectors and hamper economic growth.[27] They argue that regulations place firms at a competitive disadvantage as pollution reduction and cleanup costs lead to higher prices and reduced market share (e.g., McGuire 1982). Others, however, argue that regulatory pressures could enhance firm performance by encouraging innovation, thereby increasing economic prosperity (e.g., Porter 1991; Porter and van der Linde 1995). Yet there is limited research that looks at the underlying forces driving firms' varying responses to environmental regulations. Thus, the goal of this paper is to examine whether and how competition plays a crucial role in shaping corporate environmental policies when firms face stringent regulations and whether such policies bear significant economic consequences.

The conventional wisdom is that environmental regulations pose adverse consequences to

[26] https://www.pewresearch.org/fact-tank/2019/02/07/more-republicans-say-stricter-environmental-regulations-are-worth-the-cost/

[27] Following Bristow (2005), competitiveness is loosely defined as the ability of a firm to survive, compete, and grow in its market.

many U.S. companies. The severity of such effects may vary with firms' product market competition. Firms that enjoy market power should experience a minimal negative economic impact on their product markets' competitive position as increased regulatory costs are passed through to product prices with little concerns for losing market share. Also, the opportunity cost for productive investments crowd out by abatement should be small as firms facing less competition have fewer incentives to invest in innovation due to the "replacement effect" (Tirole 1988).[28] However, the negative consequences can be exceptionally costly for firms in fiercely competitive product markets. Economic theory posits that these firms are incentivized to develop innovation as a differentiation strategy to gain competitive advantages over their rivals (e.g., Aghion et al. 2005). Such benefits arising from innovative activity would result in better product-market performance and, in turn, a lower regulatory burden. Hence, product market competition ought to strengthen environmental regulations in promoting new pollution-reducing technologies (hereafter "green innovation").

We exploit the "nonattainment" status of U.S. counties as an exogenous source of variation in environmental regulation to examine whether competition affects firms' strategic responses to increased regulatory pressures. The Environmental Protection Agency (EPA) establishes National Ambient Air Quality Standards (NAAQS) for six widespread pollutants to act as a benchmark in assessing regional air quality. Counties whose pollutant concentrations are above (below) the specified threshold are designated as nonattainment (attainment) areas. Nonattainment counties are subject to much stricter regulatory monitoring and enforcement than attainment counties. Furthermore, we leverage the granularity of the recently available plant location data from Dun & Bradstreet and innovation output data from PATSTAT to construct a sample of innovative firms residing in 2,951 different counties during the 1996-2017 period.

Using county-level nonattainment designations as a quasi-natural experiment in a triple-difference setting, we study whether competition drives firms' green innovations when facing tight environmental regulation. Green innovations are identified as environmentally-sound tech-

[28] A monopolist gains less from innovating than a competitive firm as the former is *replacing* itself as a monopolist.

nologies (ESTs) by the United Nations Framework Convention on Climate Change (UNFCCC).[29] Based on 523,791 firm-county-year observations and two different widely-employed firm-specific competition measures,[30] we find that competitive firms generate significantly more green innovation in response to an exogenous increase in environmental regulatory stringency than less competitive firms. For example, firms in the top competition-ranked decile experience an approximately 8% increase in green innovation output relative to firms in the bottom decile following a nonattainment shock to one of their production locations. This evidence is robust to both two- and three-year-ahead innovative activity, more rigorous controls for county characteristics through county×year fixed effects, alternative classifications of pollution emitters, and the removal of firm-specific control variables.

One possible concern would be the endogeneity of nonattainment designations and regulatory stringency. Plausibly, a nonattainment status is not randomly assigned but hinges on county-specific characteristics such as the intensity of local business activity. Similarly, regulatory stringency could be endogenously driven by unobserved county-wide determinants, including the lobbying power of residing firms and strategic considerations of local governments, among others. However, the rigorous county×year fixed effects should largely alleviate such issues by controlling for all systematic differences across counties that may confound the causality of a nonattainment-induced regulatory shock. Nevertheless, to address any remaining concerns, we repeat the baseline analysis while restricting the sample to include only county-years whose pollutant concentrations are marginally above or below the NAAQS standards. In doing so, we reasonably ensure that any status change in a county arises from small variations in local emissions rather than heterogeneity in regional attributes. Alternatively, our results could also be spurious if the competition is endogenous. To mitigate such concern, we exploit large import tariff reductions to provide exogenous variations in a competitive environment. Import tariffs act as a barrier to entry for foreign rivals, so large cuts could lead to sharp shifts in competitive pressure that U.S. firms face from abroad. The findings from both quasi-natural experiments

[29] The list of ESTs is obtained from WIPO's website, https://www.wipo.int/classifications/ipc/en/green_inventory/.

[30] The competition measures are developed by Hoberg and Phillips (2010; 2016) and Hoberg, Phillips, and Prabhala (2014), namely, product market fluidity measure (Fluidity), and total product similarity score (Similiarity).

suggest that our baseline results are robust to potential endogeneity issues and that they capture a causal effect of competition on firms' strategic responses to regulatory changes.

Our analysis further shows that the relocation cost is a crucial mechanism that compels firms to innovate when responding to tightened environmental policies and heightened competitive pressure. In particular, we contend that competitive firms facing higher relocation costs would be more determined to foster green innovation in reacting to regulations than those facing lower costs. The reasons are twofold. First, firms facing high costs cannot readily shift their local production and must remain in areas undergoing nonattainment classifications and face the associated adverse consequences. These firms tend to bear a higher regulatory burden than companies with more mobility but choose to stay following policy shocks. In combating such negative regulatory impacts, locally entrenched competitive firms would have stronger incentives to innovate relative to those that can easily relocate. Second, the relocation cost would induce innovation as an alternative means to minimize compliance costs. Hence, regulations are more effective in triggering innovative activity among less mobile firms. Using plant fixed costs and the extent of agglomeration economies to measure relocation costs, we find evidence supporting the mechanism. Specifically, the baseline relationship is significantly more pronounced for industries that are less geographically mobile.

Next, we explore the possible sources of gain in competitive strengths arising from green innovation. In particular, competitive firms' innovative response to environmental regulations may lead to increased product differentiation and better customer attraction than other firms in less competitive markets. Consistent with this idea, we show that firms at the top competition-ranked decile achieve a 6% reduction in product similarity and a 5% increase in the number of corporate customers relative to firms in the bottom competition-ranked decile after a regulatory shock. Further analyses show that business expansion is concentrated in corporate customers that are unable to generate green innovation themselves, suggesting that newly developed emissions-cutting technologies can help competitive firms in accessing markets with strong demand for green inventions and products.

Finally, we evaluate the economic consequences of the heterogeneous firm responses to environmental regulations. Our results suggest that competitive firms achieve better post-regulatory-shock operating performance than their less competitive counterparts. Specifically, a higher level of competition is associated with significant increases in the treatment effects of a nonattainment shock on market share growth, pricing power, and profitability. We interpret the better product-market performance as an outcome of competitive firms' stronger incentives to innovate and differentiate, thereby reducing and, at times, even outweighing the compliance cost. Their performance in the financial market further substantiates this interpretation. We find that the market reacts more favorably to firms facing intense competition as measured by their buy-and-hold abnormal returns for the one year following a nonattainment shock. Also, in line with better performance, competitive firms are less likely to cut jobs in the regulated regions, challenging the conventional view that environmental regulations decrease labor demand.

This study makes an important contribution to the real impact of environmental regulations on firm competitiveness. One strand of the literature studies the effects of environmental regulations on green innovation. For example, Lanjouw and Mody (1996), Jaffe and Palmer (1997), and Brunnermeier and Cohen (2003) find that stricter regulations lead to higher R&D expenditures and more environmental patents. Gray and Shadbegian (1998), Popp and Newell (2012), and Aghion et al.(2016) show that increased green inventions crowd out other productivity-improving innovation and hence can be detrimental to firm competitiveness. In contrast, Calel and Dechezleprêtre (2016) find no evidence of firms diverting investments from productivity to abatement. Lanoie et al. (2011) also suggest a positive link between environmental innovation and business performance. Our paper advances this research by showing that competition plays a vital role in the interplay between regulatory stringency and innovative activity. Our study is the first to look at competition as a critical underlying mechanism that shapes corporate environmental policies in firms' response to stringent environmental regulations. Furthermore, our comprehensive approach to examining the innovation policies and a series of economic consequences allows us to better draw conclusions on the overall impact of environmental regulations and firm responses on competitiveness.

Our work also helps to address the criticism that value-enhancing innovation triggered by environmental regulations would be inconsistent with firm value-maximization (e.g., Palmer, Oates, and Portney 1995). Thus far, prior research takes a theoretical approach to show that this is not the case. For example, Ambec and Barla (2007) and Ambec et al. (2013) argue that asymmetric information about environmental quality creates a "market for lemons" where only dirty products would be supplied, and green investments would be curbed. Environmental regulations can reduce such information asymmetry and encourage green innovation by revealing information that benefits those who supply clean products. Other theoretical work such as Simpson and Bradford (1996) and Mohr (2002) similarly provide certain conditions under which post-regulatory value-enhancing innovation is consistent with value-maximizing goals. However, little is known whether these theoretical predictions hold in the data. Our study provides new empirical evidence that, under a competitive environment, regulations foster value-enhancing innovation for profit-maximizing firms. A recent study by Bartram, Hou, and Kim (2019) is related to our work. The authors empirically show that financial constraints play an important role in plant closure decisions when firms face environmental regulations. However, their study focuses on abatement performance rather than the competitiveness of affected firms.

Our paper also contributes to the corporate social responsibility (CSR) literature. Prior studies suggest that firms can "do well by doing good" as they benefit from high product quality signaling (e.g., Fisman, Heal, and Nair 2006; Siegel and Vitaliano 2007), increased customer willingness to pay (e.g., Bagnoli and Watts, 2003; Baron 2008, 2009), improved employee morale and retention (e.g., Turban and Greening 1997), and positive CSR spillovers to suppliers (e.g., Dai, Liang, and Ng 2020) among others. Fernandez-Kranz and Santalo (2010) and Flammer (2015) also document that firms under intense competition tend to strategically engage in CSR practices searching for competitive advantages. Our study expands this line of research by showing that competitive firms foster green innovation to better differentiate themselves from their rivals.

Finally, our results have important policy implications. They suggest that policy efforts to protect environments could benefit firms in competitive markets. Stringent environmental policy improves the environment and competitiveness by pushing competitive firms into developing cost-reducing clean technologies and more efficient ways to produce green products. Therefore, environmental regulations promote growth through green innovation that is more environmentally friendly.

The remainder of the paper is organized as follows. Section 3.2 details the nonattainment designation. Section 3.3 describes the data and construction of the main sample. Section 3.4 formulates the empirical methodology used to conduct the main analyses and reports the results. Section 3.5 investigates a potential mechanism behind the relationship. Section 3.6 explores possible gains in firms' strategic positions, and Section 3.7 analyzes the resulting corporate environmental policies' economic consequences. The final section concludes.

3.2 Identification Strategy - Nonattainment Designations

Following the 1977 amendments to the Clean Air Act (CAA), EPA mandates every county in the United States to be classified as either an attainment or a nonattainment zone using the NAAQS standards as a benchmark. The NAAQS is established by EPA for six widespread pollutants (carbon monoxide, sulfur dioxide, lead, nitrogen dioxide, total suspended particulates, and ozone), specifying the maximum level of concentrations allowed without harming public health and the environment. EPA reviews, and if necessary, revises the NAAQS every five years to ensure adequate protection of air quality. Once a new set of standards is enforced, it triggers a classification process in which counties whose pollutant concentrations above (below) the most recent thresholds are designated as nonattainment (attainment) areas. The nonattainment areas are required to provide State Implementation Plans (SIPs) detailing the implementation, maintenance, and enforcement of local air quality management programs to better comply with the standards. When these counties attain the regulatory standards, they get reclassified as attainment zones. They remain at this status until the next NAAQS revision and classification process. While SIPs vary state-by-state, they generally follow EPA's guidelines in curbing emissions. Beyond the necessary emissions control, inspections and regulatory oversight are also more frequent in nonattainment areas. Thus, the existing polluting plants in nonattainment counties face significantly more stringent environmental regulations than similar polluters in attainment counties.

Such regulatory variations across attainment and nonattainment counties provide an appropriate setting for our study's identification strategy. First, it is reasonable to assume that regulations in nonattainment counties are significantly more stringent than those in attainment counties and effectively enforced on polluting plants. All SIPs must be approved by EPA to ensure a sufficient level of regulatory stringency for nonattainment areas. Failure to provide a satisfactory plan would result in the enforcement of the Federal Implementation Plan (FIP) developed by EPA. Upon approval, those control measures would be enforceable in state and federal courts, giving both the states and EPA legal standings to monitor progress and fine noncompliers. Furthermore, EPA can penalize states that do not sufficiently enforce the regulations, such as withholding federal grants and suspending new facility constructions (e.g., Dancy 1994; Becker and Henderson 2000; Greenstone 2002). These abatement programs in nonattainment areas are effective, as evident in the decline of emissions and the increase in plant operating costs relative to attainment areas (Becker and Henderson 2001; Chay and Greenstone 2005).

Second, nonattainment designations are as good as randomly assigned across counties. All counties are evaluated on the same NAAQS standards, so a nonattainment status should be exogenous to all county-specific characteristics other than local air quality conditions. While one might argue that economic activities affect air quality, such concern is less critical given a low correlation between the nonattainment status and the number of local production facilities. Existing studies also alleviate such concern by showing that nonattainment is often related to wind patterns, causing air pollutants to travel and accumulate in certain regions (Cleveland et al. 1976; Cleveland and Graedel 1979). Furthermore, only exogenous revisions of NAAQS rather than any substantial changes in county-level conditions can trigger a change from attainment to nonattainment designation. This regulatory design is consistently depicted in Figure 3.1.[31] Each panel of the figure illustrates the number of counties experiencing status change for one pollutant. A positive (negative) value indicates a net switch from attainment (nonattainment) to nonattainment (attainment) status. According to Figure 1, a net switch always reaches a local peak in few years following a standard revision but tends to stay non-positive for the remaining period, suggesting that only NAAQS revisions would drive nonattainment classifications. Nevertheless, we address any remaining concerns by restricting the sample to county-years, where the regional pollutant concentration is marginally above or below the standards. Our approach reasonably ensures that a status change is as good as randomly assigned while holding other county-specific conditions constant.

Lastly, the induced regulations are free from county-wide influences. EPA's approval of SIPs limits the variance in regulatory stringency across counties, and its enforcement power curbs the states' ability to overlook non-compliers. Thus, county-wide influences, such as local firms' collective lobbying power, the county's political environment, and other local government considerations, would have little effects on regional regulations. We also eliminate any remaining endogeneity concern by including county×year fixed effects, which remove all unobserved time-varying county characteristics.

3.3 Data and Sample Construction

This study employs data from several different sources: (i) plant and location data from Dun & Bradstreet made available via Mergent; (ii) innovation output data from World Patent Statistical Database (PASTAT) maintained by European Patent Office (EPO); (iii) product market competition measures developed in Hoberg et al. (2014) and Hoberg and Phillips (2010; 2016), which are made available via Hoberg and Phillips data library; (iv) historical CAA nonattainment designations information from EPA Green Book; (v) criteria pollutant emissions data from EPA's Enforcement and Compliance History Online (ECHO); (vi) supplier-customer relation-

[31] Historical NAAQS are obtained from the EPA website: https://www.epa.gov/criteria-air-pollutants/naaqs-table.

ship data from Factset Revere and Compustat's customer segment files; (vii) stock returns from CRSP; and (viii) firm financial information from Compustat.

We match the information on plants with a minimum of ten employees with publicly traded parent companies in Compustat using a linking table between plant DUNS numbers and CUSIP identifiers provided by Mergent. The matched data is used to form an initial sample of firm-county-level observations describing the number of plants a public firm has in a county each year. We restrict the sample to innovative firms with at least one patent filed (and granted) two years ahead to construct green innovation. Since nonattainment-induced regulatory shocks are only effective towards local "polluters", our sample further excludes non-emitting plants. Data limitations in ECHO render classifications of "polluters" and "nonpolluters" at the firm-level improbable. Plant-level emissions information on the six criteria pollutants is only available for years 2005, 2008, 2011, and 2014, and less than 10% of such data can be matched to a plant DUNS number.[32] To circumvent such data challenge, we define "polluters" at the industry-level, specifically, as those 3-digit SIC industries with positive total emissions over the four years during which ECHO data is available. Finally, we remove any observations with missing values for control variables and exclude financial and regulated utility firms (SIC codes 4900-4999 and 6000-6900). The selection process yields a sample of 523,791 firm-county-year observations, consisting of 1,932 unique innovative firms residing in 2,951 counties over the 1996-2017 period. Our sample period is bounded by the availability of Hoberg and Phillips' competition data. The actual number of observations varies across analyses, given different data availability for the main variables of interest. The definitions for all the key variables are depicted in Appendix A.5.

3.3.1 Measures of green innovation

We construct measures of green innovation using data drawn from PATSTAT. The database contains more than 100 million patent records from over 40 patent authorities worldwide filed as

[32]Using a linking table between ECHO's unique identifier FRS and DUNS number made available on EPA's website https://echo.epa.gov/tools/data-downloads, about 25,000 of over 260,000 plant-county-year observations are matched to Dun & Bradstreet.

far back as 1844. It provides detailed information on each of the patent applications, including the date of the application, the applicant's (owner's) name, citations made (backward) and received (forward) by each patent, the patent's technology field identified using International Patent Classification (IPC), and the grant status. We manually match the applicant information with firms in Compustat to obtain patents owned by U.S. corporations. Since most of a patent's value is achieved when the patent is granted and the owner can enforce its exclusive right, we focus on patent applications that are eventually granted.

From our sample of patent applications, we extract those relating to clean technologies. Our selection relies heavily on the work by the World Intellectual Property Organization (WIPO). The WIPO constructs a comprehensive list of IPCs considered environmentally-sound technologies (ESTs) from the information on essential green technologies provided by the United Nations Framework Convention on Climate Change. The list, also known as the IPC Green Inventory, contains 200 topics on alternative energy production, energy conservation, transportation, waste management, agriculture and forestry, and nuclear power generation.

Focusing on these ESTs, we construct four measures to capture green innovation output. The first measure is the total number of EST patent applications a firm files in a given year (Green Patents), following earlier studies (e.g., Brunnermeier and Cohen 2003; Aghion et al. 2016). It suffers from a truncation problem due to the lag between a patent's application year and its grant year. Many patent applications filed in the last few years of the sample period were still under review and hence are not included in our sample. In fact, we observe a gradual decline in the number of patents since 2015, which coincides with about two years of application-grant lag on average. Following Hall et al. (2001; 2005), we correct for this truncation bias using weight factors estimated from the application-grant lag distribution of the patents filed and granted between 2010 and 2015.

The second measure is the total number of forward citations a firm's EST patents receive in subsequent years (Green Cites). Green Cites is a better metric to assess the quality of green patents by distinguishing breakthrough green innovation from incremental discoveries.[33] This citation measure also suffers from a truncation problem, whereby patents continue to be cited after the end of our sample period, but we only observe citations received up to 2017. To address this issue, we scale the citation measure by the technology-field-average citation counts (measured at the 3-digit IPC level) each year, following Hall et al. (2001; 2005).

Besides the firm-specific measures of green innovation, we take similar approaches to construct two more firm-county-specific proxies. Specifically, a slight variation of Green Patents is the number of a firm's EST patent applications cited by its local corporate customers with at least one plant residing in the same county (Green Patents^{Local}). Such a localized measure serves two purposes: (1) to gauge the impact of a regulatory shock on local innovative activity; and (2) to capture a firm's innovative efforts in maintaining or accessing the local product market. Similarly, Green Cites^{Local} is defined as the number of citations on a firm's green patents received from local customers. All measures are adjusted for truncation biases.

We use the natural logarithm of the above four measures in our analysis. To avoid losing observations with zero green patents and citations, we add one to the actual values when calculating the log form.

3.3.2 Measures of product market competition

This study employs two firm-specific measures of product market competition.[34] First, we use the product market fluidity measure (Fluidity) introduced in Hoberg et al. (2014). The authors analyze product descriptions in 10-K filings and construct Fluidity to capture the extent to which rivals with similar product vocabulary as a firm are changing their product keywords in the next year. It captures competitive threats from two dimensions: (1) the overlap of keywords between the firm and its rivals; and (2) the dynamic changes of rivals' products. Thus, fluidity reflects

[33] In a previous version of the working paper, we construct another green innovation measure that considers all patents filed by a firm and count the number of forward citations they receive from other firms' green patents (Cites By Green). Such a measure accounts for inventions that may not necessarily classify as ESTs but are crucial components on which other green technologies are built. Analyses using Cites By Green yield similar findings as other proxies. Results can be provided upon request.

[34] We additionally employ Herfindahl-Hirschman Index as another measure of competition in a previous version of the paper. The analysis results are qualitatively similar as those from using the firm-level competition measures.

both the degree of product similarity with competitors and the product market's instabilities arising from competitor actions. A higher value is associated with a more significant competitive threat for a firm.

The second measure is the total product similarity score (Similarity) constructed by Hoberg and Phillips (2010, 2016). It also relies on the information drawn from 10-K filings. Using product keywords, the authors compute firm-by-firm pairwise cosine similarities to group firms into industries, known as text-based network industries (TNIC). The similarity score is then obtained by taking the sum of cosine similarities across all firm rivals in the same TNIC industry. It increases with both the number of competitors and product relatedness of each competitor, thereby reflecting the level of competitive pressure that a firm faces.

3.3.3 Summary statistics

Table 3.1 reports county-level characteristics by state. Columns (1) and (2) document the average number of firms and plants per county in each state. Massachusetts has the highest number of innovative firms and plants per county on average (46 and 109, respectively), whereas South Dakota has the lowest (2 and 3, respectively). This observation comes as no surprise given that Massachusetts is ranked as one of the most innovative states and South Dakota the least.[35] Column (3) shows the number of counties in each state that was nonattained at least once during the sample period. Column (5) reports the number in Column (3) as a percentage of the total number of counties in the sample. Hawaii, North Dakota, Oklahoma, South Dakota, and Vermont have the lowest percentage of nonattainment counties (0%) in the sample, an indication of their healthy air quality conditions according to the NAAQS. On the other hand, all the counties in Connecticut, Delaware, New Jersey, Massachusetts, and Rhode Island were once nonattained. Prior research attributes the low air quality in Connecticut, Delaware, and New Jersey to the pollution transported from upwind states (e.g., Cleveland et al. 1976, 1979).[36] The last column documents the average period of nonattainment status in each state. Mississippi,

[35] An example of such ranking would be Bloomberg's annual State Innovation Index.
[36] https://www.law.nyu.edu/centers/state-impact/issues/clean-air/clean-air-act-and-upwind-pollution.

Iowa, Florida, and Minnesota have the shortest average duration of 4 years, while Connecticut, Delaware, New Jersey, Massachusetts, and Rhode Island have the longest of 20 years).

Table 3.2 presents summary statistics of the key variables used in this study. About 46% of the firm-county-years in the sample are in nonattainment counties. Conditioning on having plants in a county, an average firm owns about two plants in an area and employs over 50 workers (ln(1+50)=3.932). On average, a firm has 2.3 (ln(1+2.293)=1.192) granted EST patents per year, which is comparable to previous studies (e.g., Brunnermeier and Cohen 2003), and these patents receive about one technology-field-adjusted citation (ln(1+0.924)=0.654). The Fluidity measure has an average of 0.058 and a median of 0.052, which is consistent with the statistics reported in Hoberg et al. (2014).[37] Similarity takes on an average value of 0.024 and a median value of 0.013.

Drawn from the innovation literature, we control for a set of firm characteristics that may affect innovation output. They include the natural logarithm of total assets (Size), growth opportunities as measured by Tobin's Q (TobinQ), leverage ratio (Leverage), asset tangibility (Tangibility), R&D expenditures (R&D), capital expenditures (CapEx), profitability (ROA); and the natural logarithm of the number of a firm's local employees (Employees). An average firm has a book value of $5.412 billion, a Tobin's Q of 1.995, a leverage ratio of 23.8%, and a ROA of 0.140. In addition, R&D expenditures, capital expenditures, and tangible assets account for 3.4%, 4.6%, and 25.3% of an average firm's total assets, respectively.

3.4 Environmental Regulation, Competition, and Green Innovation

In this section, we examine whether competition influences corporate environmental policies when firms face stricter pollution regulations. Specifically, we investigate the effect of competition on a firm's green innovative output in its response to an exogenous increase in environmental regulatory stringency. We also conduct several tests to ensure robustness of our baseline evidence.

[37] Fluidity and Similarity are scaled by 100 in this study.

3.4.1 Baseline evidence

To examine the role of competition in shaping a firm's innovative response to environmental regulation, we estimate the following triple-difference model using pooled ordinary least squares (OLS) regressions:

$$\begin{aligned}\text{Green Innovation}_{y,t+z} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c \\ & + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} \\ & + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \qquad (3.1)\end{aligned}$$

where Green Innovation$_{y,t+z}$ denotes firm i's or firm-county i,c's green innovation outcomes at years $t+2$ and $t+3$, including Green Patents, Green Cites, Green Patents^{Local}, and Green Cites^{Local}. To reflect the long-term nature of investment in innovation, we consider the innovation output generated two and three years ahead. Comp$_{i,t}$ denotes one of the competition measures Fluidity and Similarity at year $t-1$. Lagged competition measures are used to alleviate reverse causality concerns or omitted variables simultaneously affecting a firm's competitive environment and the regional regulatory stringency. $Treat_c$ is a binary indicator that equals 1 if the county c has ever been classified as a nonattainment county during the sample period and 0 otherwise. $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise. $X_{i,c,t}$ is a vector of control variables defined earlier, measured for firm i in county c at the end of year t. A detailed definition of all variables is provided in Appendix Table A.5. We control for firm, county, and year fixed effects, which subsume the time-invariant $Treat$. Since $Treat$ would always equal to 1 when $Post$ is 1, $Post$ is perfectly correlated to $Post \times Treat$ and $Post\times$ Comp is perfectly correlated to $Post \times Treat \times$ Comp. Thus, $Post$ and $Post\times$ Comp are omitted in regressions. Standard errors are clustered at the firm-year level.

Table 3.3 contains the results of our main tests. Panels A and B of the table show the regression results where the dependent variables are firm-level and firm-county level green innovation at year $t+2$, respectively. The primary coefficient of interest is α_1, the triple interaction term

$Post \times Treat \times$ Comp, which captures the difference in treatment effects of a nonattainment shock across firms with varying degrees of competition. The α_1 estimates are all positive across different green innovation output measures. These estimates are mostly statistically significant at the 1% level, suggesting that competitive firms generate more green innovation in response to a regulatory change than firms with less competitive concerns. For example, Columns (1)-(2) of Panel A indicate that firms in the top competition-ranked decile produce about 2% (e.g., 0.343/1.192×(0.103-0.024)=0.023, where 0.024 and 0.103 are the 10th and 90th percentile values of Fluidity, respectively) more EST patents than firms in the bottom decile following a nonattainment shock to one of their production locations. Such an effect has a significant bearing on a firm's overall green innovative investments since a median firm operates in eight nonattainment counties simultaneously, resulting in an aggregate impact of about 16%. The differential treatment effects on patent quality are also large. Columns (3)-(4) show that top competition-ranked decile firms receive about 4%-5% (e.g., 0.411/0.654×(0.103-0.024)=0.050) more post-shock citations for their EST patents relative to bottom decile firms.

Panel B reveals strong influences of regional environmental regulations on local innovative activity. The triple interaction coefficients for Green Patents^{Local} are positive and statistically significant at the 1% level, suggesting that competitive firms are more likely to adopt green innovation locally under stringent regulations than firms facing less competitive pressure. In terms of economic magnitude, the relative difference in the treatment effects between the top and bottom competition-ranked decile firms ranges from 23% to 42%. The findings on Green Cites^{Local} further substantiate the importance of competition in encouraging post-shock local green innovation. The α_1 estimates are positive and significant in all specifications. Specifically, the point estimates are 0.025 ($t-$stat= 2.81) in Column (3) and 0.027 ($t-$stat= 3.41) in Column (4).

The difference-in-difference coefficient of $Post \times Treat$, α_2, on the other hand, indicates a negative treatment effect on less competitive firms. As shown in Panels A and B, the α_2 estimates are negative and statistically significant across all specifications. Such results, at the minimum, suggest that, without competitive pressure, environmental regulations alone are ineffective in encouraging green innovation, consistent with our *prior*. Interestingly, rules can go as far as to inhibit innovative activity for these firms. One potential explanation for such a negative impact on innovation would be the crowding-out effects of compliance costs. As previously hypothesized, less competitive firms have fewer incentives to innovate and can easily forego innovative investments for abatement expenditure.

We repeat our above tests using firm- and firm-county level green innovation at year $t + 3$ and report these results in Panels C and D. While the findings are broadly consistent with those shown in Panels A and B, the α_1 estimates are slightly weaker, indicating that competitive firms' green innovative output occurs within the first two years following the shock. Taken together, our results provide strong and consistent evidence that product market competition strengthens environmental regulation in promoting green innovation. However, to conserve space, we shall report only results using two-year-ahead innovation in subsequent sections.

Our above findings advance the existing literature on the relationship between environmental policies and green innovation. While existing studies (e.g., Lanjouw and Mody 1996; Jaffe and Palmer 1997; Brunnermeier and Cohen 2003) point to an overall increase in green innovation activity for firms affected by environmental regulations, our results attribute such a boost to mainly competitive firms. Our findings suggest that regulations do more good for competitive firms than for other affected companies to the extent that green innovation may lead to enhanced firm performance and more robust growth.[38]

3.4.2 Robustness tests

We undertake a rich set of robustness tests for our baseline results. First, to control for any omitted county-specific characteristics, we repeat the baseline analysis using firm and county×year fixed effects. Such specification accounts for all systematic differences across counties, including factors that may potentially confound the causal relationship between regulations and firm

[38] We show in later sections that green innovation indeed contributes to the improvement of firm competitiveness.

behaviors. This approach helps to alleviate potential endogeneity concerns one may have over nonattainment designations and local regulatory stringency. Panel A of Table 3.4 presents the estimated results for firm-level green innovation measures. The multiplicative fixed effects subsume all the time-variant county-level variables, including the interaction term $Post \times Treat$, but the coefficient of $Post \times Treat \times$ Comp remains strongly positive. The coefficient estimates are statistically significant across all four sets of regressions, confirming our baseline findings on the asymmetric regulatory effects across firms in different competitive environments. Unreported analyses of firm-county-level green innovation measures yield a similar conclusion. That is, they generate significant results in all specifications.

Second, we test our findings against alternative classifications of polluting industries. One may argue that the current definition is incapable of eliminating all the non-polluters from the sample, and hence the baseline results could be driven by those non-polluters. While plausible, it should underestimate our coefficients since non-polluters are not subject to stricter regulations induced by nonattainment shocks. Nonetheless, to alleviate this concern, we apply more rigid definitions of polluting industries: (1) industries with average emissions of at least 100 tons per firm; (2) industries with above-median industry-total emissions. As shown in Panels B and C of Table 3.4, the results suggest that while the two alternative classifications, respectively, eliminate about 9% and 19% of the main sample, the α_1 estimates remain materially unaffected.

Finally, we address the potential issues arising from bad controls. To the extent that regional environmental regulations have other influences on a firm than its corporate environmental policies, firm-specific controls may themselves be outcomes of nonattainment treatment effects. For example, a firm's growth opportunities, as measured by Tobin's Q, may hinge on regulations and their impacts on corporate investment decisions. Having those endogenous variables as controls would produce biased estimates. To rule out such concerns, we remove the vector of time-variant control variables $X_{i,c,t}$ from the regression models and repeat our baseline analysis. The results, reported in Panel D of Table 4, show more robust estimates of the triple interaction variable in terms of both the magnitude and statistical significance than their baseline regression counterparts.

Overall, our key evidence is robust to a battery of tests and consistently suggests that competitive firms generate significantly more green innovation output following nonattainment shocks than their less competitive peers.

3.4.3 Additional endogeneity tests

As discussed in earlier sections, there should remain little concerns over the endogeneity of nonattainment designations and regulatory stringency. Nevertheless, we conduct an additional robustness check to support the causal interpretation of our baseline findings. Specifically, we re-estimate the baseline regressions using only the subsample of county-years whose pollutant concentrations are marginally above or below the NAAQS. Such an approach reasonably captures county status changes arising from small variations in local emissions rather than the heterogeneity in regional attribute, thereby, in effect, randomly assigns regulatory shocks across counties.

We employ county-level emissions data available in EPA's Air Quality System (AQS) database. For each of the six pollutants, we define a bandwidth around the NAAQS threshold as 10% above and below the threshold values and restrict the sample to county-years falling within the bandwidth.[39] Since NAAQS are revised every few years, so are the bandwidths. For example, between 1997 and 2007, the EPA requires the annual 4th highest daily maximum (4th maximum) 8-hour ozone concentration of fewer than 0.08 parts per million (ppm). The bandwidth of ozone concentration is, therefore, set to 0.072 and 0.088 ppm during the ten years. When the standard drops to 0.075 ppm in 2008, the revised bandwidth becomes 0.068-0.083 ppm. The restricted sample consists of about 150,603 firm-county-year observations. Table 3.5 presents the regression results. The estimates of α_1 are qualitatively similar to what we have found in the baseline analysis, with statistical significance in three of the four regressions on firm-level outcomes. Untabulated firm-county-level regression results reach a similar conclusion.

[39] Applying a narrower bandwidth at 5% around the threshold eliminates about 90% of the main sample and yields similar, albeit weaker, results as those from using 10%.

These findings underscore the causal relationship between environmental regulations and green innovativeness.

Another potential endogeneity concern arises from product market competition. Our results could be spurious if the competition is endogenously determined by regulatory pressure or other unobservable shocks. To allay this concern, we exploit large import tariff reductions in the U.S. to provide exogenous variations in a competitive environment. Prior literature suggests that significant reductions in tariff rates will expose domestic firms to foreign rivals, leading to sharp increases in competition faced by U.S. corporations (e.g., Frésard 2010; Valta 2012). Using import data from Schott (2008), we compute the tariff rate for each industry-year as the collected duties divided by the custom value of imports.[40] Following Huang et al. (2017) and Chen et al. (2020), we identify large tariff reduction events as industry-years that experience tariff rate decreases relative to the previous year by more than four times the median tariff rate reduction during our sample period. To ensure that these tariff rate reductions reflect only non-transitory changes in the competitive environment, we exclude declines preceded or followed by a tariff increase greater than 80 percent of the reduction. Our robust test uses a dummy indicator, $\text{Tariff}_{i,t-1}$, which equals to 1 for the two years after the industry has experienced a large tariff cut and 0 otherwise, in place of $\text{Comp}_{i,t-1}$ in Eq. (3.1).

As reported in Table 3.6, the estimates on $Post \times Treat \times$ Comp are positive and mostly statistically significant at the 5% level. The results confirm our prediction that competitive firms generate more green innovation in response to increased regulatory pressure than their less competitive counterparts. For instance, as shown in Column (1), an analysis of Green Patents yields an α_1 estimate of 0.035, indicating that firms in industries with tariff reductions develop about 3% (0.035/1.192=0.029) more EST patents following a nonattainment shock relative to other firms in industries without tariff reductions. In contrast, the coefficient on $Post \times Treat$ is negative and statistically significant, suggesting a reduction in green innovation for those firms not experiencing tariff reductions. Such a finding is also consistent with our *prior* that

[40] The U.S. import data for the period 1996-2017 is obtained from Peter K. Scott's website: https://faculty.som.yale.edu/peterschott/international-trade-data/.

environmental regulations are ineffective in stimulating green innovation without competitive pressure.

Overall, the various endogeneity tests reported in this section support the causal interpretation of the combined effects of environmental regulation and competitive pressure on corporate environmental policies.

3.5 A Key Mechanism

In this section, we explore whether the cost of relocation is a critical underlying mechanism that compels firms to innovate when responding to tightened environmental policies and heightened competitive pressure. We posit that such a cost would intensify the real impacts of regulatory and competitive pressures for two reasons. First, firms facing higher relocation costs are geographically less mobile. These firms would be forced to remain in the local region following policy shocks and face the associated adverse consequences. In contrast, relocation would be easier for firms with more mobility to avoid significant compliance costs. Consequently, among the companies that remain following regulatory changes, those with less mobility tend to bear the disproportionate regulatory burden than their counterparts with greater mobility and, in turn, react more strongly to policy shocks. Second, higher relocation costs would induce alternative means of minimizing compliance costs, including integrating green innovation into their business strategies. Hence, the more geographically entrenched the firms are, the more likely they will respond through innovative activity.

If the cost of relocation is a crucial mechanism, our baseline relationship ought to be more pronounced for firms with less mobility. In particular, immobility should provide stronger incentives for competitive firms to innovate when facing severe negative consequences of regulations. Conversely, it would have little stimulating effects on less competitive firms given limited regulatory impacts on their competitiveness and a lack of desire for these firms to invest in innovation due to the "replacement effect". If anything, the higher regulatory costs induced by immobility may further divert resources from innovation to abatement through stronger crowding out effects.

To empirically test this mechanism, we conduct subsample analyses based on two alternative definitions of industry mobility. Our first measure of immobility is the industry-total plant fixed costs. Industries that sink a large amount of investments into local plants are less likely to close and relocate their local production, and hence, face a higher relocation cost. Following Ederington, Levinson, and Minier (2005), we use data from the NBER-CES Manufacturing Industry Database developed by Bartelsman, Becker, and Gray (2013) and define industry mobility as real structures capital stock scaled by the total value of shipments.[41] To overcome the coverage limitation of the data, we compute the industry means over the data period in constructing a time-invariant measure of plant fixed costs.

Another measure of immobility is the extent of agglomeration economies of an industry. Existing literature (e.g., Marshall 1920; Ellison and Glaeser 1999; Ellison, Glaeser, and Kerr 2010) demonstrate that firms concentrated in the same geographic area may benefit from economies of agglomeration in the form of reduced costs of transporting goods, people, and ideas. Such gains represent opportunity costs for those firms moving their plants away from the region. Thus, industries that enjoy agglomeration economies also face a high cost of relocation. Taking a similar approach as Ellison et al. (2010), we estimate each industry's geographic concentration. The measure is defined in Eq. (3.2) as shown below.

$$\text{Agglomeration}_{l,t} = \frac{\sum_c^C (s_{l,c,t} - x_{c,t})^2}{1 - \sum_c^C x_{c,t}^2}, \tag{3.2}$$

where $s_{l,c,t}$ is the share of industry l's employment contained in county c during year t; and $x_{c,t}$ is the mean employment share in county c across all industries. The construct measures deviations from randomly distributed employment patterns. It equals to zero when industry employment is randomly distributed across all C counties but increases with geographic clustering of employees in industry l. To identify industries with higher cost of relocation, we divide the sample into terciles every year based on each of the immobility measures. Industries in the top tercile of

[41] The plant fixed cost data is available at the 3-digit SIC industry level for the period 1996-2011 on the NBER website: https://www.nber.org/research/data/nber-ces-manufacturing-industry-database.

the distribution is grouped into the most mobile subsample, while those in the bottom tercile is grouped into the least mobile subsample. We re-estimate the main regressions separately for each subsample and present the results in Table 3.7.

Analyses based on plant fixed costs and agglomeration economies are reported in Panels A and B, respectively. Consistent with our prediction, the significant impact of environmental policies and competition is primarily concentrated in immobile industries. The estimates on the triple-interaction term are positive and mostly significant at the 5% level within the least mobile subsample, as shown in Columns (1)-(2) and (5)-(6) of both panels. An inter-decile increase in competition is associated with about a 2%-5% (e.g., 0.694/1.192$\times$(0.103-0.024)=0.050) increase in post-regulatory green patents and 4-6% (e.g., 0.496/0.654$\times$(0.103-0.024)=0.060) increase in forward citations. These results are in clear contrast to the insignificant α_1 estimates within the most mobile subsample, as shown in Columns (3)-(4) and (7)-(8). The mobile estimates are also generally smaller in magnitude relative to those in the immobile group.

As predicted, the coefficient on $Post \times Treat$ tends to be negative and are marginally significant within the least mobile industry subsample, suggesting a slightly negative regulatory impact on the innovative responses of less competitive and immobile firms (Columns (1)-(2) and (5)-(6)). The regulatory impact on more mobile industries is similarly negative but largely insignificant (Columns (3)-(4) and (7)-(8)). Such findings support the notion that environmental regulations have limited stimulating effects on green innovation for firms with little competitive concerns. It is also consistent with our conjecture that immobility may further reduce post-regulatory innovation output for these firms through crowding-out effects.

Taken together, the results in subsample analyses indicate that environmental regulations can trigger stronger reactions from firms with less mobility. These findings provide strong support to the cost of relocation mechanism.

3.6 Possible Gains in Competitive Firms' Strategic Positions

Thus far, the results demonstrate that competition plays a vital role in firms' strategic responses to environmental regulations. In this section, we explore the possible sources of gains in competitive strengths arising from these responses. More specifically, we examine whether regulation-induced green innovation would help competitive firms better achieve product differentiation and attract more corporate customers than less competitive firms.

3.6.1 Product differentiation

We contend that firms fostering green innovation after regulatory shocks would benefit from better product differentiation. To test this prediction, we construct two alternative proxies of product differentiation. Our first measure is the patent originality score proposed by Trajtenberg, Jaffe, and Henderson (1997). This score gauges the novelty of an invention by examining the breadth of technology domain on which the invention relies, as defined in Eq. (3.3) shown below.

$$\text{Patent Originality}_{j,t} = 1 - \sum_{k}^{n} p_{j,k,t}^{2}, \tag{3.3}$$

where $p_{j,k,t}$ is the percentage of backward citations made by patent j to patent class k (at the 3-digit IPC level) out of n patent classes. Patent Originality$_{j,t}$ takes on a higher value when patent j is built on a large number of diverse technology fields, and vice versa. As suggested by Trajtenberg et al. (1997), innovation advanced from a broad diversity of knowledge sources, as opposed to the same technology domain, should lead to more original output. Hence, a higher originality score indicates a greater degree of product novelty. We average the originality measure across all patents filed by firm i at year $t+2$ to proxy for product differentiation arising from green innovation.

Another measure of novelty is the product similarity score. To the extent that green innovation is an effective differentiating strategy, the product similarity score (Hoberg and Phillips 2010; 2016) between a competitive firm and its rivals should be reduced following a nonattainment shock. To facilitate comparison, we take the negative average value of the scores between firm i and its peers in the same industry at year $t+2$ (Product Dissimilarity). Similar to the Patent Originality score, a greater Product Dissimilarity value signifies more product novelty.

We next evaluate the differential treatment effects of nonattainment shocks across firms with varying degrees of competition by re-estimating Eq. (3.1) with a product differentiation measure in place of Green Innovation, as follows.

$$\begin{aligned}\text{Product Diff}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c \\ & + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} \\ & + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{3.4}$$

where Product Diff$_{i,t+2}$ denotes firm i's product differentiation measure at year $t+2$.

Table 3.8 presents the results. The estimates of the $Post \times Treat \times$ Comp coefficient are consistently positive in Columns (1)-(2) when Patent Originality is the dependent variable and in Columns (3)-(4) when Product Dissimilarity is the outcome variable. These α_1 estimates are mostly statistically significant at the 5% level, indicating that competitive firms achieve more originality or dissimilarity following a nonattainment shock than their less competitive peers. In terms of the economic magnitude, there is a 1.3% relative difference in the treatment effects between the top and bottom *Similarity*-ranked decile firms,[42] which translates to an aggregate impact of about 10% (e.g., 0.013×8 nonattainment counties ≈ 0.10; or 0.017×8 ≈ 0.14). Furthermore, in Column (3), an estimate of 0.029 ($t-$stat=3.64) on the triple-interaction term indicates that firms at the top Fluidity-ranked decile achieve a 7% (0.029/0.032×(0.103-0.024)=0.071), where 0.032 is the mean value of Product Dissimilarity) reduction in product similarity relative to firms in the bottom Fluidity-ranked decile after a regulatory shock. Regressions using Similarity further suggest an approximately 2% (0.013/0.032×(0.048-0.010)=0.015) reduction. In contrast, the coefficient on $Post \times Treat$ is, in general, not significantly different from zero, indicating minimal post-regulatory product differentiation achieved for less competitive firms. This finding is not surprising given a lack of innovative response from these firms.

[42] In Column (2), a relative difference of 1.3% is obtained from 0.102/0.310×(0.048-0.010)=0.013, where 0.310 is the mean value of *Patent Originality*, and 0.010 and 0.048 are the 10th and 90th percentile values of *Similarity*, respectively.

The combined results support our prediction that regulation-induced green innovation allows competitive firms to better differentiate their products than others.

3.6.2 Corporate customer attraction

To the extent that green innovation can generate more business through product differentiation and quality signaling, we expect competitive firms to gain more customers following a nonattainment shock than less competitive firms. We employ two measures to capture such an effect. The first measure is the natural logarithm of each firm's total number of corporate customers at year $t+2$. This metric evaluates the regulatory and competitive impacts on the overall firm-level customer attraction. The other measure is the natural logarithm of the number of corporate customers owning at least one plant in county c during year $t+2$. It is used to gauge the local impact on affected counties.

We re-estimate Eq. (3.4) using either customer count measure as the dependent variable and report the results in Panel A of Table 3.9. The panel provides supportive evidence that firms facing intense competition are better able to attract customers following regulatory shocks compared to less competitive firms. As seen in Columns (1)-(2), the estimated coefficients for the triple-interaction term are positive but statistically significant when Fluidity is employed as a proxy for competition. These findings indicate that firms at the top competition-ranked decile achieve a 1.7% increase in the overall firm-level number of customers relative to firms in the bottom competition-ranked decile following a nonattainment shock, or an aggregate increase of about 14% given a median of eight nonattainment counties per firm-year. Such results are consistent with the notion that new clean technologies can help attract customers interested in green innovation and products. Columns (3)-(4) report the local attraction of customers drawn in by the green innovativeness of firms' local facilities. They show positive and statistically significant coefficients on $Post \times Treat \times$ Comp in the two specifications, indicating a 4%-6% increase in the treatment effects on the number of local customers from bottom to top competition-ranked decile firms. These results are consistent with our previous findings that competitive firms produce more green innovation adopted by local corporate customers following a regulatory shock.

The $Post \times Treat$ coefficient estimates are negative across all four sets of regressions but are only statistically significant in Columns (3)-(4). While less competitive firms tend to experience a loss in local customers who may switch to greener and more innovative products, such a loss has a limited impact on the total customer count at the firm-level. These findings are line with the notion that environmental regulations have little negative influences on the competitive position of those firms facing less intense competition.

We further investigate which corporate customers are more attracted to post-shock competitive firms. In particular, we compare the effects on customers who are unable to generate green innovation themselves (hereafter "non-green customers") with those who are able to (hereafter "green customers"). Non-green customers are defined as those who do not have any EST patent applications in a given year, whereas green customers are those with at least one EST patent application. We then replicate our triple-difference OLS regressions in Panel A using the ratio of non-green customers to green customers as the dependent variable and present the results in Panel B. The dependent variable for Columns (1)-(2) is the ratio of a firm's total number of non-green customers to its total number of green customers at year $t+2$, whereas the dependent variable for Columns (3)-(4) is the ratio of a firm's number of local non-green customers in county c to its number of local green customers.

Panel B shows positive and significant triple interaction coefficients, suggesting that a competitive firm's business increases through its corporate customers that do not generate green technologies themselves. The α_1 estimates range between 0.924 in Column (1) and 1.072 in Column (3) and are significant at the 10% level, indicating that competitive firms can better access these markets that are likely more reliant on external sources of green inventions. In particular, a significant increase in the number of local non-green customers would come as no surprise since they are also subject to the same regulatory shock as their local suppliers. These non-green customers would, in turn, have a strong demand for green innovation and green products to comply with the regulation. The results complement our previous findings and support our prediction that green innovation can help more competitive firms generate more business.

In sum, contrary to conventional wisdom, environmental regulations can do good to firms, particularly to those in highly competitive product markets. Tighter pollution policies incentivize these firms to exploit green innovation as a competitive strategy to boost their business.

3.7 Economic Consequences of Corporate Environmental Policies

In the preceding sections, we have established that firms facing intense competition invest in green innovation in response to stricter environmental regulations and, simultaneously, achieve competitive strengths in their respective product markets. We now turn to investigate the economic consequences of such a strategic decision. This issue is of paramount importance to economists and policy makers interested in the overall impact of environmental regulations on the competitiveness of business sectors and economic growth. To provide insights into this issue, we examine the operating and market performances of affected firms and their employment conditions following regulatory changes.

3.7.1 Product market performance

We posit that gaining competitive advantages through green innovation would allow firms in competitive markets to experience better post-regulatory-shock product market performance than less competitive firms. To test this conjecture, we again conduct analyses using triple-difference regression models, where the dependent variable, Firm Performance$_{i,t+2}$, represents a firm's product market performance at year $t+2$, as follows.

$$\begin{aligned} \text{Firm Performance}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c \\ & + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} \\ & + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \qquad (3.5) \end{aligned}$$

Our study employs three firm-level product market performance measures: market share growth, price markup, and profit margin. Market Share Growth is computed as the difference in sales-based market share between the current and the previous year, expressed in percentage. It captures the product market expansion associated with a firm's ability to attract customers following a regulatory shock. Markup is the ratio of sales to the differences in sales and EBITDA, and Profit Margin is defined as the net income divided by total sales. They measure the extent to which gains in businesses translate to pricing power and profitability. Table 3.10 reports estimates of model (3.5).

A few notable results emerge from the table. Our findings suggest that a higher level of competition is associated with significant increases in the treatment effect of a nonattainment shock on firm performance. Columns (1)-(2) document the impact of a county-level shock on a firm's overall market share growth. The $Post \times Treat\times$ Comp coefficient estimates are positive and statistically significant in all specifications. In Column (1), an increase in competition measured by Fluidity from the bottom to the top decile of its distribution would lead to a 23% increase in the treatment effects of a regulatory shock.[43] In Column (2), an inter-decile increase in Similarity is associated with a 14% relative difference in treatment effects. The coefficient on $Post \times Treat$ reveals, at most, a weak negative impact on less competitive firms at year $t + 2$. The estimates are marginally significant in Column (1) and statistically insignificant in Column (2). Collectively, the results point to an overall increased market share growth for competitive firms due to stricter environmental regulations.

Results on Markup and Profit Margin presented in Columns (3)-(4) and (5)-(6), respectively, suggest that a favorable impact on market expansion can also translate to higher pricing power and profitability. The triple interaction coefficients are positive and statistically significant for both outcome variables and across all specifications, indicating that firms facing tougher competition enjoy a higher post-regulatory-shock markup and profit margin than their less competitive counterparts. In particular, the α_1 estimates for Markup range from 0.068 ($t-$stat= 2.31) in Column (3) to 0.078 ($t-$stat= 1.74) in Column (4), and the estimates for Profit Margin range from 0.100 ($t-$stat= 1.71) in Column (5) to 0.206 ($t-$stat= 1.87) in Column (6). Similar to the results on Market Share Growth, less competitive firms also do not appear to suffer significant negative regulatory impacts on their price markup and profitability. The $Post\times Treat$ coefficient estimates are negative but largely insignificant, except for the regression on Markup shown in Column (3). This specification yields a statistically significant α_2 estimate of -0.003, albeit small. Taken together, the α_1 and α_2 estimates suggest an overall improvement in product

[43] This percentage is computed as follows: 0.190/0.066×(0.103-0.024)=0.227, where 0.066 is the average market share growth value for firms in our sample.

market performance for competitive firms following regulatory shocks.

These results complement our earlier findings on the innovative activity induced by environmental regulations and directly associate enhanced firm performance with clean technology development. Such an observation makes a critical addition to the literature as very few existing studies are able to show that green innovation leads to better firm performance. Most of these studies are limited to analyzing green technology patenting without drawing any inferences on the profitability and growth of regulated firms (e.g., Brunnermeier and Cohen 2003; Calel and Dechezleprêtre 2016). Some even suggest the possibility that despite new green inventions, there are high opportunity costs to diverting resources away from other productive investments, potentially hampering firm performance (Gray and Shadbegian 1998; Popp and Newell 2012; Aghion et al. 2016). Our analyses on a series of economic consequences allow us to better draw a conclusion on the overall impact of environmental regulation on firm competitiveness.

A prior study by Lanoie et al. (2011) is related to our work, except it employs postal survey data. The authors show that regulation-induced green innovation has positive effects on business performance but find no evidence that the cost-saving innovation can more than compensate for compliance costs. Our findings, instead, yield a stronger conclusion: the resulting positive operating outcomes suggest that the benefits arising from innovative responses to environmental regulations can outweigh the associated regulatory burden. These results are broadly consistent with prior studies that have found positive regulatory effects on firm productivity in the long-run (e.g., Berman and Bui 2001; Lanoie et al. 2008), supporting the notion that environmental policies can do more good than harm to firms. However, in contrast to prior research, our study finds that such positive effects from regulations are concentrated among competitive firms.

3.7.2 Market performance

In the preceding subsection, our analyses have shown that competitive firms enjoy better product market performance arising from their green innovative activity than firms in less competitive environments. We now test whether the financial market would react more favorably to these competitive firms and their associated benefits that reduce the regulatory burden.

One challenge we face in analyzing firms' market performance is identifying the actual announcement dates of nonattainment shocks. To circumvent this issue, we rely on long-run abnormal returns to observe market reactions to regulatory shocks instead of attempting short-term stock performance measures in narrow event windows around county status changes. Following He and Huang (2016), we calculate the one-year-ahead buy-and-hold abnormal returns (BHAR) using both the Fama-French three-factor and Fama-French-Carhart four-factor models over the one year following a nonattainment shock.[44] To assess the heterogeneous market reactions to county-level shocks, we estimate the following triple-interaction model using pooled OLS regressions:

$$\begin{aligned}\text{BHAR}_{i,t+2} \quad = \quad & \alpha_1 \text{Event}_{c,t} \times \text{Comp}_{i,t-1} + \alpha_2 \text{Event}_{c,t} + \alpha_3 \text{Comp}_{i,t-1} \\ & + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{3.6}$$

where $\text{BHAR}_{i,t+1}$ denotes the BHARs measured over the one-year period between t and $t+1$; and $\text{Event}_{c,t}$ is a dummy indicator that equals 1 for county c during the year in which c switches from an attainment to a nonattainment status.

Table 3.11 reports the regression results. We find evidence that competition has important influences over the market reactions to regulatory shocks. Columns (1)-(2) and Columns (3)-(4) document the effects on Fama-French 3-factor BHAR and Fama-French 4-factor BHAR, respectively. Consistent with our expectation, the coefficient on Event$\times$ Comp is positive and statistically significant for both BHAR measures and in all specifications, suggesting that investors react more positively to competitive firms undergoing nonattainment shocks than to firms with less competitive pressure. For example, Column (1) reports an estimate of 1.234 ($t-$stat= 2.67), implying that an inter-decile increase in $Fluidity$ would result in about 10 percentage points higher in the Fama-French 3-factor BHAR (1.234$\times$(0.103-0.024)=0.097) following a nonattainment event. Similarly, Column (3) shows that the Fama-French 4-factor

[44]Untabulated results show that using one-year-ahead cumulative abnormal returns as dependent variables would lead to qualitatively similar findings.

BHAR during the one-year following a nonattainment shock is approximately 13 percentage points (1.690×(0.103-0.024)=0.133) higher for firms in the top Fluidity-ranked decile than firms in the bottom decile.

In contrast, the negative Event coefficients suggest an adverse market reaction to nonattainment shocks for firms in less competitive environments. The negative α_2 estimates in Model (3.6) range from -0.043 in Column (2) to -0.112 in Column (3) and are all statistically significant at the 1% level, implying a negative market reaction to a nonattainment event by 4-11 percentage points for less competitive firms.

The combined results indicate that while less competitive firms experience a negative BHAR following a nonattainment shock, the BHAR increases significantly with the competition. Such a pattern substantiates our hypothesis that investors expect competitive firms to extract more benefits from their strategic responses to environmental regulations than their less competitive peers, and the market incorporates such heterogeneity into stock prices.

3.7.3 Social welfare implications

Operating and market performance reveal the effects of environmental policies on firms' competitiveness. We now investigate how these effects influence the firms' abilities to create jobs and maintain labor demand. Policy makers and economists often view environmental regulations as detrimental to regional employment and their social welfare implications. We challenge this conventional view and argue, instead, that gaining competitive advantages and boosting businesses through green innovation would allow firms in competitive markets to better maintain their local employment than their less competitive counterparts.

To assess how regulations affect firms' local labor demand, we re-estimate Eq.(3.5) using the number of employees a firm has in a county during year $t+2$ as the dependent variable and report the results in Table 3.12. As demonstrated by the positive and significant coefficient on $Post \times Treat \times$ Comp, a higher level of competition is associated with significant increases in the treatment effect of a nonattainment shock on local employment. Column (1) reports a coefficient estimate of 0.914 ($t-$stat= 2.88), indicating that firms in the top Fluidity-ranked decile have about 2% (0.914/3.932$\times$(0.103-0.024)=0.018) more local employees than firms in the bottom decile following a regulatory shock. Column (2) implies a 1% relative difference in the treatment effects for an inter-decile change in Similarity. The coefficient estimates of $Post \times Treat$ are negative for regressions against both competition measures but are only marginally significant at the 10% level in Column (1). They indicate that environmental regulations have, at most, a weak negative impact on the local employment of firms with less competitive concerns.

Collectively, the results point to a net increase in regional employment for competitive firms following regulatory changes, possibly to satisfy the growing business gained through innovative responses. Our findings contradict prior claims that environmental regulations reduce labor demand (e.g., Kahn 1997; Greenstone 2002) and suggest that environmental policies may benefit regional social welfare given the appropriate corporate targets.

3.8 Conclusion

The conventional wisdom contends that environmental regulations impose onerous compliance costs on businesses and impede productivity and economic growth, thereby adversely affecting firm competitiveness. However, the existing literature has not fully explored the outcomes and implications of these regulatory and enforcement changes across different counties in the United States. The variation in the nonattainment status across counties provides a unique opportunity to test the impact of environmental rules in diverse economic and environmental settings. Our study, therefore, exploits these county-level nonattainment designation variations as a quasi-natural experiment to examine whether and how the intensity of product market competition influences firms' strategic responses to strict environmental policies. Using detailed plant-level information with publicly traded parent companies in the United States, we find that heightened competitive pressure induces firms to develop significantly more green innovation output when facing increased environmental regulatory stringency. We also explore whether there are sources of gains in competitive strengths arising from this green innovation strategy. Our findings indicate that regulation-induced green innovation helps competitive firms to improve competitiveness and differentiate themselves from competing rivals through product differentiation. These firms are also able to attract more corporate customers following a nonattainment shock than their less competitive counterparts.

A 2012 survey by the National Association of Manufacturers (NAM) reveals that U.S. manufacturers, especially small manufacturers with fewer than 50 employees, bear a disproportionate share of the regulatory burden and that such regulatory compliance costs are often not affected by economies of scale.[45] Resources complying with burdensome environmental regulations hinder manufacturers' ability to innovate and make better products. Yet there is virtually no prior research that looks at the economic consequences of these increasingly stricter environmental laws. Motivated by the survey, we examine the economic consequences of competitive firms' green innovation strategy. The findings suggest that competitive firms can increase their market share growth, markup, and profit margin and enjoy favorable market reactions, as measured by the firms' one-year buy-and-hold abnormal returns. We attribute our results to these firms' ability to leverage their strategic environmental policies to reduce the regulatory burden. It is important to stress that our evidence does not necessarily contradict the NAM's 2012 survey findings. The survey indicates that some of the costs associated with regulatory compliance are fixed costs, hence a firm with fewer employees bears roughly the same cost as a firm with many employees. Thus, on average, such costs put undue stress on smaller manufacturing firms that have to reallocate their resources toward abatement.

While our study provides new evidence that tighter pollution policies stimulate green innovation among firms in highly competitive product markets and, in turn, increase firm performance, it does not necessarily suggest the need for more government intervention to promote a greener environment. Several schools of economics push for a limited governmental role in economic markets, unless in extreme cases of market failure (see, e.g., Stigler, 1971; Posner, 1974; Peltz-

[45] "The cost of federal regulation to the U.S. economy, manufacturing and small business" by W. Mark Crain and Nicole V. Crain of the National Association of Manufacturers; https://www.nam.org/wp-content/uploads/2019/05/Federal-Regulation-Full-Study.pdf

man, 1976). They argue that corporations are incentivized to behave in an environmentally responsible manner by their commitment to stakeholders, their desire to preserve reputation, and their objective to improve long-term growth (e.g., Hart and Zingales 2017). Hence, we are inclined to argue that environmental regulation acts only as a catalyst to encourage corporations to become greener. With growing stakeholder engagement on corporate policy directions,[46] firms could have a greater desire to meet their environmentally-conscious stakeholders' demand and protect the environment, even without regulatory enforcement. Nonetheless, there are various economic costs and other environmental benefits that are beyond the current scope of our study. We will leave these issues for future research.

[46] In August 2019 Business Roundtable, 181 CEOs publicly committed to lead their corporations for the benefits of all stakeholders – customers, employees, suppliers, communities, and shareholders.

Figure 3.1: NAAQS Revisions and Net Changes in Nonattainment Counties

The figure shows the net changes in the number of nonattainment counties by criteria pollutant during the sample period 1996-2017. The net changes, defined as the difference in the number of nonattainment counties between the current year and the previous year, are plotted as solid orange lines. The years of NAAQS revisions are illustrated by vertical dashed lines.

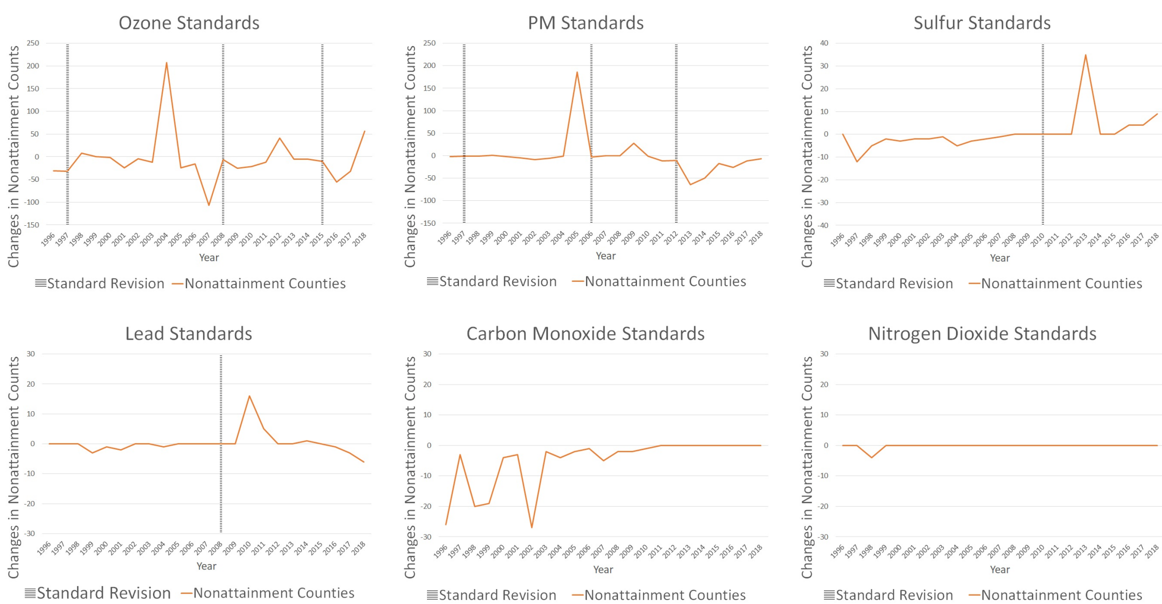

Table 3.1: Distribution of County Characteristics by State

This table reports the average number of firms per county, the average number of plants per county, the number of counties ever obtained a nonattainment status, the number of counties, the percentage of counties ever obtained a nonattainment status, and the average nonattainment period in years for the sample period from 1996 to 2017.

State	No. of Firms per County	No. of Plants per County	No. of Counties Nonattained	No. of Counties	% of Counties Nonattained	Nonattained Period (years)
Alabama	7.31	11.59	4	62	6.45	11.75
Arizona	22.73	74.60	9	15	60.00	16.33
Arkansas	4.49	6.30	1	74	1.35	9.00
California	38.45	133.39	44	58	75.86	16.20
Colorado	9.63	17.94	16	59	27.12	9.63
Connecticut	42.74	109.79	8	8	100.00	20.00
Delaware	31.64	57.62	3	3	100.00	19.67
Florida	19.41	42.62	2	66	3.03	4.00
Georgia	6.47	11.34	28	150	18.67	14.36
Hawaii	25.15	55.64	0	4	0.00	0.00
Idaho	4.32	6.09	6	41	14.63	12.50
Illinois	9.58	26.80	14	97	14.43	15.21
Indiana	7.93	13.17	31	90	34.44	7.42
Iowa	3.91	5.36	2	99	2.02	4.00
Kansas	3.67	5.58	1	98	1.02	5.00
Kentucky	4.26	6.55	10	115	8.70	11.40
Louisiana	7.74	12.69	8	62	12.90	12.50
Maine	9.29	12.95	10	16	62.50	8.30
Maryland	22.27	48.47	14	23	60.87	17.79
Massachusetts	45.78	109.07	14	14	100.00	19.86
Michigan	11.40	25.86	29	83	34.94	5.72
Minnesota	7.62	14.80	9	86	10.47	4.22
Mississippi	4.28	5.29	1	80	1.25	4.00
Missouri	5.49	9.60	7	111	6.31	13.29
Montana	2.80	3.31	10	49	20.41	15.80
Nebraska	3.65	5.62	1	74	1.35	5.00
Nevada	10.24	24.12	5	17	29.41	12.00
New Hampshire	12.21	17.52	4	9	44.44	16.50
New Jersey	40.17	84.37	21	21	100.00	19.90
New Mexico	6.62	11.31	2	30	6.67	12.50
New York	21.62	52.44	30	62	48.39	17.63
North Carolina	9.37	16.08	22	100	22.00	6.23
North Dakota	2.51	3.02	0	45	0.00	0.00
Ohio	13.85	29.04	40	88	45.45	10.50
Oklahoma	5.17	8.87	0	75	0.00	0.00
Oregon	10.55	19.40	11	35	31.43	8.36
Pennsylvania	17.09	32.82	49	67	73.13	13.65
Rhode Island	20.84	36.46	5	5	100.00	20.00
South Carolina	9.53	15.44	1	46	2.17	12.00
South Dakota	2.50	3.04	0	59	0.00	0.00
Tennessee	7.00	12.22	15	94	15.96	7.73
Texas	7.80	18.49	22	238	9.24	16.18
Utah	8.97	16.59	7	27	25.93	14.43
Vermont	6.46	8.16	0	14	0.00	0.00
Virginia	7.91	14.98	19	97	19.59	7.58
Washington	13.94	34.40	7	38	18.42	6.86
West Virginia	3.75	4.64	12	54	22.22	10.25
Wisconsin	9.56	15.97	12	71	16.90	13.50
Wyoming	4.43	5.32	4	22	18.18	6.75

Table 3.2: Summary Statistics

This table shows summary statistics for the main variables employed in this study over the sample period 1996-2017. It provides the number of observations (NObs), mean, standard deviation (Std Dev), and various levels of percentiles from the 5th to the 95th percentile. NAttain is an indicator variable that equals 1 if a firm is in an nonattainment county during the year and 0 otherwise; Plants is the number of plants a firm owns in a county; Employees is the number of employees a firm has in a county; competition measures include product market fluidity (Fluidity), total product similarity score (Similarity), the average log number of rival firms sharing at least one common corporate customer (PeerCount), the average log number of rival firms sharing at least one common major corporate customer who each account for, at the minimum, 10% of the supplier's sales (MPeerCount), and Herfindahl-Hirschman Index defined at the two-digit SIC level (HHI); firm response measures include plant closure indicator (PlantClosure), market share growth (MktGrowth), markups (Markup), and net profit margin (Margin); control variables include log of total assets (Size), Tobin's Q (TobinQ), leverage ratio (Leverage), asset tangibility (Tangibility), cumulative R&D stock (R&D), capital expenditure (CapEx), cash holdings (Cash), and log number of employees a firm has in a county (Employees). Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at 1% and 99%.

Variable	NObs	Mean	Std Dev	1st	25th	50th	75th	99th
Innovation Variables								
Green Patents	523,791	1.192	1.325	0.000	0.000	0.693	2.197	4.710
Green Cites	520,541	0.654	0.997	0.000	0.000	0.000	1.103	3.980
Green Patents^{Local}	477,686	0.018	0.111	0.000	0.000	0.000	0.000	0.693
Green Cites^{Local}	477,686	0.004	0.026	0.000	0.000	0.000	0.000	0.201
Competition Variables								
Fluidity	462,547	0.058	0.031	0.011	0.034	0.052	0.074	0.156
Similarity	490,050	0.024	0.028	0.010	0.011	0.013	0.022	0.180
Firm-specific Characteristics								
NAttain	523,791	0.456	0.498	0.000	0.000	0.000	1.000	1.000
Plants	523,791	2.139	4.022	1.000	1.000	1.000	2.000	15.000
Size	523,791	8.597	1.845	3.427	7.491	8.831	9.975	12.248
TobinQ	523,791	1.995	1.105	0.800	1.275	1.657	2.320	6.716
Leverage	523,791	0.238	0.156	0.000	0.132	0.223	0.323	0.713
Tangibility	523,791	0.253	0.170	0.024	0.125	0.210	0.334	0.695
R&D	523,791	0.034	0.053	0.000	0.001	0.017	0.042	0.287
CapEx	523,791	0.046	0.034	0.005	0.023	0.036	0.060	0.174
ROA	523,791	0.140	0.096	-0.274	0.100	0.142	0.191	0.332
Employees	523,791	3.932	1.255	2.398	2.890	3.714	4.718	7.419

Table 3.3: The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on green innovation as follows:

$$\begin{aligned}\text{Green Innovation}_{y,t+2} &= \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ &\quad + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ &\quad + FE + \epsilon_{i,c,t},\end{aligned}$$

where Green Innovation$_{y,t+2}$ denotes firm i's or firm-county's green innovation and is measured by Green Patents, Green Cites, Green Patents^{Local} and Green Cites^{Local}; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; Comp$_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firm-level Green Innovation in Year $t+2$				
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.343*	0.579***	0.411**	0.642***
	(2.01)	(3.72)	(2.39)	(4.61)
Post×Treat	-0.021*	-0.011*	-0.023**	-0.013**
	(-1.99)	(-1.88)	(-2.42)	(-2.86)
Treat×Comp	-0.408***	-0.387**	-0.508***	-0.513***
	(-3.10)	(-2.67)	(-3.63)	(-3.73)
Comp	-1.305	-2.437*	-0.248	-1.062
	(-0.75)	(-1.76)	(-0.15)	(-0.93)
Size	0.293***	0.299***	0.215**	0.209***
	(4.56)	(4.48)	(2.80)	(3.10)
TobinQ	0.052*	0.061**	0.053*	0.055*
	(1.83)	(2.14)	(2.05)	(2.08)
Leverage	0.015	0.084	0.045	0.086
	(0.05)	(0.29)	(0.22)	(0.41)
Tangibility	0.318	0.387	0.588	0.709
	(0.60)	(0.74)	(0.98)	(1.18)
R&D	2.044**	2.055**	1.496*	1.433*
	(2.67)	(2.58)	(1.97)	(1.84)
CapEx	1.165	1.521*	-0.309	-0.005
	(1.74)	(2.06)	(-0.32)	(-0.01)
ROA	0.158	0.273	-0.180	-0.068
	(0.50)	(0.87)	(-0.62)	(-0.22)
Employees	0.000	-0.001	0.001	0.000
	(0.18)	(-0.51)	(0.62)	(0.17)
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	459,335	486,671
Adj R^2	0.816	0.808	0.724	0.721

Table 3.3: The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation – Continued

	Panel B: Firm-County Level Green Innovation in Year $t+2$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.097**	0.111***	0.025**	0.027***
	(2.31)	(3.56)	(2.81)	(3.41)
Post×Treat	-0.005*	-0.002**	-0.001***	-0.001***
	(-2.14)	(-2.36)	(-3.03)	(-3.32)
Treat×Comp	-0.013	0.036	-0.003	0.012
	(-0.27)	(0.79)	(-0.22)	(0.99)
Comp	-0.017	0.111	-0.013	0.023
	(-0.11)	(0.75)	(-0.38)	(0.70)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	459,335	486,671
Adj R^2	0.816	0.808	0.724	0.721

	Panel C: Firm-Level Green Innovation in Year $t+3$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.355*	0.553***	0.513**	0.717***
	(2.01)	(3.73)	(2.70)	(4.57)
Post×Treat	-0.022*	-0.012**	-0.036***	-0.022***
	(-1.99)	(-2.12)	(-3.04)	(-4.07)
Treat×Comp	-0.416**	-0.336*	-0.553***	-0.506***
	(-2.26)	(-2.04)	(-4.51)	(-3.37)
Comp	-2.159	-1.358	-0.112	-1.177
	(-1.16)	(-0.89)	(-0.05)	(-1.06)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	376,504	397,775	373,906	395,019
Adj R^2	0.822	0.814	0.724	0.717

	Panel D: Firm-County Level Green Innovation in Year $t+3$			
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.135*	0.203***	0.050**	0.086***
	(2.05)	(3.02)	(2.15)	(3.08)
Post×Treat	-0.008*	-0.005**	-0.003*	-0.002**
	(-1.81)	(-2.42)	(-2.00)	(-2.60)
Treat×Comp	-0.015	0.099	0.000	0.000
	(-0.16)	(1.17)	(0.00)	(0.00)
Comp	-0.112	0.087	-0.065	-0.018
	(-0.44)	(0.18)	(-0.75)	(-0.13)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	338,654	358,846	338,654	358,846
Adj R^2	0.277	0.276	0.267	0.267

Table 3.4: Robustness Tests

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on green innovation as follows:

$$\begin{aligned}\text{Green Innovation}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & + FE + \epsilon_{i,c,t},\end{aligned}$$

where Green Innovation$_{i,t+2}$ denotes firm i's green innovation and is measured by Green Patents and Green Cites; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; Comp$_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. In Panel A, the regression model contains firm and county*times*year fixed effects (*FE*). In Panels B and C, the models are estimated on subsamples of firms from industries with average per-firm emissions greater than 100 tonnes and industries with above-median total emissions, respectively. In Panel D, the triple-difference model is estimated with no firm-specific control variables. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Control for Firm and County×Year Fixed Effects				
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.970*	1.871***	0.937**	1.502***
	(1.82)	(4.10)	(2.24)	(3.63)
Treat×Comp	-1.236**	-1.180**	-1.233**	-1.538***
	(-2.41)	(-2.46)	(-2.84)	(-3.91)
Comp	-3.338	-4.714***	-0.816	-1.848
	(-1.32)	(-2.89)	(-0.49)	(-1.60)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	453,028	479,984	450,622	477,401
Adj R^2	0.278	0.283	0.253	0.261

Table 3.4: Robustness Tests – Continued

Panel B: Industries with Average Per-Firm Emissions > 100 Tonnes				
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.320*	0.596***	0.474**	0.654***
	(1.70)	(3.79)	(2.55)	(5.19)
Post×Treat	-0.021*	-0.013**	-0.028**	-0.014***
	(-1.78)	(-2.25)	(-2.63)	(-2.93)
Treat×Comp	-0.413***	-0.370***	-0.543***	-0.502***
	(-2.69)	(-2.76)	(-3.73)	(-3.80)
Comp	-0.782	-2.350*	-0.154	-1.128
	(-0.47)	(-1.78)	(-0.08)	(-0.98)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	421,278	448,057	418,240	444,849
Adj R^2	0.793	0.786	0.724	0.720
Panel C: Industries with Above-Median Total Emissions				
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.571**	0.627***	0.609***	0.653***
	(2.60)	(3.84)	(3.12)	(4.94)
Post×Treat	-0.038**	-0.015**	-0.038***	-0.015**
	(-2.63)	(-2.12)	(-3.12)	(-2.67)
Treat×Comp	-0.597***	-0.400**	-0.667***	-0.526***
	(-2.94)	(-2.73)	(-4.12)	(-3.86)
Comp	-1.636	-2.539*	-0.398	-1.160
	(-0.82)	(-1.85)	(-0.20)	(-0.96)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	373,058	396,120	370,176	393,068
Adj R^2	0.817	0.808	0.735	0.730
Panel D: Without Firm-Specific Characteristics				
	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.379**	0.578***	0.444**	0.659***
	(2.06)	(3.53)	(2.46)	(4.65)
Post×Treat	-0.024*	-0.012*	-0.026**	-0.014**
	(-2.09)	(-1.80)	(-2.49)	(-2.84)
Treat×Comp	-0.464***	-0.404**	-0.554***	-0.535***
	(-3.47)	(-2.63)	(-3.77)	(-3.75)
Comp	-0.945	-2.612	0.175	-1.216
	(-0.55)	(-1.73)	(0.11)	(-1.12)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	459,335	486,671
Adj R^2	0.812	0.803	0.721	0.717

Table 3.5: Subsample Analysis of County-Level Emissions Marginally Above or Below NAAQS Thresholds

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on on green innovation using a subsample in which the county-level pollutant concentrations are 10% above or below the NAAQS threshold, as follows.

$$\begin{aligned}\text{Green Innovation}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & + FE + \epsilon_{i,c,t},\end{aligned}$$

where Green Innovation$_{i,t+2}$ denotes firm i's green innovation and is measured by Green Patents and Green Cites; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; Comp$_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.698*	0.724**	0.496	0.803**
	(1.87)	(2.46)	(1.43)	(2.76)
Post×Treat	-0.045*	-0.019*	-0.032	-0.020*
	(-2.09)	(-2.00)	(-1.51)	(-1.85)
Treat×Comp	-0.677***	-0.288	-0.525**	-0.391*
	(-2.96)	(-1.56)	(-2.36)	(-1.74)
Comp	-0.837	-1.930	0.554	-1.008
	(-0.50)	(-1.36)	(0.34)	(-0.83)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	139,883	145,275	138,696	144,012
Adj R^2	0.816	0.808	0.713	0.709

Table 3.6: Effects of Environmental Regulations and Import Penetration on Green Innovation

This table reports regression results from triple-difference models that examine the joint effects of environmental regulations and import tariff reduction (*Tariff*) on green innovation, as follows.

$$\begin{aligned}\text{Green Innovation}_{y,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Tariff}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Tariff}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Tariff}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Tariff}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & + FE + \epsilon_{i,c,t},\end{aligned}$$

where Green Innovation$_{y,t+2}$ denotes firm i's or firm-county's green innovation and is measured by Green Patents, Green Cites, Green Patents^{Local} and Green Cites^{Local}; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; Tariff$_{i,t-1}$ is a binary indicator that equals to 1 if there is a significant import tariff rate reduction in the industry in previous year and 0 otherwise; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. *FE* denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Green Patents (t+2)		*Green Cites (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Tariff	0.035**	0.017*	0.007**	0.001**
	(2.35)	(1.88)	(2.81)	(2.52)
Post×Treat	-0.035**	-0.019**	-0.007***	-0.002***
	(-2.28)	(-2.16)	(-3.25)	(-3.63)
Treat×Tariff	-0.009	-0.019**	0.000	0.000
	(-0.68)	(-2.69)	(0.04)	(1.45)
Tariff	0.392**	0.217***	0.023*	0.003
	(2.75)	(3.77)	(1.80)	(1.22)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	406,878	404,026	372,938	372,938
Adj R^2	0.804	0.7287	0.229	0.241

Table 3.7: The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation by Industry Type

This table reports subsample regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on green innovation , as follows.

$$\begin{aligned}\text{Green Innovation}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\ & + FE + \epsilon_{i,c,t},\end{aligned}$$

where Green Innovation$_{i,t+2}$ denotes firm i's green innovation and is measured by Green Patents and Green Cites; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; Comp$_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. We divide firms into three terciles based on the degree of industry mobility they belong to. Industry mobility is measured by its plant fixed cost or agglomeration of economies. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firms Grouped by Plant Fixed Costs

	Green Patents (t+2)				*Green Cites (t+2)*			
	Least Mobile Industry		Most Mobile Industry		Least Mobile Industry		Most Mobile Industry	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post×Treat×Comp	0.694**	0.732***	0.300	1.264	0.496*	0.661***	-0.229	0.157
	(2.31)	(3.05)	(0.78)	(1.55)	(1.78)	(3.09)	(-0.66)	(0.30)
Post×Treat	-0.054**	-0.029**	-0.002	-0.013	-0.025	-0.013	0.021	0.003
	(-2.47)	(-2.35)	(-0.06)	(-0.55)	(-1.29)	(-1.16)	(0.78)	(0.18)
Treat×Comp	-0.279	-0.403*	-0.644**	-1.078*	-0.499**	-0.587***	-0.133	-0.133
	(-0.86)	(-1.72)	(-2.20)	(-2.08)	(-2.05)	(-2.87)	(-0.43)	(-0.24)
Comp	0.054	0.812	0.147	-1.668	3.666**	1.170	-2.695	-2.847
	(0.02)	(0.46)	(0.05)	(-0.25)	(2.20)	(0.61)	(-0.90)	(-0.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	71,923	76,459	72,539	76,450	71,636	76,173	71,892	75,803
Adj R^2	0.876	0.860	0.852	0.852	0.822	0.816	0.762	0.766

Table 3.7: The Effect of Competitive Firms' Environmental Regulatory Response on Green Innovation by Industry Type – Continued

	Panel B: Firms Grouped by an Industry's Agglomeration of Economies							
	Green Patents (t+2)				*Green Cites (t+2)*			
	Least Mobile Industry		Most Mobile Industry		Least Mobile Industry		Most Mobile Industry	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post×Treat×Comp	0.551*	0.956**	0.330	0.372	0.734***	0.986***	0.214	0.539
	(1.77)	(2.59)	(1.29)	(1.43)	(3.08)	(4.16)	(0.89)	(1.68)
Post×Treat	-0.029	-0.018	-0.022	-0.013	-0.041**	-0.020**	-0.014	-0.016
	(-1.24)	(-1.52)	(-1.27)	(-1.33)	(-2.52)	(-2.20)	(-0.85)	(-1.60)
Treat×Comp	-0.422*	-0.667***	-0.557*	-0.387	-0.554***	-0.791***	-0.423	-0.337
	(-2.10)	(-3.46)	(-1.99)	(-1.23)	(-3.42)	(-4.80)	(-1.44)	(-1.26)
Comp	-5.618	-0.544	-0.572	-0.819	-4.114	-2.084	-1.842	-1.741
	(-1.66)	(-0.16)	(-0.20)	(-0.42)	(-1.22)	(-0.82)	(-0.78)	(-0.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	125,340	134,585	118,399	123,509	125,057	134,302	117,589	122,696
Adj R^2	0.861	0.846	0.834	0.829	0.802	0.798	0.745	0.744

Table 3.8: The Effect of Competitive Firms' Environmental Regulatory Response on Product Differentiation

This table reports regression results from triple-difference models that examine competitive firms' environmental regulatory response on product differentiation as follows:

$$
\begin{aligned}
\text{Product Diff}_{i,t+2} &= \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\
&\quad + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} \\
&\quad + FE + \epsilon_{i,c,t},
\end{aligned}
$$

where Product $\text{Diff}_{i,t+2}$ is measured by firm i's patent originality score and average similarity score at $t+2$; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $\text{Comp}_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Patent Originality(t+2)		*Average Similarity (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.001	0.102**	0.029***	0.013**
	(0.03)	(2.32)	(3.64)	(1.99)
Post×Treat	0.000	-0.002	-0.001*	-0.000
	(0.22)	(-1.69)	(-1.93)	(-0.01)
Treat×Comp	-0.025	-0.079*	0.005	-0.021***
	(-0.75)	(-1.94)	(0.62)	(-2.93)
Comp	0.470*	0.344	-0.149***	0.025***
	(1.92)	(1.11)	(-15.59)	(3.61)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	362,970	384,332	211,536	222,444
Adj R^2	0.557	0.555	0.514	0.501

Table 3.9: The Effect of Competitive Firms' Environmental Regulatory Response on Corporate Customer Relationships

This table reports regression results from triple-difference models that examine competitive firms' environmental regulatory response on attracting corporate customers as follows:

$$\begin{aligned}\text{Customers}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 Comp_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},\end{aligned}$$

where $\text{Customers}_{i,t+2}$ is defined by firm i's total number of corporate customers, number of local corporate customers, ratio of non-green customers to green customers, ratio of local non-green customers to local green customers; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $\text{Comp}_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Number of Corporate Customers			
	Total No. of Customers (t+2)		*No. of Local Customers (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Post×Treat×Comp	0.300**	0.311	0.271*	0.825***
	(2.00)	(1.10)	(1.67)	(2.63)
Post×Treat	-0.014	0.011*	-0.018*	-0.023***
	(-1.48)	(-0.70)	(-1.81)	(-3.31)
Treat×Comp	-0.121	-0.003	0.585**	0.692
	(-1.05)	(-0.01)	(2.10)	(1.14)
Comp	1.629	3.657	0.575	0.116
	(1.39)	(1.40)	(0.91)	(0.09)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	462,413	489,919	462,413	489,919
Adj R^2	0.838	0.834	0.662	0.657
	Panel B: Ratio of Non-Green to Green Corporate Customers			
	Non-Green/Green Customers (t+2)		*Non-Green/Green Local Customers (t+2)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Post×Treat×Comp	0.924*	0.929*	1.072*	0.925*
	(1.69)	(1.94)	(1.81)	(2.09)
Post×Treat	-0.039	-0.003	-0.093*	-0.052*
	(-0.89)	(-0.09)	(-1.94)	(-2.04)
Treat×Comp	-1.517***	-0.734	0.580	0.107
	(-2.67)	(-1.42)	(0.85)	(0.14)
Comp	5.538***	-2.548***	-1.861	-0.383
	(10.49)	(-4.15)	(-0.86)	(-0.23)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	210,027	215,167	107,731	109,839
Adj R^2	0.687	0.688	0.553	0.555

Table 3.10: The Effect of Competitive Firms' Environmental Regulatory Response on Operating Performance

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on operating performance as follows:

$$\begin{aligned}\text{OpPerformance}_{i,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} \\ & + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},\end{aligned}$$

where $\text{OpPerformance}_{i,t+2}$ is measured by firm i's market share growth, markup, and profit margin; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $\text{Comp}_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Market Share Growth		*Markup*		*Profit Margin*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Post×Treat×Comp	0.190*	0.234**	0.068**	0.078*	0.100*	0.206*
	(2.08)	(2.51)	(2.31)	(1.74)	(1.71)	(1.87)
Post×Treat	-0.011*	-0.004	-0.003**	-0.001	-0.004	-0.003
	(-1.88)	(-1.64)	(-2.18)	(-1.40)	(-1.50)	(-1.44)
Treat×Comp	-0.157*	-0.191**	-0.040	-0.039	-0.133***	-0.250***
	(-1.78)	(-2.83)	(-1.60)	(-1.13)	(-2.62)	(-2.60)
Comp	-0.423	0.329	-0.008	-0.257	-0.015	-0.567
	(-0.73)	(1.20)	(-0.06)	(-1.42)	(-0.08)	(-1.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
NObs	461,927	489,414	462,292	489,798	462,100	489,603
Adj R^2	0.234	0.218	0.855	0.852	0.767	0.765

Table 3.11: The Effect of Competitive Firms' Environmental Regulatory Response on Market Performance

This table reports regression results from triple-difference models that examine the effect of competitive firms' environmental regulatory response on market performance as follows:

$$\text{BHAR}_{i,t+1} = \alpha_0 + \alpha_1 \text{Event}_{c,t} \times \text{Comp}_{i,t-1} + \alpha_2 \text{Event}_{c,t} + \alpha_3 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},$$

where $\text{BHAR}_{i,t+1}$ is measured by a one-year buy and hold abnormal return using either the Fama-French three-factor or four-factor model; $\text{Event}_{c,t}$ equals 1 for county c during the year in which c switches from an attainment to a nonattainment status; $\text{Comp}_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Fama-French 3-factor BHAR (t+1)		*Fama- French 4-factor BHAR (t+1)*	
	Fluidity	*Similarity*	*Fluidity*	*Similarity*
Variable	(1)	(2)	(3)	(4)
Event×Comp	1.234***	1.205**	1.690***	1.807***
	(2.67)	(2.38)	(3.20)	(3.38)
Event	-0.086***	-0.043***	-0.112***	-0.058***
	(-3.14)	(-3.49)	(-3.59)	(-4.46)
Comp	-0.085	-0.716	-0.626	-0.856
	(-0.09)	(-0.60)	(-0.62)	(-0.63)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
NObs	454,487	481,742	454,487	481,742
Adj R^2	0.229	0.223	0.232	0.228

Table 3.12: The Effect of Competitive Firms' Environmental Regulatory Response on Firm-County-Level Employment

This table reports regression results from triple-difference models that examine competitive firms' environmental regulatory response on firm-county-level employment:

$$\begin{aligned}\text{Labor}_{i,c,t+2} \quad = \quad & \alpha_0 + \alpha_1 Post_{c,t} \times Treat_c \times \text{Comp}_{i,t-1} + \alpha_2 Post_{c,t} \times Treat_c + \alpha_3 Treat_c \times \text{Comp}_{i,t-1} \\ & + \alpha_4 Post_{c,t} \times \text{Comp}_{i,t-1} + \alpha_5 Post_{c,t} + \alpha_6 Treat_c + \alpha_7 \text{Comp}_{i,t-1} + \sum_{k=1}^{K} \beta_k X_{ki,c,t} + FE + \epsilon_{i,c,t},\end{aligned}$$

where $\text{Labor}_{i,c,t+2}$ is defined by the log of one plus firm i's two-year ahead number of firm-county-level employees; $Treat_c$ is a binary variable that equals 1 if the county has ever been classified as a nonattainment area during the sample period and 0 otherwise; $Post_{c,t}$ is a binary variable that equals 1 for county c during the years in which c has a nonattainment status and 0 otherwise; $\text{Comp}_{i,t-1}$ denotes competition and is measured by Fluidity or Similarity; $X_{i,t}$ is a vector of controls including Size, TobinQ, Leverage, Tangibility, R&D, CapEx, Cash, and Employees. Construction of the variables is presented in Appendix Table A.5. All variables are winsorized at the 1st and 99th percentiles. FE denotes firm, county, and year fixed effects. NObs is the number of firm-county-year observations, and $\bar{R}^2$ is the adjusted R-squared value. All $t-$statistics reported in parentheses are computed based on adjusted standard errors clustered at the firm-year level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Fluidity	*Similarity*
Variable	(1)	(2)
Post×Treat×Comp	0.914**	0.696*
	(2.88)	(1.98)
Post×Treat	-0.039*	-0.005
	(-2.08)	(-0.46)
Treat×Comp	0.928**	0.947**
	(2.65)	(2.61)
Comp	-0.757*	-1.068***
	(-2.01)	(-3.26)
Controls	Yes	Yes
Fixed Effects	Yes	Yes
NObs	462,413	489,919
Adj R^2	0.145	0.143

Table A.1: Variable Definitions and Data Sources for Essay 1

Variable	Definition	Data Source
Customer Concentration		
Customer Sales	The sum of sales to all major corporate customers divided by the supplier's total sales. A firm accounting for at least 10% of its supplier's total sales is defined as a major corporate customer.	Compustat
Customer HHI	The sum of squared sales percentages to major corporate customers.	Compustat
Largest Customer	The sales percentage to the major corporate customer who accounts for the largest share of the supplier's total sales.	Compustat
Institutional Ownership		
ST%	The number of shares owned by short-term institutional investors divided by total number of shares outstanding. Institutional investors whose average portfolio churn rate over the last four quarters is higher than at least 2/3 of all institutions are defined as short-term.	13F
LT%	The number of shares owned by long-term institutional investors divided by total number of shares outstanding. Institutional investors whose average portfolio churn rate over the last four quarters is lower than at least 2/3 of all institutions are defined as long-term.	13F
NCross ST%	The number of shares owned by short-term institutional investors of a firm who do not simultaneously own any of the major corporate customers of the firm, divided by total number of shares outstanding.	13F
NCross LT%	The number of shares owned by long-term institutional investors of a firm who do not simultaneously own any of the major corporate customers of the firm, divided by total number of shares outstanding.	13F
Trans%	The number of shares owned by transient institutional investors divided by total number of shares outstanding. Transient investors are identified following Bushee's (1998 and 2001) classification of 13F institutional investors.	Bushee's Website
Dedi%	The number of shares owned by dedicated institutional investors divided by total number of shares outstanding. Dedicated investors are identified following Bushee's (1998 and 2001) classification of 13F institutional investors.	Bushee's Website
Firm Characteristics		
Size	The log of market capitalization of a firm.	Compustat
Tobin's Q	Total assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets.	Compustat
Book-to-Market	Book value of equity divided by market capitalization of a firm.	Compustat
Age	The log of one plus the number of years since the first year the firm appears in Compustat.	Compustat
Div. Yield	Dividends divided by market capitalization of a firm.	Compustat
Price	The log of stock price.	CRSP
$\mathrm{R}eturn_{-3,0}$	Past 3-month cumulative stock return.	CRSP
$\mathrm{R}eturn_{-12,-3}$	9-month cumulative stock return ended 3 months prior to the fiscal year-end.	CRSP
Turnover	The monthly trading volume divided by total number of shares outstanding, averged over the past year.	CRSP
Forecast Error	The absolute difference between the actual EPS and the median consensus analyst forecasts last reported prior to the fourth fiscal quarter end, scaled by the stock price at the beginning of the fiscal quarter.	IBES
PostFD	A dummy variable equal to one after the adoption of Fair Disclosure Regulation in 2000, and zero otherwise.	
Customer Industry M&A	The weighted average customer industry M&A intensity for a supplier, where industry M&A intensity is the aggregate M&A costs divided by the aggregate sales over all firms within an customer industry averaged over the last five years, and the weights are the percentage of supplier's sales to each customer industry.	Compustat
Customer Reg Index	The one-year-lagged weighted average customer industry Regulation Index for a supplier, where Regulation Index is an industry-wide measure computed by McLaughlin and Sherouse (2018) counting the number of federal regulatory restrictions applicable to each 6-digit NAICS industry, and the weights are the percentage of supplier's sales to each customer industry. The measure is expressed in natural log.	RegData
Short Selling Activity		
Short Interest	The number of shares shorted on the 15th business day of each month divided by the total number of shares outstanding at the end of the month.	Compustat
Disp Short Interest	The standard deviation of monthly short interests over the past 12 months.	Compustat

Table A.2: Variable Definitions and Data Sources for Essay 2

Variable	Definition	Data Source
Measures of Stock Price Crash Risk		
NCSKEW	Negative of the ratio of the third moment to standard deviation cubed of firm-specific abnormal weekly returns during a fiscal year.	CRSP
DUVOL	Log ratio of the standard deviation of firm-specific abnormal weekly returns of the down weeks to that of the up weeks. Down (up) is defined as the return above (below) the annual mean.	CRSP
Crash Count	The number firm-specific weekly returns exceeding 3.09 standard deviation below the mean firm-specific weekly return over the fiscal year.	CRSP
Measures of Competition		
Peer Count	The number of customer-connected peers, averaged across all customers of the supplier, and transformed to natural log value. Customer-connected peers are defined as those firms within the same Hoberg and Phillip's (2010; 2016) text-based network industry classification (TNIC) industry as a supplier and are servicing at least one common customer.	Revere; Hoberg and Phillips (2010, 2016)
Peer Sales	The sum of the customer-connected peers' sales to each customer of the supplier, scaled by customer's cost of goods sold, averaged across all customers of the supplier.	Revere; Compustat
Peer Sales	The sum of the customer-connected peers' sales to each customer of the supplier, scaled by customer's cost of goods sold, averaged across all customers of the supplier.	Revere; Compustat
Peer Similarity	The average product similarity score with all customer-connected peers, averaged again across all customers of the supplier.	Revere; Hoberg and Phillips (2010, 2016)
Non-Linked Peer Count	The log number of total supplier peers not sharing a common customer with a supplier. Non-Linked Peers are identified as mutual competitors of a supplier in the Revere Relationship database (FactSet Revere) and within the same Hoberg and Phillip's (2010) TNIC industry as a supplier.	Revere; Hoberg and Phillips (2010, 2016)
Non-Linked Peer Similarity	The average product similarity with all supplier peers not sharing a common customer with a supplier.	Revere; Hoberg and Phillips (2010, 2016)
Identification Strategy Variables		
Customer M&A Intensity	The prior five years' moving average of total customer M&A transaction values divided by the customer's total sales, weighted averaged across all customers of the supplier, where the weights are the percentage of supplier's sales to each customer.	SDC
Post× Treat	A interaction dummy variable equal to one if the connected peers of a firm file for Chapter 11 bankruptcy during the year, and zero otherwise.	Ma et al. (2019)
Peer Disaster	A dummy variable equal to one if the connected peers of a firm are hit by a major natural disaster during the year, and zero otherwise.	Dun & Bradstreet; FEMA
Mechanism Variables		
Peer Count (CompAl)	Peer Count computed on those customer-connected supplier peers who have formed business alliances with the focal firm, where business alliances are defined as pairs of firms committed to any of the following forms of business relationship: (i) research collaboration; (ii) integrated product offering; (iii) joint venture; (iv) cross-ownership in equity stakes; (v) products, patents, and intellectual property licensing; (vi) use of each other's manufacturing, marketing, and distribution services.	Revere
Peer Sales (CompAl)	Peer Sales computed on those customer-connected supplier peers who have formed business alliances with the focal firm.	Revere
Peer Similarity (CompAl)	Peer Similarity computed on those customer-connected supplier peers who have formed business alliances with the focal firm.	Revere
Peer Count (CusAl)	Peer Count computed on those supplier peers connected to common customers who have formed business alliances with the focal firm.	Revere
Peer Sales (CusAl)	Peer Sales computed on those supplier peers connected to common customers who have formed business alliances with the focal firm.	Revere
Peer Similarity (CusAl)	Peer Similarity computed on those supplier peers connected to common customers who have formed business alliances with the focal firm.	Revere

Table A.2: Variable Definitions and Data Sources for Essay 2 – Continued

Variable	Definition	Data Source
# Inst	The log number of institutional owners of the firm.	13F
Media Coverage	The log number of unique news sources covering a firm over its fiscal year.	Ravenpack
High Dispersion	A dummy variable equal to one if analyst forecast dispersion is above the fourth quartile of all firms in the same industry-year, and zero if it is below the first quartile. Analyst forecast dispersion is defined as the standard deviation of annual EPS forecasts, scaled by the stock price at the beginning of the fiscal year.	IBES
Direct Disclosure Measures		
All News	Ratio of the number of firm-specific negative-news disclosure events to the number of firm-specific positive-news disclosure events in a given year. An event is considered as negative-news (positive-news) event if it results in a negative (positive) cumulative abnormal return from the Fama-French 4-factor model during the 3-day window around the announcement (-1,1). Disclosure events are earnings announcements, conference presentations, client announcements, earnings calls, product-related announcements, and corporate guidance events from Capital IQ Key Development. The firm and year observations with less than 4 events are removed.	Capital IQ
5% Significant News	Ratio of the number of firm-specific negative-news disclosure events associated with CAR(-1,1) less than -5% to the number of firm-specific positive-news disclosure events associated with CAR(-1,1) greater than 5% in a given year.	Capital IQ
10% Significant News	Ratio of the number of firm-specific negative-news disclosure events associated with CAR(-1,1) less than -10% to the number of firm-specific positive-news disclosure events associated with CAR(-1,1) greater than 10% in a given year.	Capital IQ
Comment Letters	Number of different corporate filings in SEC from the supplier triggered a comment letter from SEC's review division requesting clarifications, additional information, or disclosure adjustments of the filings.	Audit Analytics
Occurrence of Restatements	An indicator equal to one if the supplier have a material restatement filed in Form 8-K in a given year, and 0 otherwise.	Audit Analytics
Size	The log of market price multiplied by the number of oustanding shares outstanding.	Compustat
MB	Market value of common equity divided by book value of common equity.	Compustat
Leverage	Long-term debt divided by total assets.	Compustat
ROA	Income before extraordinary items divided by total assets.	Compustat
Δ Turnover	Average monthly stock turnover within a fiscal year minus that of the previous year.	CRSP
AbAccr	The prior three years' moving sum of the absolute value of discretionary accruals, where discretionary accruals are estimated from the modified Jones model (Dechow, Sloan, and Sweeney, 1995).	Compustat
Sigma	The standard deviation of firm-specific weekly returns over the fiscal-year period.	CRSP
Return	The mean of firm-specific weekly returns over the fiscal-year period.	CRSP
MktShare	The proportion of a fimr's sales in the 2-digit SIC industry. .	Compustat
HHI Index	The sum of squared market shares of all firms in the same 2-digit SIC industry.	Compustat
Fluidity	A "cosine" similarity between a firm's products and the changes in the rivals' products, scaled between 0 and 1.	Hoberg and Phillips (2010, 2016)
Customer Concentration	The sum of the squared sales percentages to all major corporate customers of a firm, where major corporate customers are those accounting for at least 10% of the firm's total revenue.	Compustat
Bankruptcy	A dummy variable equal to one if a firm files for Chapter 11 bankruptcy during the year, and zero otherwise.	Ma et al.(2019)
Disaster	A dummy variable equal to one if a firm is hit by a major natural disaster during the year, and zero otherwise.	Dun & Bradstreet; FEMA

Table A.3: Additional Robustness Tests

This table reports additional robustness results from regressing supplier stock price crash risk on each proxy for existing competition, and additional controls, as follows:

$$\text{Crash Risk}_{i,t+1} = \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} + \alpha_2 \text{Additional Control} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t},$$

where $X_{ki,t}$ is a vector of controls, including size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). Panels A and B conduct the same analysis as Table 2 with additional controls. Panel A controls for customer concentration, whereas Panel B replicates the panel regressions of Table 2, except the sample excludes the global financial crisis years of 2008-2009. The three measures of connected peer threats include Peer Count, Peer Sales, and Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R^2 are reported. Construction of the variables is presented in Appendix Table A.2.

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Control for Customer Concentration									
Peer Count_t	0.027***			0.014***			0.019***		
	(5.04)			(3.96)			(4.52)		
Peer Sales_t		0.366**			0.214**			0.184*	
		(2.55)			(2.40)			(1.74)	
Peer Similarity_t			1.068***			0.580***			0.551***
			(5.14)			(4.45)			(3.43)
Customer	0.110**	0.140***	0.104**	0.058*	0.074**	0.053*	0.012	0.035	0.015
Concentration_t	(2.22)	(2.76)	(2.08)	(1.94)	(2.42)	(1.77)	(0.32)	(0.93)	(0.40)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.3: Additional Robustness Tests – Continued

	NCSKEW_{t+1}			DUVOL_{t+1}			Crash Count_{t+1}		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel B: Exclude Global Financial Crisis Years 2008 and 2009								
Peer Count_t	0.027***			0.014***			0.017***		
	(4.72)			(3.87)			(3.92)		
Peer Sales_t		0.391***			0.229**			0.198*	
		(2.59)			(2.42)			(1.76)	
Peer Similarity_t			1.145***			0.659***			0.520***
			(5.25)			(4.82)			(3.10)
NObs	25,241	23,948	25,241	25,241	23,948	25,241	25,252	23,959	25,252
Adj-R^2	0.024	0.024	0.025	0.027	0.026	0.027	0.018	0.018	0.017
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4: Supplier Business Risk and Stock Price Crash Risk

This table reports results from regressing supplier stock price crash risk on each proxy for existing competition as well as on a proxy for a supplier's product market pricing power, as follows::

$$\text{Crash Risk}_{i,t+1} = \alpha_0 + \alpha_1 \text{Connected Peer Threat}_{i,t} + \alpha_2 \text{Business Risk}_{i,t} + \sum_{k=1}^{K} \beta_k X_{ki,t} + \text{FE}_t + \epsilon_{i,t},$$

where $X_{ki,t}$ is a vector of controls, including size, market-to book equity value (MB), leverage, return on assets (ROA), change in stock turnover, abnormal accruals (AbAccr), standard deviation of returns (Sigma), past stock return, as well as year and industry fixed effects (FE). Business Risk of a suppiler is proxied by: (i) supplier market power, measured as the price-cost margin scaled by sales; (ii) supplier operating risk, measured as annual standard deviation of a firm's quarterly operating income before depreciation over total assets; (iii) supplier operating performance is measured by subtracting the number of positive product market news from the number of negative product market news occurred in a calendar year. The three measures of connected peer threats include Peer Count, Peer Sales, and Peer Similarity. The three measures of stock price crash risk are NCSKEW, DUVOL, and Crash Count. $t-$statistics of the regression coefficients are shown in parentheses and are computed based on standard errors clustered at the firm level. The number of observations (NObs) and adjusted R^2 are reported. Construction of the variables is presented in Appendix Table A.2.

	NCSKEW$_{t+1}$			DUVOL$_{t+1}$			Crash Count$_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Supplier Market Power$_{t+1}$									
Peer Count$_t$	0.029***			0.015***			0.018***		
	(5.29)			(4.27)			(4.34)		
Peer Sales$_t$		0.431***			0.234**			0.203*	
		(2.93)			(2.57)			(1.81)	
Peer Similarity$_t$			1.033***			0.535***			0.500***
			(4.84)			(4.03)			(3.01)
Supplier Market Power$_{t+1}$	-0.002	-0.004	-0.002	-0.002	-0.003	-0.001	-0.002	-0.003	-0.002
	(-0.76)	(-1.26)	(-0.54)	(-0.92)	(-1.47)	(-0.74)	(-0.86)	(-1.28)	(-0.75)
NObs	26,987	25,618	26,987	26,987	25,618	26,987	26,991	25,622	26,991
Adj-R^2	0.027	0.026	0.027	0.030	0.029	0.030	0.018	0.018	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.4: Supplier Business Risk and Stock Price Crash Risk – Continued

	$NCSKEW_{t+1}$			$DUVOL_{t+1}$			$Crash\ Count_{t+1}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Supplier Operating $Risk_{t+1}$									
Peer $Count_t$	0.029***			0.014***			0.019***		
	(5.32)			(4.16)			(4.50)		
Peer $Sales_t$		0.408***			0.235***			0.190*	
		(2.85)			(2.66)			(1.80)	
Peer $Similarity_t$			1.130***			0.610***			0.546***
			(5.50)			(4.74)			(3.46)
Supplier Operating	0.821**	0.940**	0.786**	0.641***	0.712***	0.623***	0.124	0.190	0.115
$Risk_{t+1}$	(2.11)	(2.38)	(2.02)	(2.69)	(2.92)	(2.61)	(0.43)	(0.64)	(0.40)
NObs	25,320	23,973	25,320	25,320	23,973	25,320	25,324	23,977	25,324
Adj-R^2	0.025	0.024	0.025	0.028	0.027	0.028	0.017	0.017	0.017
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Supplier Operating $Performance_{t+1}$									
Peer $Count_t$	0.029***			0.014***			0.019***		
	(5.32)			(4.16)			(4.50)		
Peer $Sales_t$		0.408***			0.235***			0.190*	
		(2.85)			(2.66)			(1.80)	
Peer $Similarity_t$			1.130***			0.610***			0.546***
			(5.50)			(4.74)			(3.46)
Supplier Operating	0.016**	0.017***	0.017**	0.010**	0.010**	0.010**	0.013**	0.014**	0.013**
$Performance_{t+1}$	(2.47)	(2.59)	(2.52)	(2.12)	(2.21)	(2.14)	(2.33)	(2.52)	(2.47)
NObs	28,585	27,123	28,585	28,585	27,123	28,585	28,598	27,136	28,598
Adj-R^2	0.025	0.024	0.025	0.027	0.026	0.027	0.018	0.017	0.018
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5: Variable Definitions and Data Sources for Essay 3

Variable	Definition	Data Source
Measures of green innovation (firm-specific)		
Green Patents	The natural logarithm of one plus firm i's total number of green patents filed (and eventually granted) during the year, where green patents are those classified as environmentally sound technologies (ESTs) by WIPO based on their IPC patent classes	WIPO; PATSTAT
Green Cites	The natural logarithm of one plus the total number of citations received by firm i's green patents filed (and eventually granted) during the year	WIPO; PATSTAT
Measures of green innovation (firm-county-specific)		
Green Patents^{Local}	The natural logarithm of one plus the number of firm i's green patents filed during the year that have received citations from its local customers, where local customers are those with at least one plant in county c when citing firm i's patents	Dun & Bradstreet; WIPO; PATSTAT
Green Cites^{Local}	The natural logarithm of one plus the number of citations received by firm i's green patents filed during the year from its local customers	Dun & Bradstreet; WIPO; PATSTAT
Measures of competition		
Fluidity	Constructed by Hoberg, Phillips, and Prabhala (2014), which is a "cosine" similarity score between firm i's own word usage in its 10-K product descriptions and the aggregate changes in the product key words used by its competitors within the same TNIC industry	Hoberg-Phillips Data Library
Similarity	Constructed by Hoberg and Phillips (2016), which measures the total "cosine" similarity score between firm i's products and those of its peers within the same TNIC industry	Hoberg-Phillips Data Library
Tariff	A dummy variable equals to 1 for the two years after a major tariff reduction in firm i's industry and is equal to 0 for other years and for firms in industries without tariff changes; tariff rates are defined as the collected duties divided by the custom value of imports for each industry; a major tariff reduction event is defined as a decline in the tariff rate by more than 4 times larger than the average tariff reduction of the industry during the sample period, and it is not preceded or followed by a major tariff increase greater than 80% of the reduction	WITS World Bank
Identification Strategy Variables		
$Treat$	A binary variable that equals 1 if a county has ever been classified as a nonattainment area and 0 if otherwise.	EPA Green Book
$Post$	A binary variable that equals 1 for a county during years in which the county has a nonattainment status and 0 if otherwise.	EPA Green Book
$Event$	A binary variable that equals 1 for a county during the year in which the county switches from an attainment status to a nonattainment status	EPA Green Book
Measures of product differentiation, customer attraction, and other firm performance		
$Patent\ Originality$	One minus the sum of squared percentage of backward citations made by a patent to each patent class (at the three-digit IPC level), averaged across all patents filed by firm i during a year	PATSTAT
$Average\ Similarity$	The average of Hoberg and Phillip's (2016) product similarity score between firm i and its competitors in the same TNIC industry	Hoberg-Phillips Data Library
Total No. of Customers	The natural logarithm of one plus the total number of corporate customers firm i has in a year	Revere
No. of Local Customers	The natural logarithm of one plus the total number of local corporate customers firm i has in a year	Revere
Non-Green/Green Customers	The ratio of the number of corporate customers with no green patents to the number of corporate customers with at least one green patent	Revere; PATSTAT
Non-Green/Green Local Customers	The ratio of the number of local customers with no green patents to the number of local customers with at least one green patent	Revere; PATSTAT
Market Share Growth	Market share growth as the difference in firm i's market share between the current year and the previous year, scaled by the previous year's market share	Compustat
Markup	Ratio of sales to the difference of sales and earnings before interest, taxes, depreciation, and amortization	Compustat
Profit Margin	Income before extraordinary items divided by sales	Compustat
3-Factor BHAR	One-year buy-and-hold abnormal return obtained using the Fama-French three-factor model	CRSP
4-Factor BHAR	One-year buy-and-hold abnormal return obtained using the Fama-French Carhart four-factor model	CRSP

Table A.5: Variable Definitions and Data Sources for Essay 3 – Continued

Variable	Definition	Data Source
Control Variables		
Size	The natural logarithm of total assets.	Compustat
TobinQ	Total assets plus the market value of equity minus the book value of equity minus deferred taxes divided by total assets.	Compustat
Leverage	Total debt divided by total assets.	Compustat
Tangibility	Gross property, plant, and equipment divided by total assets.	Compustat
R&D	Research and development expenditures divided by total assets	Compustat
CapEx	Capital expenditure divided by total assets.	Compustat
ROA	operating income before depreciation divided by total assets	Compustat
KZIndex	KZ index defined as $-1.002\times$ cash flow $+0.283\times$ Tobin's Q$+3.139\times$ Leverage $-39.368\times$ dividends $-1.315\times$ cash holdings	Compustat
Employees	The natural logarithm of one plus the number of employees each firm has in a county during a year	Dun & Bradstreet

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