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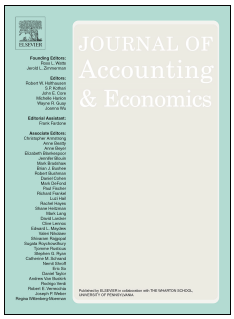

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Peer Effects in Corporate Disclosure Decisions

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Abstract

This study examines peer effects in corporate disclosure decisions. Peer effects suggest that the average behavior of a group influences the behavior of individual group members. Consistent with peer effects, I find that disclosures made by industry peers induce firm disclosure. Peer effects in disclosure are more pronounced when a firm's strategic uncertainty is higher, indicating that peer firm disclosure reduces the external uncertainty arising from the firm's interaction with its industry peers and thus increases the precision of managerial private information. I also find that peer effects are stronger when a firm's dependence on external financing is greater, suggesting that peer firm disclosure increases the costs on firm visibility and reputation in capital markets. Overall, these findings suggest that peer firm disclosure shapes a firm's information environment.

Keywords: Peer Effects, Disclosure, Management Forecasts, 8-K Flings, and Press Releases

JEL Classification: M40; M41

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1. Introduction

Economic theory suggests that peer effects are present in various contexts: the average behavior of a group influences the behavior of individual group members (Manski, 1993). An implicit assumption in most disclosure studies is that a firm's disclosure decision is primarily based on firm-specific factors (Leuz and Wysocki, 2016). However, since firms in the same industry are interdependent (Devenow and Welch, 1996; Lieberman and Asaba, 2006; Leary and Roberts, 2014), corporate disclosure decisions could also respond to peer firm disclosure. In this paper, I explore whether disclosures made by industry peers affect a firm's disclosure decisions. Additional cross-sectional tests delve into the mechanisms linking peer effects to disclosure decisions.

There are two potential mechanisms underlying peer effects in disclosure. First, peer effects would generate positive informational externalities if managers receive useful information from peer firm disclosure that complements their private information. Prior research suggests that managers are reluctant to disclose less precise information due to high uncertainty of the external environment (Waymire, 1985; Chen, Matsumoto, and Rajgopal, 2011; Kim, Pandit, and Wasley, 2015). However, according to mosaic theory, economic agents combine individual pieces of information to form a superior expectation and improve the precision of private information (e.g., Pozen, 2005; Cheynel and Levine, 2020).[1] A significant component of the external uncertainty of the firm arises from intense interactions with peers (Gaspar and Massa, 2006; Irvine and Pontiff, 2009; Peress, 2010). This kind of uncertainty is attributable to

[1] Pozen (2005, p.639) states that "the significance of one item of information may frequently depend upon knowledge of many other items of information." Shroff, Verdi, and Yost (2017, p.187) also note that "peer information can provide additional context for evaluating firm information, which can make these two sources of information complements rather than substitutes." Consistent with this idea, Jennings, Seo, and Soliman (2020) provide evidence that market participants use industry peers' firm-specific performance to evaluate their own-firm's performance.

factors beyond managers' control and thus hard to predict. Since peer firm disclosures could help managers understand the potential impact of peers' actions on a firm's competitive environment, managers would use peer firm disclosures to satisfy their need for information and develop their information mosaic. Thus, peer firm disclosures increase the precision of managerial private information, triggering voluntary disclosure by the firm (e.g., Verrecchia, 1990).

Second, peer firm disclosures would cause payoff externalities and impose additional costs on two factors that are not mutually exclusive: firm visibility and reputation in capital markets (e.g., Manski, 2000; Bikhchandani and Sharma, 2000).[2] Investors may not be aware of all firms in capital markets, but firms have incentives to expand their investor base in order to reduce the cost of capital and increase firm value (Merton, 1987). Consistent with this idea, prior research demonstrates that investors are attention-constrained and that firms use voluntary disclosures to attract investor attention and keep investors informed about the firm (Cohen and Frazzini, 2008; Barber and Odean, 2008; Engelberg and Parsons, 2011; Lou, 2014). Furthermore, voluntary disclosure is an essential signaling mechanism that builds a reputation for transparency in capital markets (Leland and Pyle, 1977; Trueman, 1986; Merton, 1987). Graham, Harvey, and Rajgopal (2005, p.54) report that "92.1% of the survey respondents believe that developing a reputation for transparent reporting is the key factor motivating voluntary disclosures." Therefore, if peer firms' increased disclosures were to shift investors' attention toward peer firms and lead investors to perceive non-disclosing firms as being less transparent and of lower quality, firms would respond to peer firm disclosures by changing their disclosure strategies in order to increase capital market benefits that would otherwise be lacking (e.g., Akerlof, 1970; Grossman and Hart, 1980; Grossman, 1981; Merton, 1987; Fishman and Hagerty, 1989).

[2] Manski (2000) states that payoff externalities occur when multiple agents share common resources (constraints interactions), meaning that one agent's action affects the other agents' payoffs or utilities. Prior research also shows that the payoff externalities could occur through reputation concerns (Bernheim, 1994; Scharfstein and Stein, 1990).

Indeed, motivated by potential peer effects in disclosure, prior research finds a significant commonality among firms' disclosure policies within industries (e.g., Botosan and Harris, 2000; Houston, Lev, and Tucker, 2010; Allee, Christensen, Graden, and Merkley, 2020). However, regressing firm *i*'s disclosure on peer firm *j*'s disclosure neither provides causal evidence for nor does it determine the economic magnitude of peer effects (Manski, 1993; Angrist, 2014). The identification problem arises from confounding (common) factors such as similar firm fundamentals in the same industry and common shocks. The direction and the magnitude of biases resulting from the common factors are ex-ante unclear. Firms in the same industry may adopt similar disclosure policies due to similar firm fundamentals, leading to an upward bias in the OLS regression. It is also possible that peer firm *j*'s disclosure pertains to common factors and firm *i*'s managers are already endowed with information regarding such common factors. In this case, managers are less likely to respond to peers' actions which do not update managerial private information (Manski, 2000; Bikhchandani and Sharma, 2000), introducing a downward bias in the OLS regression. Therefore, in order to address the identification problem, empirical investigation of peer effects requires an instrument able to capture variation in ex-ante peer characteristics that predate the outcome variable and are not affected by common shocks (Angrist and Pischke, 2008).

I use peer firms' lagged idiosyncratic equity return shocks (hereafter, peer idiosyncratic return shocks) as an instrument to identify peer effects in disclosure (Leary and Roberts, 2014). The identifying assumption is that the instrument affects firm disclosure primarily through its effect on peer firm disclosure (the exclusion restriction: see Section 2.2. for details). Stock price changes reflect the occurrence of economic events (Zhang, 2008; Owens, Wu, and Zimmerman, 2016), altering a firm's disclosure strategy. Stock price changes are also a significant

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consideration for managers in making disclosure decisions (e.g., Verrecchia, 1983; Sletten, 2012). Thus, the instrument is relevant in the current research setting.

I use the frequency of management forecasts as a primary proxy for firm disclosure. Management forecasts are pervasive and represent a broad spectrum of voluntary disclosure (Anilowski, Feng, and Skinner, 2007; Armstrong, Core, and Guay, 2014; Guay, Samuels, and Taylor, 2016). Moreover, management forecasts represent one of the crucial disclosure mechanisms by which firms can signal their quality, affect market expectations about firm value, and establish a reputation for firm transparency (Trueman, 1986; Williams, 1996). Firms within the same six-digit GICS industry are classified as peers.

Using 181,089 firm-quarter observations between 2002 and 2014, I find that the average frequency of peer firm management forecasts has a significantly positive impact on the frequency of own-firm management forecasts. The two-stage least squares (2SLS) estimation includes firm-specific characteristics, peer firm average characteristics, and firm and quarter fixed effects.[3] Results from a series of sensitivity and robustness tests suggest that the evidence of peer effects is robust and unlikely to be driven by common shocks. The peer effect estimate suggests that a one standard deviation increase in peer firm disclosure leads to a 0.412 standard deviation increase in a firm's disclosure.[4] I find that the coefficient estimate from OLS suggests that a one standard deviation increase in peer firm disclosure is associated with a 0.227 standard deviation increase in a firm's disclosure, which is approximately half the size of the economic

[3] This peer effect estimate represents the marginal effects due to firm fixed effects in the model. Thus, the long-lasting peer effects cannot be estimated in this regression. In Section 4.3, I examine intertemporal peer effects to shed light on the timing of peer responses.

[4] The peer effect estimate obtained from 2SLS may represent the Local Average Treatment Effect, i.e., LATE, rather than the Average Treatment Effect, i.e., ATE (e.g., Angrist and Imbens, 1994; Armstrong, 2013). In this case, the external validity of the peer effect estimate may be questionable. To alleviate this concern, I examine alternative peer effect estimates using alternative identification strategies and provide evidence that the economic magnitude of this peer effect estimate is consistent. I discuss this issue in detail in Section 4.2.

magnitude from the 2SLS estimation. Overall, findings suggest that peer effects represent a significant determinant in corporate disclosure decisions.

Having documented evidence on peer effects in disclosure, I perform cross-sectional tests to understand the underlying mechanisms. First, I expect to find stronger peer effects for firms that are exposed to greater uncertainty of the strategic environment, as the extent to which peer firm disclosure complements a firm's information set likely increases with the level of uncertainty driven by peers' strategic actions in the product markets. Using product market fluidity (Hoberg, Phillips, and Prabhala, 2014) and the Competitive Strategic Measure (Sundaram, John, and John, 1996; Chod and Lyandres, 2011), I find evidence consistent with my expectation. Second, I find that a firm is more likely to respond to peer firm disclosure when the firm's dependence on external financing is higher (Rajan and Zingales, 1998). Firms with greater dependence on external financing have stronger incentives to keep investors informed about them and signal their quality and transparency in capital markets in order to distinguish themselves from non-disclosing firms. As the potential costs of non-disclosure in response to peer disclosure would be greater for such firms, peer effects are more likely to alter those firms' disclosure strategies. Overall, the cross-sectional results shed light on the mechanisms behind peer effects in disclosure. Moreover, providing evidence of heterogeneous peer effects in the cross-section further reinforces the validity of the identification strategy.

I conduct additional analyses for further insights. First, I find that peer firm disclosure is more likely to provoke other firms' bad news disclosures. Prior research suggests that firms tend to hide bad news when market participants are uncertain whether firms are endowed with private information (Dye, 1985; Jung and Kwon, 1988). As such, if rational market participants also learn about whether a firm has information by observing peer firm disclosures (Dye and Sridhar,

1995), the reduced uncertainty of market participants would prompt bad news disclosure of the firm. Second, I find that a firm's disclosure induced by its peers improves the firm's stock liquidity. This result supports my argument that peer firm disclosure contributes to an improvement in the precision of managerial private information, which reduces information asymmetry and increases stock liquidity (Verrecchia, 2001). Third, I examine peer effects in other disclosure decisions. I find evidence of peer effects in firm-initiated press releases and voluntary 8-K filings, indicating that peer effects can be applied to a broad spectrum of disclosure decisions.

This study contributes to the literature in three ways. First, I provide empirical evidence on causal peer effects in corporate disclosure decisions. Prior theoretical research in the disclosure literature recognizes the importance of peers (Dye and Sridhar, 1995; Gul and Lundholm, 1995; Acharya, Demarzo, and Kremer, 2011; Heinle and Verrecchia, 2015). Most prior empirical research, however, does not consider peer effects and thus does not exploit the information in the industry.[5] Rather, researchers routinely include industry fixed effects in the regression model to sweep out industry averages (e.g., Li, 2010; Ali, Klasa, and Yeung, 2014). Findings in this paper suggest that firms do not make disclosure decisions in isolation but rather consider both firm-specific factors and peer firm disclosure; further, the extent to which a firm responds to peer firm disclosure varies within the industry.

Second, findings in this study indicate that industry peer disclosure is a complement to a firm's information environment, whereas most prior studies focus on substitution effects.

[5] Tse and Tucker (2010) find evidence on clustered earnings warnings in the same industry. However, I follow prior disclosure studies that typically exclude earnings warnings and thus do not examine peer effects in earnings warnings. Earnings warnings are a part of a firm's earnings announcement strategy rather than representing voluntary disclosure (e.g., Rogers and Stocken, 2005; Bonne and White, 2015). Tse and Tucker also argue that earnings warnings are clustered because managers want to attribute their earnings shortfalls to negative common external factors. In contrast, I eliminate the common external shocks in my model and examine other interactive mechanisms of peer effects.

Baginski and Hinson (2016) find that firms start providing quarterly management forecasts after the cessation of quarterly management forecasts by industry peers. Using private firms that raise public capital, Shroff et al. (2017) find that peer-initiated information and firm-initiated information are substitutes. Breuer, Hombach, and Müller (2019) also find that mandating firm disclosure reduces other firms' voluntary disclosures. The rationale behind this line of research is that industry peers have correlated fundamentals and are exposed to common industry shocks, which enables market participants to use peer firm disclosure as a substitute for their own-firm disclosure. In contrast, this paper focuses on a firm's disclosure decision in response to peer firm disclosures pertaining to their idiosyncratic shocks, which would convey new information that the firm would not have received in the absence of such peer firm disclosures. Managers would incorporate such peer information into their set of information to reduce the environmental uncertainty that they face, improving the quality of managerial private information.

Third, this study adds to a growing body of research examining peer effects in various corporate decisions. Prior studies document peer effects in capital structure choice (Leary and Roberts, 2014), stock split decisions (Kaustia and Rantala, 2015), risk aversion and trust (Ahern, Duchin, and Shumway, 2014), executive compensation and acquisitions strategy (Shue, 2013), entrepreneurship (Lerner and Malmendier, 2013), financial misconduct (Parsons, Sulaeman, and Titman, 2018), and payout policy (Grennan, 2019).[6] I contribute to this line of research by providing empirical evidence of peer effects in disclosure decisions—one of the significant corporate capital market activities affecting firm value and resource allocative efficiency.

[6] Another distinct stream of research examines the diffusion of corporate practices through various common networks (e.g., Chiu, Teoh, and Tian, 2013; Brown and Drake, 2014; Cai, Dhaliwal, Kim, and Pan, 2014). The primary focus of this research is the shared networks as a mechanism diffusing corporate policies. Note that diffusion occurs even in the absence of causal interactions among firms. In contrast, as Manski (1993) points outs, the peer effects literature focuses on direct interactive mechanisms and economic incentives behind the interactions.

2. Identification of Peer Effects

2.1. Disclosure model and definitions of variables

This subsection describes the empirical disclosure model. I rely on Manski (1993), who provides the following framework for estimating peer effects.

$$y = \alpha + \beta E(y \mid x) + \gamma E(Z \mid x) + \delta Z + \eta x + u \quad (1)$$

The dependent variable, y, is an outcome variable of interest; x indicates a reference group, Z represents observable individual characteristics, and u represents unobservable individual factors. If the parameters are non-zero, both β and γ represent social interaction effects: the effect of peer firm actions (peer effects) and the effect of peer firm characteristics (contextual effects), respectively. However, researchers cannot estimate this model due to correlated effects, "wherein individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments" (Manski, 1993, p.533). That is, the identification problem arises from the fact that the outcome variable of interest is regressed on the average outcome variable of the group, which can be mechanically correlated with the former. Hence, an OLS regression that does not consider this endogeneity issue does not provide evidence of peer effects (Manski, 1993, Angrist and Pischke, 2008; Angrist, 2014). Manski (1993, p.532) refers to this issue as the reflection problem, because "the problem is similar to that of interpreting the almost simultaneous movements of a person and his reflection in a mirror." Thus, a clear identification strategy is required to overcome the reflection problem. I discuss this in detail in Section 2.2.[7]

[7] Manski (1993) shows that researchers can detect the initial evidence on the existence of social interaction effects from a reduced-form linear regression where the dependent variable is the outcome variable of interest and the primary explanatory variable is peers' exogenous characteristics. The reduced-form regression, however, cannot disentangle the peer effects (i.e., actions) from the contextual effects (i.e., characteristics) because the coefficient

Based on Equation (1), I estimate the following empirical model to examine peer effects in disclosure decisions.

$$MF\ FREQ_{i,t} = \alpha + \beta\, P\_MF\ FREQ_{-i,j,t} + \Sigma\gamma\, P\_Controls_{-i,j,t-1} + \Sigma\delta\, Controls_{i,t-1} + \mu_i + \varphi_t + \varepsilon_{i.t} \quad (2)$$

The dependent variable, $MF\ FREQ_{i,t}$, is the frequency of management forecasts for firm *i* during quarter *t* (i.e., all annual or quarterly management forecasts including revenues, capital expenditures, earnings per share, and so forth). Following prior studies, I count multiple management forecasts issued on the same day as a single forecast event (e.g., Bonne and White, 2015) and do not include forecasts made after the fiscal quarter end, that is, earnings warnings (Rogers and Stocken, 2005; Bonne and White, 2015).

The main explanatory variable of interest is $P\_MF\ FREQ_{-i,j,t}$, which is the average frequency of management forecasts of peer firms in the same industry *j* as firm *i* in quarter *t*. I exclude firm *i*'s management forecasts in computing the average frequency to avoid a mechanical correlation. I include firm-specific control variables that are regarded as primary determinants of firms' disclosure decisions (e.g., Ajinkya, Bhojraj, and Sengupta, 2005; Balakrishnan, Core, and Verdi, 2014; Boone and White, 2015). Appendix A provides details of the variable constructions. I also include peer firm averages to control for the contextual effects and denote them by the prefix "*P_*". I use the six-digit GICS industry classifications to identify industry peers.[8] I include firm fixed effects to control for time-invariant firm-specific factors that

estimate from the reduced form represents a composite parameter of β and γ. Specifically, the reduced-form regression identifies the following composite parameters: $y = \alpha / (1 - \beta) + [(\gamma + \beta\eta) / (1 - \beta)]'\ E\ (Z \mid x) + [\delta / (1 - \beta)]'\ x + \eta'\ Z$. If $\beta \neq 1$, then a statistically significant coefficient on peers' exogenous characteristics, $E\ (Z \mid x)$, provides evidence of the existence of social interaction effects because the coefficient will be zero if both γ and $\beta\eta$ are zero. See Manski (1993) and Leary and Roberts (2014) for detailed derivations.

[8] Bhojraj, Lee, and Oler (2003) document that firms in the same GICS classifications have higher returns-on-assets and growth correlations than firms that share the same SIC, NAICS, or Fama-French classification codes. They conclude that GICS is a better industry classification to identify peer firms that compete in similar product markets.

are unobservable but might affect firm disclosure decisions (Gormley and Matsa, 2013).[9] I also include calendar quarter fixed effects to control for time-variant trends in disclosure tendencies and unmeasured common shocks. Standard errors are robust to heteroskedasticity and clustered by firm, allowing within-firm dependence of residuals (Petersen, 2009; Leary and Roberts, 2014; Grennan, 2019).

2.2. Identification strategy: Peer firms' lagged idiosyncratic equity return shocks

The identification strategy of this paper is to use peer firms' lagged idiosyncratic equity return shocks as a source of exogenous variation in peer firm characteristics (Manski, 1993; Leary and Roberts, 2014). To isolate the idiosyncratic component of equity returns, I follow Leary and Roberts (2014) and use the following asset pricing model:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT}(rm_t - rf_t) + \beta_{i,t}^{IND}\left(\bar{r}_{-i,t} - rf_t\right) + \eta_{i,t} \tag{3}$$

where $r_{i,t}$ is the raw return for firm i over month t, $(rm_t - rf_t)$ is the excess market return over month t, and $\left(\bar{r}_{-i,t} - rf_t\right)$ is the excess return on an equal-weighted industry portfolio excluding firm i's return over month t.

To construct the instrument, I take the following steps. First, I estimate Equation (3) for firm i on a rolling quarterly basis using the past 60 monthly stock returns preceding the fiscal quarter (a minimum of 24 observations is required). Estimated factor loadings are firm-specific and time-variant. Second, the factor loadings are multiplied by monthly factor returns over the fiscal quarter to compute monthly expected returns. Third, I compute monthly idiosyncratic returns over the fiscal quarter by taking the difference between monthly raw returns and monthly expected returns. Fourth, to be consistent with the periodicity of accounting and disclosure variables, I compound monthly idiosyncratic returns over the fiscal quarter to obtain quarterly

[9] Including firm fixed effects also allows me to identify within-firm variation in disclosure decisions; in this way, the estimated coefficient β will capture changes in own-firm disclosure frequency in response to changes in the average frequency of peer firm disclosure (Gormley and Matsa, 2013).

idiosyncratic returns. Finally, I compute the conditional average of peer firms' quarterly idiosyncratic returns in the same industry as firm *i* (excluding firm *i*) and lag this variable by one period to obtain the instrument. The lag is essential because the instrument should lead to peer firm disclosure.

Panel A of Table 1 reports estimation statistics. The descriptive statistics are similar to those reported in Leary and Roberts (2014). The mean (median) values of the factor loading on excess market returns and excess industry returns are 0.218 (0.175) and 0.795 (0.749), respectively, and the average adjusted R-squared is approximately 25.6%.

As noted by Leary and Roberts (2014), conditional on the adequately specified asset pricing model, the conditional average of peer firm idiosyncratic equity returns excluding firm *i*'s returns will not necessarily equal zero. First, the average of peer firms' idiosyncratic returns excludes firm *i*'s return in its construction. Second, and more importantly, this is a firm-specific conditional average of peer firms' idiosyncratic returns (conditional on industry and calendar quarter). As noted, the quarterly idiosyncratic returns are computed using monthly idiosyncratic returns that are firm-specific and time-variant because each firm's monthly factor loadings are estimated separately by using rolling regressions. This estimation assumes that the extent to which firms are exposed to industry- and market-wide shocks is not the same across firms within the industry over time.

Figure 1 illustrates the distribution of the average of quarterly peer idiosyncratic return shocks. Panels A, B, C, and D use peer groups based on GICS sub-industries (eight-digit), GICS industries (six-digit), GICS industry groups (four-digit), and GICS industry sectors (two-digit), respectively. Panel A shows that the unconditional mean of the peer firm idiosyncratic returns is close to zero. However, there is considerable variation in the conditional averages, which are not

equal to zero. As expected, the variation decreases as I move from the narrower industry definition in Panel A to the broader industry definition in Panel D. To ensure that the instrument has sufficient variation and the industry consists of appropriately close peers, I use the six-digit GICS, which is the primary GICS classification scheme.

I expect that peer idiosyncratic return shocks can satisfy the relevance condition. Shocks to stock price represent the occurrence of economic events that could affect a firm's subsequent voluntary disclosure decisions (Zhang, 2008; Owens et al., 2016). Also, prior studies suggest that performance shocks affect corporate managers' incentives to provide discretionary disclosures to adjust market expectations (King, Pownall, and Waymire, 1990; Versano and Trueman, 2017).[10] Regarding the direction of the relationship, prior research provides mixed evidence. For example, Sletten (2012) finds a negative relationship between stock price and disclosure, because managers alter their disclosure strategy in response to decreases in a firm's stock price. Balakrishnan et al. (2014) also document a negative relationship between exogenous changes in firms' asset values and changes in voluntary disclosure activities. However, negative performance shocks may also discourage voluntary disclosure if negative shocks incentivize managers to withhold bad news disclosures (e.g., Kothari, Shu, and Wysocki, 2009). Managers might also respond to positive performance shocks and disclose private information to separate themselves from the pool (e.g., Akerlof, 1970). Miller (2002) finds evidence that firms experiencing an increase in earnings performance are more likely to increase disclosures. Guay et al. (2016) find similar evidence that the stock return has a significantly positive impact on the

[10] Healy and Palepu (2001, p.421) hypothesize that "given the risk of job loss accompanying poor stock and earnings performance, managers use corporate disclosures to reduce the likelihood of undervaluation and to explain away poor earnings performance." This hypothesis is consistent with survey evidence indicating that approximately 48.4% of CFOs use discretionary disclosures to correct an undervalued stock price (Graham et al., 2005).

frequency of firm disclosure.[11] In contrast, positive performance shocks may lead to less disclosure if the positive shocks increase the proprietary costs of disclosure (Verrecchia, 1983). Overall, it is not conclusive whether firm performance is positively or negatively correlated with voluntary disclosure. However, given the ample evidence establishing a link between changes in stock price and disclosure at the firm level, I expect the relationship to hold at the aggregate peer level, satisfying the instrument relevance (Wooldridge, 2010; Leary and Roberts, 2014).

I expect that the instrument could satisfy the exclusion restriction, which requires the instrument to be correlated with the outcome variable only through its impact on the endogenous variable (i.e., the instrument is not correlated with the error terms in the second stage; see Wooldridge, 2010, for details). To the extent that the asset pricing model allows for the isolation of the idiosyncratic component of stock returns, the instrument aggregates and captures peer firms' idiosyncratic return shocks, which will enable me to identify any exogenous variation of peer firm disclosures that are not driven by common industry- and market-wide shocks.

However, it is also possible that Equation (3) cannot completely eliminate systematic returns and thus that it fails to isolate purely idiosyncratic returns. For instance, Equation (3) does not include standard risk factors (e.g., Fama and French, 2018). Also, there may exist some unobservable common factors that are not captured by the excess industry and market returns in Equation (3). If those common factors remaining in the instrument are relevant to the focal firm's disclosure determinants, this leads to the violation of the exclusion restriction and thus yields inconsistent IV estimates (i.e., see Equation (5) in Larker and Rusticus, 2010, p.190). This

[11] Furthermore, if abnormal stock price run-up increases the ex-ante litigation risks of the firm (Kim and Skinner, 2012), managers can use voluntary disclosure to reduce the litigation risks (Hirst, Koonce, and Venkataraman 2008; Cao and Narayanamoorthy, 2011). Kim and Skinner (2012) find a significantly positive coefficient on the abnormal return variable in period *t-1* but a significantly negative coefficient on the abnormal return variable in period *t* in modeling the ex-ante litigation risk in period *t*. Kim and Skinner (2012, p.305) interpret this evidence as "strong prior period stock performance increases the likelihood of a reversal of fortune, which then triggers litigation."

possibility cannot be completely ruled out, as the exclusion restriction cannot be explicitly tested (Wooldridge, 2010).

To mitigate concerns related to the asset pricing model's failure to eliminate common factors, first, I examine the pairwise correlation coefficients and *t*-statistics of a firm's idiosyncratic returns with its industry peers' idiosyncratic returns. Panel B of Table 1 demonstrates the distribution of the intra-industry correlation coefficients and *t*-statistics of stock returns for 6,473 sample firms during the sample period between 2002 and 2014. To facilitate comparison, I also examine the correlation coefficients of raw returns. I find that the intra-industry correlation coefficients (*t*-statistics) of raw returns are on average 0.216 (13.676), indicating that the raw returns are significantly correlated within the industry due to common factors. In contrast, the correlation coefficients (*t*-statistics) of idiosyncratic returns are on average -0.004 (-0.031), suggesting that the parsimonious asset pricing model performs well in eliminating the effects of common factors on raw returns. Figure 2 illustrates the distribution of stock returns' pairwise correlation coefficients in Panels A and B; Panels C and D contain corresponding *t*-statistics. The figures again confirm that the parsimonious asset pricing model reasonably purges the systematic components of realized returns.

Second, I examine whether the findings in this paper are robust to using an alternative instrument obtained from the augmented asset pricing model that includes the standard common risk factors. Specifically, based on the six-factor asset pricing model (Fama and French, 2018), I include additional risk factors in Equation (3), that is, size (*SMB*), value (*HML*), profitability (*RMW*), investment (*CMA*), and momentum (*UMD*) factors, to construct the alternative instrument. I tabulate and describe the estimation results in the online appendix of the paper. I find that the results are largely similar to the findings obtained based on the parsimonious asset

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pricing model employed in the paper, and thus all inferences are unaffected. In Sections 3 and 4, I conduct additional robustness tests to further alleviate the identification concerns.

3. Data and Descriptive Statistics

I obtain data for the main tests from the CRSP, COMPUSTAT, and I/B/E/S databases, collecting all management forecasts from the I/B/E/S guidance database. 8-K filing data are downloaded from the WRDS SEC Analytics Suite. Firm-initiated press release data are obtained from RavenPack. I collect institutional ownership data from the Thomson Financial 13F database. I require at least ten firm-quarter observations in each industry for each fiscal quarter. I only keep firm-quarter observations with fiscal quarter end months of March, June, September, and December to ensure that firms' disclosure variables, return shocks, and accounting variables are aligned with those of their peers (Kothari, Lewellen, and Warner, 2006).

Requiring firm-quarter observations to have sufficient data to calculate the independent and dependent variables in the regressions, my final sample consists of 181,089 firm-quarter observations over the sample period between 2002 and 2014. I do not include forecasts made before 2002 to avoid any confounding effects of disclosure regulation (i.e., RegFD) on peer effects. The number of observations for any particular test varies depending on the availability of data necessary for each test. I winsorize all ratios at 1% and 99% levels to mitigate the influence of extreme observations.

Table 2 presents descriptive statistics for the primary variables. The average number of management forecasts ($MF\ FREQ_{i,t}$) is 0.501, suggesting that, on average, firms have one management forecast event over two fiscal quarters. I note that the mean and the median values of other variables are similar to those reported in prior research. For example, the mean (median)

values of market-to-book ratio, return on assets, and institutional ownership are 1.790 (1.312), -0.006 (0.005), and 0.496 (0.523), respectively, which are similar to those found in prior studies (e.g., Bergman and Roychowdhury, 2008). I do not tabulate peer firm average characteristics for the sake of brevity, but the mean values of firm-specific variables and the corresponding peer firm averages are the same, given the construction of the averages.

Table 3 provides correlations among the main variables. In Panel A, $MF\ FREQ_{i,t}$ is positively correlated with $P\_MF\ FREQ_{-i,j,t}$ (correlation of 0.37), suggesting that disclosure activities in the same industry are significantly correlated.[12] $MF\ FREQ_{i,t}$ is positively correlated with firm size ($Size_{i,t-1}$), profitability ($Return\ on\ Assets_{i,t-1}$), the number of analysts following the firm ($Coverage_{i,t-1}$), and the fraction of shares owned by institutions ($INSTOWN_{i,t-1}$), and it is negatively correlated with the level of R&D expenditures ($R\&D_{i,t-1}$) and earnings volatility ($Earning\ Volatility_{i,t-1}$). These correlations are consistent with the idea that the disclosure frequency increases with demand for information and earnings performance (Miller, 2002; Ajinkya et al., 2005; Boone and White, 2015) but decreases with proprietary costs and information uncertainty (Verrecchia, 1983; Waymire, 1985).

In Panel B, I examine the correlations between firm *i*'s stock returns and the instrument. Similar to the result in Panel B of Table 1, I find that the contemporaneous correlation between the average of peer firm raw returns ($P\_Return_{-i,j,t-1}$) and own-firm raw returns ($Return_{i,t-1}$) is equal to 0.46, suggesting that stock returns in the same industry are highly correlated due to common factors. However, the contemporaneous correlation between the instrument, i.e., the

[12] The correlation between the instrument and the peer firm disclosure is -0.02, which may cause a weak instrument problem (e.g., Wooldridge, 2010; Larker and Rusticus, 2010). However, a just-identified 2SLS estimation produces a median unbiased estimate when the first-stage F-statistic rejects the null hypothesis that the instrument is weak (Stock and Yogo, 2005; Angrist and Pischke, 2008; Cameron and Trivedi, 2005). It is also noteworthy that if (1) the instrument is truly irrelevant, or (2) the instrument has a non-zero correlation with the endogenous variable but the first-stage F-statistics are low, then the 2SLS estimation is biased toward OLS (Angrist and Pischke, 2008). I also perform additional tests to ensure that the inferences are weak-instrument robust. See Section 4.2 for more detail.

average of peer firm idiosyncratic returns in quarter *t-1* (*P_Return Shock*$_{-i,j,t-1}$), and *Return*$_{i,t-1}$ is shrunk substantially and equal to 0.09. The contemporaneous correlation between the instrument and own-firm idiosyncratic returns in quarter *t-1* (*Return Shock*$_{i,t-1}$) is further reduced and equal to -0.02. More importantly, the correlation between the instrument and own-firm raw returns in quarter *t* (*Return*$_{i,t}$), in which the disclosure variable is measured, is equal to 0.00 and statistically insignificant. This correlation suggests that the instrument has a limited spillover effect on own-firm stock return, and thereby the instrument is less likely to give rise to confounding effects in quarter *t*. To control for the remaining correlation in the firm's stock return, I include the firm-specific idiosyncratic equity returns in all regression analyses (Leary and Roberts, 2014). Hence, combined with control variables and fixed effects, the identifying variation of peer effects is the within-firm time-series variation in the component of peer firm idiosyncratic returns shocks that are orthogonal to covariates included in the model.

To ensure that the instrument is generally not correlated with observable firm-specific fundamentals affecting corporate disclosure decisions, I estimate partial correlations between the instrument and the firm-specific characteristics. I present the results in Panel C of Table 3, demonstrating that the instrument is generally not correlated with a firm's primary determinants of disclosure. In some cases, the instrument is statistically correlated with some firm characteristics. For example, Column 1 shows that *Return on Assets*$_{i,t-1}$ (-0.005) and *Coverage*$_{,t-1}$ (0.000) are statistically correlated with the instrument at the 10% level. Although these partial correlations are statistically significant, the economic magnitudes are close to zero. (Note that these remaining correlations are not problematic, because they are controlled for in the IV estimation.) The results are similar when I use one-period-ahead peer idiosyncratic return shocks (*P_Return Shock-*$_{i,j,t}$) as a dependent variable in Column 2. These results are reassuring, because

they suggest that the instrument is not a better measure of firm *i*'s disclosure determinants than other determinants, supporting the validity of the instrument (Leary and Roberts, 2014; Jiang, 2017).

4. Empirical Results

4.1. The effect of the instrument on firm disclosure

The identification assumption is that the instrument affects firm disclosure primarily through its impact on peer firm disclosure. I begin the empirical analysis by validating this identifying assumption. Similar to Leary and Roberts (2014), I perform two-way dependent sorts using quintiles of peer firm disclosure ($P\_MF\ FREQ_{-i,j,t}$) and quintiles of the instrument ($P\_Return\ Shock_{-i,j,t-1}$) and examine whether firm disclosure is sensitive to either peer firm disclosure or the instrument, holding the other fixed.

Table 4 presents the results. In Panel A, all firm-quarter observations are first sorted into quintiles based on the instrument ($P\_Return\ Shock_{-i,j,t-1}$), as denoted in the first column. Each quintile is further conditionally sorted into quintiles based on peer firm disclosure ($P\_MF\ FREQ_{-i,j,t}$) as denoted in the top row. This process generates 25 groups. I then calculate the average frequency of management forecasts for each group. Panel A shows that the average frequency of management forecasts increases with peer firm disclosure quintile, holding the instrument fixed. For example, holding the third quintile of $P\_Return\ Shock_{-i,j,t-1}$ fixed, the average frequency of management forecasts increases from 0.070 to 0.856 when moving from the first quintile to the fifth quintile of $P\_MF\ FREQ_{-i,j,t}$, and the difference between those two quintiles is significantly different from zero at the 1% level (see "High - Low" column).

In Panel B, I examine whether the frequency of own-firm disclosure increases with the instrument, holding peer firm disclosure fixed. First, all firm-quarter observations are sorted into quintiles based on peer firm disclosure ($P\_MF\ FREQ_{-i,j,t}$), as denoted in the first column. Each quintile is (conditionally) further sorted into quintiles based on the instrument ($P\_Return\_Shock_{-i,j,t-1}$), as denoted in the top row. Similar to Panel A, I compute the average frequency of management forecasts for each intersection of quintiles. Panel B indicates that the average frequency of management forecasts does not vary with the instrument, holding peer firm disclosure fixed. For example, in the third quintile of $P\_MF\ FREQ_{-i,j,t}$, the average frequency of management forecasts for the first quintile of the $P\_Return\_Shock_{-i,j,t-1}$ variable is 0.506, that of the fifth quintile of $P\_Return\_Shock_{-i,j,t-1}$ is 0.524, and the difference between those two quintiles is insignificantly different from zero.

In an untabulated test, I use the multivariate regression framework to corroborate the above findings (e.g., Kaustia and Rantala, 2015; Jiang, 2017). Specifically, I regress firm disclosure on the instrument and peer firm disclosure and find that the coefficient on the instrument is statistically not different from zero, consistent with the results in Table 4.[13] The above findings suggest that peer firm disclosure is the primary channel through which peer idiosyncratic return shocks affect firm disclosure.

4.2. IV estimates of peer effects in corporate disclosure decisions

Panel A of Table 5 reports the estimation results of peer effects. I first report the OLS results in Column 1 for the benchmark.[14] Similar to prior studies (Botosan and Harris, 2000; Houston et al., 2010; Allee et al., 2020), $P\_MF\ FREQ_{-i,j,t}$ is significantly positively associated

[13] In the reduced-form regression without the peer firm disclosure control variable, the coefficient on the instrument is significantly negative at the 1% level, suggesting the existence of peer effects in disclosure (Manski, 1993; Angrist and Pischke, 2008; Leary and Roberts, 2014). See footnote 7 for more details.

[14] Note that I do not use a non-linear model with firm and quarter fixed effects because of the incidental parameters problem (Neyman and Scott, 1948).

with $MF\ FREQ_{i,t}$ at the 1% level (coefficient 0.555, t=20.095). The coefficient estimate suggests that a one standard deviation increase in $P\_MF\ FREQ_{-i,j,t}$ is associated with a 0.227 standard deviation increase in $MF\ FREQ_{i,t}$. As noted in Section 2.1., however, this finding cannot be attributed to causal peer effects due to the reflection problem (Manski, 1993; Angrist, 2014). As for the other significant variables, a one standard deviation increase in firm size is associated with an increase of 0.289 standard deviations in $MF\ FREQ_{i,t}$, and a one standard deviation increase in analyst following is associated with an increase of 0.083 standard deviations in $MF\ FREQ_{i,t}$. It is noteworthy that the coefficients on other peer firm characteristics and behaviors are largely insignificant and statistically indistinguishable from zero except for the peer firm averages of R&D ($P\_R\&D_{-i,j,t-1}$), leverage ($P\_Leverage_{-i,j,t-1}$), and institutional ownership ($P\_INSTOWN_{-i,j,t-1}$). However, the economic magnitudes of those significant variables are also very small. A one standard deviation increase in $P\_R\&D_{-i,j,t-1}$, $P\_Leverage_{-i,j,t-1}$, and $P\_INSTOWN_{-i,j,t-1}$ is associated with 0.048, 0.022, and -0.048 standard deviation increase in $MF\ FREQ_{i,t}$, respectively.[15] These results suggest that the peers' other actions or characteristics (i.e., contextual effects) do not play a significant role in the current research setting (Manski, 1993).

Columns 2 and 3 demonstrate the estimation results from 2SLS estimation wherein the endogenous variable is the average frequency of peer firm management forecasts for firm i in industry j in period t (excluding firm i), and the instrument is peer idiosyncratic return shocks for firm i in industry j in period t-1 (excluding firm i). Column 2 presents the first-stage results. The partial correlation between the instrument and the peer firm disclosure variable is statistically significant (coefficient=-0.154, t=-13.451), indicating that the instrument satisfies the relevance condition (Wooldridge, 2010). I also note that the first-stage F-statistic is equal to 314.889,

[15] Peer firm averages are lagged by one period to be consistent with other control variables in the regression model. Untabulated results show that the coefficients have similar economic magnitudes when contemporaneous peer firm averages are used in the model.

indicating that the instrument easily passes the weak instrument test (Stock and Yogo, 2005; Cameron and Trivedi, 2005; Wooldridge, 2010).

Column 3 presents the second-stage results. There is a significantly positive coefficient on $P\_MF\ FREQ_{-i,j,t}$ at the 1% level, providing evidence of causal peer effects in disclosure decisions. The coefficient estimate suggests that a one standard deviation increase in peer firm disclosure is associated with a 0.412 (=1.011×0.301/0.738) standard deviation increase in $MF\ FREQ_{i,t}$.[16] Below the *t*-statistic, I provide a 95% confidence interval for the peer effect estimate that is robust to weak instruments (Moreira, 2001, 2003; Moreira and Poi, 2003; Finlay and Magnusson, 2009; Chaney, 2013), which is centered around the point estimate.[17] As for the other significant variables, a one standard deviation increase in firm size (analyst following) leads to an increase of 0.258 (0.085) standard deviations in $MF\ FREQ_{i,t}$, suggesting that the marginal effect of the peer firm disclosure exceeds most other firm-specific disclosure determinants.[18] I also find that the marginal effects of other peer firm averages (i.e., contextual effects) are generally insignificant, consistent with the results in Column 1. Overall, these findings in Panel A suggest that the peer effect is a significant determinant of disclosure.

[16] I acknowledge that this peer effect estimate might not represent the population's ATE but might instead represent LATE if there exist heterogeneous treatment effects in the observed data (e.g., Armstrong, 2013). Therefore, I add as a caveat the possibility that the coefficient estimates on other disclosure determinants represent ATEs, and thus it may not be appropriate to compare the economic magnitude of the peer effect estimate with those of other coefficient estimates. To alleviate this concern of external validity, I perform additional sensitivity tests, which are discussed shortly.

[17] The STATA post-estimation 'weakiv' complements 'condivreg,' which implements the conditional tests in Moreira (2001, 2003) and offers weak instrument robustness tests for a larger class of models. Specifically, the command calculates the Lagrange multiplier or minimum distance versions of weak instrument robustness tests of the endogenous variable's coefficient in an IV estimation. If a model is just-identified, the confidence interval is derived from the Anderson-Rubin (AR) test statistic as described in Finlay and Magnusson (2009).

[18] This economic magnitude of the peer effect estimate is consistent with those in prior studies. For example, Grennan (2019) examines peer effects in dividend payouts and finds that the marginal effect is larger than many previously identified dividend determinants such as profitability and investment. Leary and Roberts (2014) also find that the marginal effects of peers' capital structure changes exceed those of most other firm-specific determinants. Kaustia and Rantala (2015) estimate the economic magnitude of peer effects in stock split decisions to be comparable with an increase of 40–50% in the stock price. Survey evidence suggests that the behavior of competitors is an important consideration in CFOs' financial decision-making (Graham and Harvey, 2001).

One caveat to the identification strategy of this paper is that disclosure may not be the only outcome variable that firms change in response to their performance shocks. It is possible that peer firm idiosyncratic equity returns affect peers' other competitive actions such as investment, which in turn could affect the focal firm's disclosure decisions. Thus, an alternative explanation would be that the peer effect documented in this paper could be driven by peers' other competitive actions rather than peer firm disclosure. Thus, controlling for peers' actions or characteristics in 2SLS is crucial to rule out this alternative explanation. Also, the findings in Column 1 of Panel A are reassuring because they suggest that peers' other actions or characteristics have minimal impact on firm disclosure. To further reduce this concern, I perform a placebo test based on 2SLS where the endogenous variable is peer firm investment and the instrument is peer firm idiosyncratic return shocks. The untabulated result shows that peer firm investment does not affect firm disclosure, suggesting that peer firms' other actions do not play a significant role in affecting firm disclosure in the current research setting.[19]

In addition, in Panel B, I perform several robustness checks by including additional control variables motivated by alternative explanations. First, I replace own-firm idiosyncratic return shock in period *t-1* with lagged and contemporaneous own-firm raw returns and find a similar peer effect estimate. The alternative explanation is that the instrument might contain some systematic shocks in period *t* or in period *t-1* that give rise to possible confounding effects. Given that the systematic shocks should be better captured by the firm's raw returns rather than its peers' lagged idiosyncratic returns, this finding should alleviate such concerns. This finding also suggests that potential systematic shocks that might remain in the instrument do not

[19] Similar to the analyses in Table 4, I also examine whether peer firm idiosyncratic return shocks are associated with own-firm disclosure only through their effects on peer firm investments. Unlike the results in Panel B of Table 4, I find that the instrument is sensitive to firm disclosure even after holding the peer firm investment constant (untabulated), indicating that the exclusion restriction may not hold in this alternative research setting.

constitute the identifying variation. Second, I additionally include more control variables that are known to affect a firm's disclosure decisions and their corresponding peer firm averages in order to mitigate concerns that some omitted firm-specific factors and peer firm actions may be correlated with peer firm disclosure, driving peer effects in disclosure. Specifically, I include the following additional control variables: an indicator for firms with losses, stock return volatility, an indicator for net equity issuance exceeding 1% of total assets, an indicator for net debt issuance exceeding 1% of total assets, and litigation risks based on Kim and Skinner (2012). Column 2 indicates that the peer effect estimate is robust to the inclusion of these additional control variables and peer firm averages in the model. Third, I include contemporaneous control variables in the regression to examine whether the timing of variable measurement affects the identification. Column 3 shows that the coefficient on the peer firm disclosure variable remains the same. Lastly, in Column 4, I combine all robustness tests in Columns 1–3 and find a consistent estimate of peer effects in disclosure.

To further mitigate concerns related to the identification strategy, I follow suggestions presented in Larker and Rusticus (2010) and Angrist and Pischke (2008) and conduct sensitivity tests: I use an overidentified model with multiple weak instruments and compare the peer effect estimate obtained from the overidentified 2SLS with that of the limited information maximum likelihood (LIML). Specifically, I include three additional lags of peer idiosyncratic return shocks as potential candidates for weak instruments because I expect the correlation between peer firm idiosyncratic return shocks and peer firm disclosure to decrease when there is a time interval between them. The idea is that if the estimation uses multiple weak instruments, the 2SLS estimation leads to a biased estimate toward OLS. In contrast, LIML is less precise but less

biased than 2SLS in such a situation (Angrist and Pischke, 2008). Therefore, if the former produces an estimate similar to the latter, this suggests that the instrument is valid.

Panel C of Table 5 shows the results. Column 1 indicates that peer idiosyncratic return shocks in quarter *t-4* in the first stage are a weak and invalid instrument (the first-stage F-statistic is 1.885). In Column 2, I use peer idiosyncratic return shocks in quarter *t-3*, and I find that this variable it is significantly negatively associated with peer firm disclosure at the 1% level. The first-stage F-statistic is slightly increased and marginally exceeds the critical value (16.864). However, I do not find significant evidence of peer effects in Column 2. In Column 3, using peer idiosyncratic return shocks in quarter *t-2*, I start finding statistically significant evidence of peer effects (the first-stage F-statistic is 161.543). Column 4 shows the primary result of the paper (i.e., Panel A of Table 5). In Column 5, I use all four lags of peer idiosyncratic return shocks as multiple instruments and find that the estimate is similar. The first-stage F-statistic in Column 5 equals 137.358, which is less than that of Column 4 (314.889) because the F-statistics vary inversely with the number of instruments in the over-identified model (Angrist and Pischke, 2008). Note that the peer effect estimates in Columns 3–5 are reasonably consistent even though I use different sets of instrumental variables. This is consistent with the instrument's validity (Larker and Rusticus, 2010). It is also consistent with the just-identified model producing an approximately median unbiased IV estimate (Angrist and Pischke, 2008).[20] Therefore, these findings further reduce identification concerns. In Column 5, I report the peer effect estimate based on the LIML estimator using four lags of peer firm idiosyncratic return shocks. The LIML estimate is almost identical to the overidentified 2SLS estimate. Overall, this result substantiates the relevance and validity of the instrument in the current setting.

[20] In untabulated tests, I further increase the instrument relevance by decomposing the peer firm idiosyncratic return shocks into positive and negative values and adding more lags. I find that the peer effect estimates remain almost the same. This finding further ensures the validity of the instrument and consistency in the peer effect estimate.

To bolster my argument that the peer effect is not driven by common shocks, I follow Leary and Robert (2014) and use the peers' customer-supplier links for identification. Peer firms in this analysis are defined as the subset of firms in the same industry as firm *i* with at least one customer who satisfies the following criteria: the customer is in an industry different from firm *i*, the customer is not a customer of firm *i*, and the customer accounts for at least 10% of the peer firm's sales. The instrument for peer firm disclosure is the average idiosyncratic return shocks to those customers. Thus, the identifying variation now comes from idiosyncratic return shocks to peer firms' customers operating in a different industry with no supply chain relationship with firm *i*. In addition, similarly to Leary and Roberts, I can now control for firm *i*'s industry-average returns.

Panel D demonstrates the estimation results from 2SLS. In Column 2, I find that the second-stage coefficient on $P\_MF\ FREQ_{-i,j,t}$ is equal to 0.627, which is statistically significant at the 5% level (t=2.349). The coefficient estimate suggests that a one standard deviation increase in $P\_MF\ FREQ_{-i,j,t}$ is associated with a 0.355 standard deviation increase in $MF\ FREQ_{i,t}$. This economic magnitude of the peer effect estimate is similar to that reported in Panel A (0.412), alleviating concerns regarding external validity. Furthermore, this finding suggests that common industry shocks do not drive peer effects in disclosure in my setting.

4.3. Peer effects on future disclosures

Next, I examine whether peer firm disclosure in the current period affects own-firm disclosure in future periods. In the main empirical model, both own-firm and peer firm disclosures are measured contemporaneously. This measurement make possible a robust identification of peer effects by restricting the amount of time available for firms to react to each other and decreasing the likelihood of potential confounding effects (Leary and Roberts, 2014).

Nevertheless, this measurement does not provide any insights as to whether the magnitude of peer effects varies over a time interval. Such variation might exist if reputation concerns and adverse selection problems resulting from non-disclosure in capital markets force firms to respond to peer firm disclosure instantaneously. Thus, I expect to observe that the effects of the current period's peer disclosure should be strongest for contemporaneous own-firm disclosure and then decrease over time.

Table 6 uses $MF\ FREQ_{i,t+1}$, $MF\ FREQ_{i,t+2}$, and $MF\ FREQ_{i,t+3}$ as dependent variables in Column 1, Column 2, and Column 3, respectively. All other control variables are measured as of quarter *t*. Along with peer idiosyncratic return shocks in period *t-1*, I also use peer idiosyncratic return shocks in period *t* as an additional instrument to be consistent with the measurement of other control variables and the dependent variable. As expected, I find evidence that the strength of peer effects decreases with the increased lead time of the dependent variable in Column 1 through Column 3. Column 3 shows that the coefficient on $P\_MF\ FREQ_{-i,j,t}$ is positive but not statistically different from zero (coefficient 0.063, t=0.253).[21] Overall, in addition to providing additional insights regarding the impact of the timing of peer actions in terms of their effects for firm disclosure, these results highlight the relevance and importance of the identification strategy implemented in the current setting.

5. Cross-sectional Tests

5.1. Uncertainty and peer effects

To shed light on the mechanisms underlying peer effects in disclosure, I conduct several cross-sectional tests. The first test relates peer effects in disclosure to a firm's strategic

[21] In untabulated tests, I examine the OLS results and find that coefficient estimates on $P\_MF\ FREQ_{-i,j,t}$ are significant and similar in magnitude across all time periods, possibly due to the reflection problem (e.g., Manski, 1993).

uncertainty. A firm's uncertainty comprises firm-specific uncertainty (e.g., uncertainty related to prospects of firm products, executive turnovers, and business structure changes) and environmental uncertainty (e.g., uncertainty arising from regulatory oversight, changes in macroeconomic conditions, and new product releases by competitors). The strategic uncertainty that results from rivals' actions in product markets is an especially important component of environmental uncertainty. Strategic interactions in the product markets increase the sensitivity of firm performance to rivals' unpredictable actions, thereby heightening the riskiness of profits and uncertainty (Gaspar and Massa, 2006; Irvine and Pontiff, 2009; Peress, 2010).

In the context of management forecasts, managers must take into account the expected performance of the firm as well as the expected performance of their peers competing in the same product markets before deciding whether to issue forecasts. Strategic uncertainty is attributable to factors beyond managers' control but adversely affects managers' tendency to issue forecasts beyond the effects of firm-specific uncertainty (Kim et al., 2015). As mosaic theory describes, however, economic agents improve the precision of private information by combining multiple pieces of information (e.g., Pozen, 2005; Cheynel and Levine, 2020). If exogenous peer firm disclosures play such a role in complementing a firm's information set, they enhance the accuracy of the private information available to managers. Verrecchia (1990) shows that the disclosure threshold decreases with the precision and quality of managerial private information. Based on the above line of reasoning, I expect to observe stronger peer effects in disclosure when strategic interactions with peers are more intense. The extent to which information released by peers is more valuable in reducing strategic uncertainty is likely to increase with the firm's performance sensitivity to its rivals' actions.

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To examine this expectation, I use two proxies to capture the extent of strategic interactions in the product markets: product market fluidity and the competitive strategic measure (CSM). Product market fluidity captures instability in a firm's product market environment due to rivals' product market moves (Hoberg et al., 2014).[22] CSM is defined as the coefficient of correlation between the ratio of the change in a firm's profits to the change in its sales, and the change in the combined sales of its rivals (Sundaram et al., 1996; Chod and Lyandres, 2011). Intuitively, CSM captures the cross-partial derivative of firm value with respect to industry peers' strategic actions as measured by changes in sales. I take the absolute value of the CSM to measure the general intensity of strategic interactions between a firm and its industry peers (Chod and Lyandres, 2011).

The cross-sectional test uses 2SLS estimation with two endogenous variables: $P\_MF\ FREQ_{-i,j,t}$ and its interaction with $High\ Uncertainty_{i,t-1}$. As noted, $High\ Uncertainty_{i,t-1}$ is based on either product market fluidity or the absolute value of the CSM. The two instruments are $P\_Return\ Shock_{-i,j,t-1}$) and its interaction with $High\ Uncertainty_{i,t-1}$. Thus, the inferences from the cross-sectional tests come from the different distributions of the first-stage effects of the instruments across different subgroups (Leary and Roberts, 2014).

Column 1 of Table 7 reports estimation results using product market fluidity to define $High\ Uncertainty_{i,t-1}$. $High\ Uncertainty_{i,t-1}$ is an indicator variable equal to one if the product market fluidity for firm *i* in period *t-1* exceeds the sample median and zero otherwise. Consistent with my expectation, I find a significantly positive coefficient on the interaction term, $P\_MF\ FREQ_{-i,j,t} \times High\ Uncertainty_{i,t-1}$, at the 5% level. I also find that the coefficient on *High*

[22] The fluidity data are from http://hobergphillips.usc.edu/. The fluidity measure computes the extent to which rivals change their product descriptions relative to own-firm product descriptions in 10-K filings. Therefore, greater product market fluidity is associated with greater strategic interactions: even if a firm's product offering remains stable in a given period, concurrent changes in rivals' product market strategies increase the competitive threats to the firm and the riskiness of the firm's profits.

Uncertainty$_{i,t-1}$ is significantly negative at the 5% level. This is consistent with Mattei and Platikanova (2017), who document that product market fluidity is negatively associated with management forecast tendency. Thus, the finding in Column 1 suggests that peer firm disclosure mitigates the negative impact of such fluidity, leading to firm disclosure. In Column 2, I use the absolute value of CSM to define *High Uncertainty*$_{i,t-1}$ and find consistent evidence. In summary, these findings suggest that firms with a greater (lower) degree of product market interactions with peers are more (less) likely to respond to peer firm disclosures that are associated with peers' idiosyncratic shocks because peer-specific information is more (less) important in resolving the strategic uncertainty in the product markets.

In addition to the two strategic uncertainty measures, I examine two other fundamental volatility measures to further substantiate my argument: cash flow volatility and stock return volatility. Prior research suggests that fundamental volatility increases with intense product market interactions (Gaspar and Massa, 2006; Irvine and Pontiff, 2009; Peress, 2010). In Columns 3 and 4, *High Uncertainty*$_{i,t-1}$ is based on cash flow volatility (measured using the preceding 20 quarters of seasonally adjusted operating cash flows) and stock return volatility (measured using daily stock returns during quarter *t-1*), respectively, again finding evidence consistent with my expectation.

5.2. Capital market benefits and peer effects

Next, I examine the cross-sectional variation of peer effects conditional on firms' reputational concerns and incentives to attract investor attention in capital markets. Specifically, I expect to observe stronger peer effects when a firm's dependence on external financing is higher. The idea is that peer firms' increased disclosures would shift investors' attention toward peer firms and make investors perceive non-disclosing firms as being less transparent and of

lower quality. Thus, the firm would respond to peer firm disclosures by changing their disclosure strategies in order to increase capital market benefits (e.g., Akerlof, 1970; Grossman and Hart, 1980; Grossman, 1981; Merton, 1987; Fishman and Hagerty, 1989), especially when their dependence on external financing is greater.

To test this prediction, I follow Rajan and Zingales (1998) and measure external financing dependence, $Ext\ Fin\ Dep_{i,t-1}$, which is defined as capital expenditures less operating cash flows divided by capital expenditures for firm *i* in period *t-1*. I then create $High\ Ext\ Fin\ Dep_{i,t-1}$, which is equal to one if external financing dependence exceeds the sample median and zero otherwise. In Column 1 of Table 8, consistent with my expectation, I find a significantly positive coefficient on $P\_MF\ FREQ_{-i,j,t} \times High\ Ext\ Fin\ Dep_{i,t-1}$ at the 1% level. I find a significantly negative coefficient on $High\ Ext\ Fin\ Dep_{i,t-1}$ at the 1% level, consistent with prior research suggesting that potential litigation concerns dampen voluntary disclosure incentives, especially for firms seeking external financing (Frankel, McNichols, and Wilson, 1995).[23]

In addition to the external financing dependence measure based on the ex-ante firm characteristics, I examine the firm's actual financing activities to further support the inference. In Column 2 (Column 3), I use $Equity\ Issue_{i,t+1}$ ($Debt\ Issue_{i,t+1}$) as a conditioning variable, equal to one if the net equity (debt) issuance for firm *i* in period *t+1* exceeds 1% of total assets and zero otherwise (Leary and Roberts, 2014). I expect to find a significantly positive coefficient on the

[23] If peer firm disclosure decreases the litigation risk of the firm, then the observed result can be attributed to reduced litigation risks rather than increased costs of non-disclosure. However, to my knowledge, there is no empirical evidence or theoretical background regarding whether peer firm disclosures reduce a firm's ex-ante litigation risks. Also, arguably, peer disclosure observed in a short period should not significantly affect firm-specific fundamentals and shareholder wealth, thus leading to limited effects on a firm's ex-ante litigation risks. Consistent with this idea, in Panel B of Table 5, I include the litigation risk variable as an additional control in the estimation and find that the peer effect estimate remains qualitatively similar, suggesting that peer firm disclosure is orthogonal to the ex-ante litigation risks of the firm. Although it is unclear, I also directly examine whether peer firm disclosure affects litigation risks. In an untabulated test, I use a firm-year measure of ex-ante litigation risks as a dependent variable (Kim and Skinner 2012; Iliev, Miller, and Roth 2014) and find no evidence of peer firm disclosure reducing the ex-ante litigation risks of the firm.

interaction term in Column 2, but I expect to find a weaker result in Column 3. This is because private communications with potential lenders and published credit ratings of the firm would play a more critical role in reducing the cost of debt than management forecasts. Consistent with my expectations, I find a significantly positive coefficient on $P\_MF\ FREQ_{-i,j,t} \times Equity\ Issue_{i,t+1}$ at the 5% level in Column 2, whereas the coefficient on $P\_MF\ FREQ_{-i,j,t} \times Debt\ Issue_{i,t+1}$ is statistically insignificant.[24] Overall, these findings corroborate my argument and suggest that a firm's incentives to maintain investor attention and increase capital market benefits are also an important motive behind peer effects in disclosure.

6. Additional Tests

6.1. The characteristics of disclosure in response to peer firm disclosure

I argue that the reduced managerial uncertainty due to peer firm disclosure is one channel underlying peer effects in disclosure, and I provide consistent evidence in the cross-sectional tests. In this section, I additionally examine whether peer firm disclosure also reduces investors' uncertainty, prompting the firm to disclose bad news. Prior research suggests that firms tend to hide bad news when market participants are uncertain about the information endowment of the firm (Dye, 1985; Jung and Kwon, 1988). If rational market participants also learn about whether a firm is endowed with information through peer firm disclosure (e.g., Dye and Sridhar, 1995), this will reduce market participants' uncertainty and thus provoke the firm to disclose bad news.

[24] In all cross-sectional tests, the first-stage results are untabulated for the sake of brevity because the results are consistent with those in Panel A of Table 5: the first endogenous variable ($P\_MF\ FREQ_{-i,j,t}$) is significantly negatively associated with the first instrument ($P\_Return\ Shock_{-i,j,t-1}$), and the second endogenous variable (the interaction between $P\_MF\ FREQ_{-i,j,t}$ and a cross-sectional conditioning variable) is also significantly negatively associated with the second instrument (the interaction between $P\_Return\ Shock_{-i,j,t-1}$ and the cross-sectional conditioning variable).

To examine this prediction, I divide the frequency of management forecasts into three variables. Specifically, $MF\ BD\ FREQ_{i,t}$, $MF\ NEU\ FREQ_{i,t}$, and $MF\ GD\ FREQ_{i,t}$ are the frequencies of management forecasts for firm *i* in quarter *t* that contain bad news, neutral news, and good news, respectively.[25] Table 2 reports the descriptive statistics. As noted before, the mean value of $MF\ FREQ_{i,t}$ is 0.501. The mean values of $MF\ BD\ FREQ_{i,t}$, $MF\ NEU\ FREQ_{i,t}$, and $MF\ GD\ FREQ_{i,t}$ are 0.221, 0.097, and 0.183, respectively.

Table 9 presents the second-stage estimation results from 2SLS where the endogenous variable is $P\_MF\ FREQ_{-i,j,t}$ and the instrument is $P\_Return\ Shock_{-i,j,t-1}$. Therefore, the first-stage result is the same as Panel A in Table 5. In Column 1, the dependent variable is $MF\ BD\ FREQ_{i,t}$, and I find a significantly positive coefficient on $P\_MF\ FREQ_{-i,j,t}$ at the 1% level. In Columns 2 and 3, the dependent variables are $MF\ NEU\ FREQ_{i,t}$ and $MF\ GD\ FREQ_{i,t}$, respectively, and coefficients on $P\_MF\ FREQ_{-i,j,t}$ in both columns are positive but statistically insignificant.[26] Overall, these findings bolster the inference and suggest that peer firm disclosure also reduces investors' uncertainty, triggering the firm to disclose bad news.

6.2. Peer effects in disclosure and stock liquidity

In this section, I explore the capital market consequences of peer effects in disclosure by examining the effect of a firm's disclosure induced by peer firm disclosures on firm stock liquidity. If the reduced managerial uncertainty due to peer firm disclosures improves the quality

[25] I classify a management forecast as a bad news forecast if the management forecast is below the outstanding consensus analyst expectation; otherwise, the management forecast is classified as a good news forecast. If a management forecast is the same as the outstanding consensus analyst expectation, then the management forecast is classified as a neutral forecast. Similarly to the main empirical specification, I count multiple management forecasts issued on the same day as a single forecast event. Also, to be consistent with this measurement scheme, if a firm releases multiple management forecasts on the same day, I classify the forecast event as a single good (bad) news event if the number of management forecasts releasing good (bad) news exceeds the number of management forecasts releasing bad (good) news. If those two numbers are the same, then the forecast event is counted as a neutral forecast.

[26] In untabulated tests, I check OLS results and find that all good, neutral, and bad news forecasts are significantly positively associated with $P\_MF\ FREQ_{-i,j,t}$.

and precision of private information available to managers, then firm disclosure will reduce information asymmetry more effectively, resulting in improved stock liquidity (Verrecchia 2001). Also, if a firm's voluntary disclosure in response to peer firm disclosures enables the firm to maintain investor attention, it leads to increased stock liquidity. To examine this idea, I use 2SLS and Amihud's (2002) stock illiquidity measure (AIM). Specifically, I examine the effect of firm disclosure in period *t* in response to peer idiosyncratic return shocks on the AIM for firm *i* in period *t+1* (Balakrishnan, Billings, Kelly, and Ljungqvist, 2014).[27] Consistent with my expectation, untabulated 2SLS results show that firm disclosure motivated by peers reduces stock illiquidity.

6.3. Peer effects in alternative disclosure decisions: Press releases and 8-K filings

In this section, I additionally explore peer effects in other disclosure decisions: firm-initiated press releases and 8-K filings. I note, however, that the presence of peer effects in these alternative disclosure mechanisms may not be as clear as in managerial forecasts. On the one hand, they are crucial disclosure outlets allowing managers to disseminate information about various corporate events. Prior research suggests that managers actively utilize them to affect the firm's information environment (Balakrishnan et al., 2014; Guay et al., 2016). On the other hand, they convey heterogeneous and descriptive information such as executive promotions/turnover, asset write-offs, accounting policy changes, modifications to the rights of security holders, bankruptcy, auditor changes, and so on, which might be less helpful information for managers and investors. Moreover, prior studies suggest that the role of qualitative disclosure differs from that of forward-looking and quantitative disclosures such as managerial forecasts (Drake, Guest, and Twedt, 2014; Noh, So, and Weber, 2019). Hence, it is ex-ante unclear whether peer effects

[27] In this estimation, I assume that peer firm disclosure, which is omitted in this analysis, is the primary channel through which peer idiosyncratic return shocks affect own-firm disclosure, which is supported by results in Table 4.

also have an impact on firm-initiated press releases and 8-K filing decisions. Nevertheless, I examine peer effects in these disclosure decisions.

I first examine peer effects in firm-initiated press releases. I obtain data for this analysis from the RavenPack database that provides firm-initiated press release data after 2004. I identify 101,221 firm-quarter observations with available financial data and the firm-identifier of RavenPack between 2004 and 2014. As in the main analysis, I count the number of firm-initiated press releases during each quarter and consider multiple press releases on the same date to be a single disclosure event.[28] I exclude press releases that contain managerial forecasts to avoid their potential confounding effects. Then I take the natural logarithm of one plus the number of firm-initiated press releases to mitigate the influence of extreme observations.[29]

Estimation results from 2SLS are presented in Table 10. The endogenous variable is the peer firm average frequency of firm-initiated press releases in quarter *t* ($P\_PR\ FREQ_{-i,j,t}$), and the instrument is $P\_Return\ Shock_{-i,j,t-1}$. Column 1 shows a significantly positive coefficient on $P\_PR\ FREQ_{-i,j,t}$ at the 5% level (coefficient 1.324, t=2.343), indicating the existence of peer effects in firm-initiated press releases. In an untabulated OLS regression result, I also find a significantly positive coefficient on $P\_PR\ FREQ_{-i,j,t}$ at the 1% level. However, the coefficient estimate is considerably smaller than that from 2SLS, consistent with the result in Table 5.

Next, I investigate peer effects in firms' 8-K filing decisions. The endogenous variable is the peer firm average frequency of 8-K filings in quarter *t* ($P\_8K\ FREQ_{-i,j,t}$). In this test, I use two additional lags of peer firm idiosyncratic return shocks at the first-stage estimation, which allows more exogenous variation in the instrument and thus improves the empirical specification

[28] Based on RavenPack's recommendation, I identify firm-initiated press releases by using a relevance score of higher than 75, an event novelty score of 100, and the news type of 'press release.' A press release is defined by RavenPack as "a corporate announcement originated by an entity and distributed via a news provider."

[29] The mean (median) frequency of firm-initiated press releases per fiscal quarter during the sample period between 2004 and 2014 is 2.36 (1.00), and the maximum number is 53.

and power of test statistics.[30] I consider multiple 8-K filings on the same date to be a single filing event. I take the natural logarithm of one plus the frequency of 8-K filings to mitigate the influence of extreme observations.[31]

In Column 2, the dependent variable is the frequency of all 8-K filings, $8K\ FREQ_{i,t}$, and I find a positive but statistically insignificant coefficient on $P\_8K\ FREQ_{-i,j,t}$. One possible reason for this insignificant result is the nature of 8-K filings: 8-K filings co-mingle both voluntary and mandatory items. For most mandatory 8-K items, managers may not have sufficient discretion to alter their disclosure strategies in response to peer firm disclosure, and thus this feature may add noise to the test. To address this issue, I divide the dependent variable into two variables—the frequencies of voluntary ($Vol8K\ FREQ_{i,t}$) and mandatory 8-K filings ($Man8K\ FREQ_{i,t}$)—and examine peer effects separately.[32] I exclude voluntary 8-K filings if they were filed with the SEC immediately after the issuance of managerial forecasts (Noh et al., 2019) to ensure that peer effects in voluntary 8-K filing decisions are not an artifact of peer effects in managerial forecast decisions.

Column 3 (Column 4) of Table 10 reports the estimation result using $Vol8K\ FREQ_{i,t}$ ($Man8K\ FREQ_{i,t}$) as a dependent variable. While Column 3 shows that the coefficient on *P_8K*

[30] 8-K filings disseminate more heterogeneous information in response to a broad range of underlying events because the SEC requires firms to disclose material information to the public about their financial and managerial conditions, and firms can voluntarily make public disclosures through 8-K filings. Furthermore, the 8-K filing deadlines vary depending on the nature of each item and specific events. For most items, firms are required to file with the SEC on a timely basis. However, item 8.01, which is one of the important voluntary 8-K items, does not have a specific deadline, so managers have a substantial amount of discretion in planning 8-K filing decisions. Thus, allowing more variation in the instrument at the first-stage estimation enables me to address the above issues and helps identify sufficient exogenous variation in peer firm disclosures.

[31] The mean (median) number of total 8-K filings during the fiscal quarter in my sample period is 2.14 (2.00), and the maximum number is 57.

[32] Following prior studies (e.g., Lerman and Livnat, 2010; Noh et al., 2019), I identify voluntary 8-K filings that contain item 12 (Results of Operations and Financial Conditions), item 5 (Other Events), and item 9 (Regulation FD Disclosure) in the pre-2004 period, and those that contain item 2.02 (Results of Operations and Financial Condition), item 7.01 (Regulation FD Disclosure), and item 8.01 (Other Events) in the post-2004 period. Note that the SEC changed the labeling of these items in 2004. In untabulated tests, I limit my sample period in this analysis to 2004–2014 and find that the results are qualitatively similar.

$FREQ_{-i,j,t}$ is statistically significant and equal to 1.186 (t=3.224), the coefficient on $P\_8K\ FREQ_{-i,j,t}$ in Column 4 is equal to 0.060 and statistically insignificant (t=0.190), consistent with my expectations.[33] In summary, findings in this section suggest that peer effects are not restricted to one specific disclosure mechanism but rather apply to a broader array of disclosure decisions.

7. Conclusion

In this paper, I explore whether industry peer disclosure affects corporate disclosure decisions. In particular, to avoid the identification problem arising from common shocks affecting all firms within an industry, I use peer idiosyncratic return shocks—which eliminate common industry- and market-wide components from raw returns—as an instrument for endogenous peer firm disclosure. Using the frequency of management forecasts as my primary proxy for firm disclosure, I find that peer firm disclosure induces own-firm disclosure, providing evidence of peer effects in disclosure decisions. In cross-sectional tests, I find that peer effects are stronger when a firm's ex-ante uncertainty of the strategic environment is higher and its reputational concerns for transparency in capital markets as well as incentives to attract investor attention are greater. I also find that peer firm disclosure is more likely to induce the firm to disclose bad news. Lastly, I provide evidence of peer effects in firm-initiated press releases and voluntary 8-K filing decisions.

Overall, this paper provides strong evidence of peer effects in a firm's disclosure decisions. Also, by providing evidence that peer effects interact with firm-specific factors, this paper suggests that peer firm disclosure plays a vital role in shaping the overall information

[33] In untabulated tests, I also check the OLS regression results. Again, consistent with prior OLS regression results, there are significantly positive coefficients on $P\_8K\ FREQ_{-i,j,t}$ in all cases regardless of mandatory or voluntary 8-K filings. Also, the OLS regression significantly underestimates the magnitude of peer effects in voluntary 8-K filing decisions, which is consistent with results based on management forecasts and firm-initiated press releases.

environment of the firm. Incorporating this interactive disclosure behavior within the industry into firm-specific or industry-wide disclosure models might present an interesting avenue for future research.

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Appendix A. Variable definitions

Variables	Descriptions
MF FREQ$_{i,t}$	*MF FREQ*$_{i,t}$ is defined as the frequency of management forecasts for firm *i* in quarter *t*. Multiple management forecasts issued on the same day are considered a single forecast event.
MF BD FREQ$_{i,t}$	*MF BD FREQ*$_{i,t}$ is defined as the frequency of management forecasts disclosing bad news for firm *i* in quarter *t*. Multiple management forecasts issued on the same day are considered a single forecast event.
MF NEU FREQ$_{i,t}$	*MF NEU FREQ*$_{i,t}$ is defined as the frequency of management forecasts disclosing neutral news for firm *i* in quarter *t*. Multiple management forecasts issued on the same day are considered a single forecast event.
MF BD FREQ$_{i,t}$	*MF BD FREQ*$_{i,t}$ is defined as the frequency of management forecasts disclosing good news for firm *i* in quarter *t*. Multiple management forecasts issued on the same day are considered a single forecast event.
Size$_{i,t-1}$	*Size*$_{i,t-1}$ is defined as the natural logarithm of the market value of equity for firm *i* as of the beginning of quarter *t*.
Market-to-Book$_{i,t-1}$	*Market-to-Book*$_{i,t-1}$ is the market-to-book ratio, equal to the market value of assets divided by the book value of assets for firm *i* as of the beginning of quarter *t*. The market value of assets is equal to the sum of the market value of equity and the book value of total liabilities.
R&D$_{i,t-1}$	*R&D*$_{i,t-1}$ is defined as firm *i's* research and development expenditures divided by total assets during quarter *t-1*.
Return on Assets$_{i,t-1}$	*Return on Assets*$_{i,t-1}$ is defined as net income divided by the book value of total assets for firm *i* in quarter *t-1*.
Earnings Volatility$_{i,t-1}$	*Earnings Volatility*$_{i,t-1}$ is defined as the standard deviation of return on assets for the 16 quarters preceding quarter *t* for firm *i* (a minimum of 8 quarter observations is required).
Leverage$_{i,t-1}$	*Leverage*$_{i,t-1}$ is defined as the sum of short-term and long-term debts divided by total assets in quarter *t-1*.
Investment$_{i,t-1}$	*Investment*$_{i,t-1}$ *is* defined as the capital expenditures for firm *i* in quarter *t*, multiplied by 100 and divided by lagged total assets.
Coverage$_{i,t-1}$	*Coverage*$_{i,t-1}$ is equal to the natural logarithm of one plus the number of analysts following firm *i* as of the beginning of quarter *t*.
INSTOWN$_{i,t-1}$	*INSTOWN*$_{i,t-1}$ is equal to the percentage of firm *i*'s stock held by institutional investors as of the beginning of quarter *t*.
Return Shock$_{i,t-1}$	*Return Shock*$_{i,t-1}$ is equal to firm *i*'s quarterly idiosyncratic stock returns in quarter *t-1*. This variable is obtained by compounding monthly idiosyncratic returns. Monthly idiosyncratic return is measured as the difference between monthly stock return and expected return. Monthly

	expected return is calculated based on estimated factor loadings from the regression of monthly stock return for firm *i* on the excess market return and the excess equal-weighted industry return excluding firm *i*'s return. The regression is firm-specific and based on rolling regressions using the preceding 60 months of data (a minimum of 24 months of data is required). Industries are defined as six-digit GICS codes.
$P\_MF\ FREQ_{-i,j,t}$	$P\_MF\ FREQ_{-i,j,t}$ is defined as the average frequency of management forecasts of peer firms in the same industry as firm *i* in period *t*. Firm *i*'s management forecasts are excluded in computing the average frequency of management forecasts.
$P\_Return\ Shock_{-i,j,t-1}$	$P\_Return\ Shock_{-i,j,t-1}$ is defined as the average idiosyncratic equity returns of peer firms in the same industry as firm *i* in period *t-1*. Firm *i*'s idiosyncratic equity returns are excluded in computing the average idiosyncratic equity returns.
$Fluidity_{i,t-1}$	$Fluidity_{i,t}$ is the product market fluidity measure developed by Hoberg et al. (2014) for firm *i* as of the beginning of period *t*. This variable captures the extent to which rivals change their product descriptions relative to an own firm's product descriptions in its 10-K filings.
$CSM_{i,t-1}$	$CSM_{i,t-1}$ is defined as the coefficient of correlation between the ratio of the change of a firm's profits to the change of its sales, and the change in the combined sales of its rivals. CSM captures the cross-partial derivative of firm value with regards to industry peers' strategic actions as measured by changes in sales (Sundaram et al. 1996; Chod and Lyandres 2011).
$CF\ Vol_{i,t-1}$	$CF\ Vol_{i,t-1}$ is operating cash flows volatility for firm *i* as of the beginning of period *t* and measured using seasonally-adjusted operating cash flows from the preceding 20 quarters (a minimum of 12 quarters of data is required).
$Ret\ Vol_{i,t-1}$	$Ret\ Vol_{i,t-1}$ is quarterly stock return volatility measured as the standard deviation of daily stock returns for firm *i* in period *t-1*.
$Ext\ Fin\ Dep_{i,t-1}$	$Ext\ Fin\ Dep_{i,t-1}$ is equal to capital expenditures minus cash flows from operations divided by capital expenditures for firm *i* as of the beginning of quarter *t* (Rajan and Zingales 1998).
$Equity\ Issue_{i,t+1}$	$Equity\ Issue_{i,t+1}$ is an indicator variable equal to one if net equity issuances exceed one percent of total assets for firm *i* in period *t+1*, zero otherwise.
$Debt\ Issue_{i,t+1}$	$Debt\ Issue_{i,t+1}$ is an indicator variable equal to one if net debt issuances exceed one percent of total assets for firm *i* in period *t+1*, zero otherwise.

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Figure 1
Distribution of peer idiosyncratic return shocks

This figure presents the empirical distribution of quarterly peer idiosyncratic return shocks between 2002 and 2014. The distribution is truncated at the 1st and 99th percentiles to ease the presentation. Peer group is defined based on Eight-Digit GICS (Sub-Industry) in Panel A, Six-Digit GICS (Industry) in Panel B, Four-Digit GICS (Group) in Panel C, and Two-Digit GICS (Sector) in Panel D.

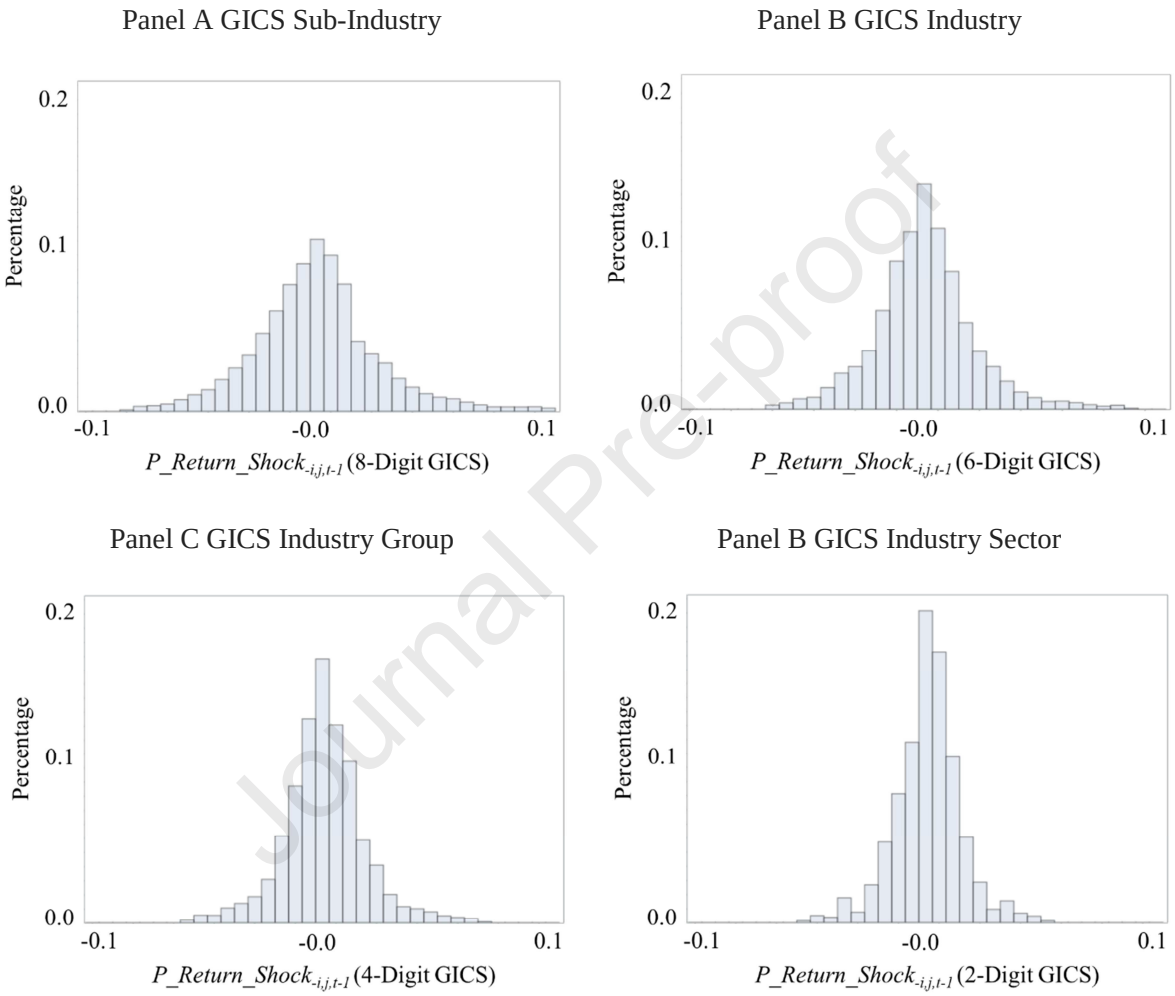

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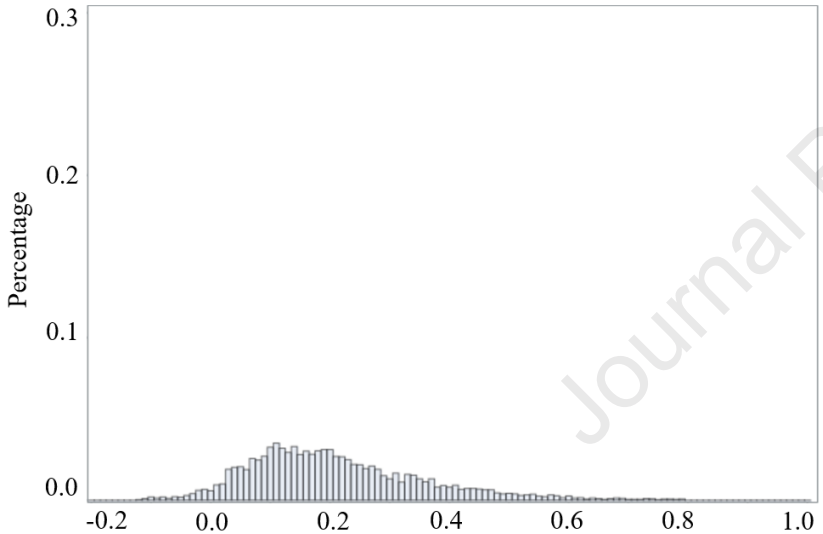
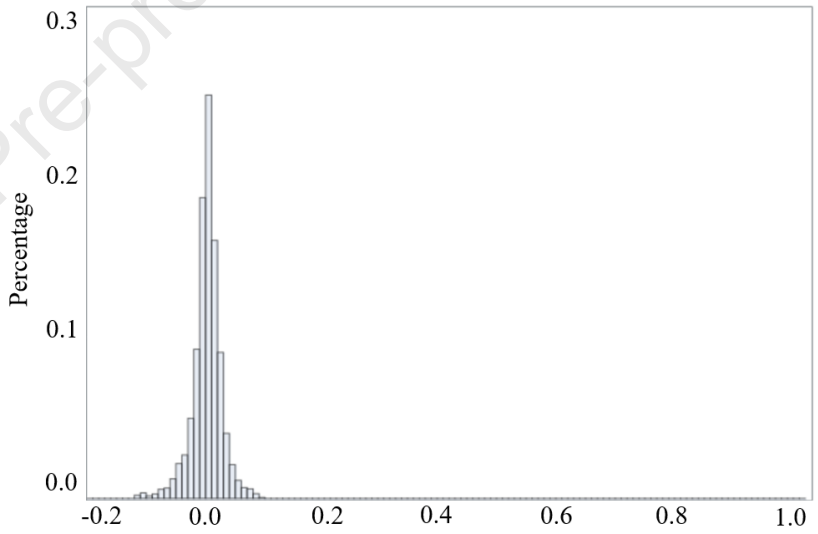
Figure 2
Distribution of intra-industry pairwise correlation coefficients of stock returns

This figure presents the empirical distribution of stock returns' pairwise correlation coefficients and *t*-statistics for the sample firms with their industry peers between 2002 and 2014. Peer group is defined based on the six-digit GICS industry. The distribution is truncated at the 1st and 99th percentiles to ease the presentation. Panel A (Panel B) demonstrate the distribution of raw (idiosyncratic) returns' pairwise correlation coefficients. Panel C (Panel D) presents the distribution of *t*-statistics of raw (idiosyncratic) returns' pairwise correlations coefficients.

Panel A Correlation coefficients of raw returns



Panel B Correlation coefficients of idiosyncratic returns



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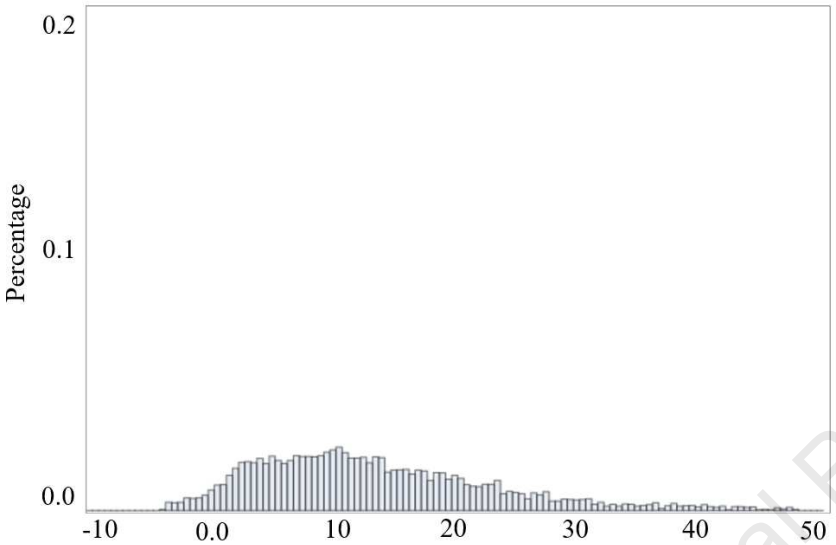
Panel C *t*-statistics of raw return correlations



Panel D *t*-statistics of idiosyncratic return correlations

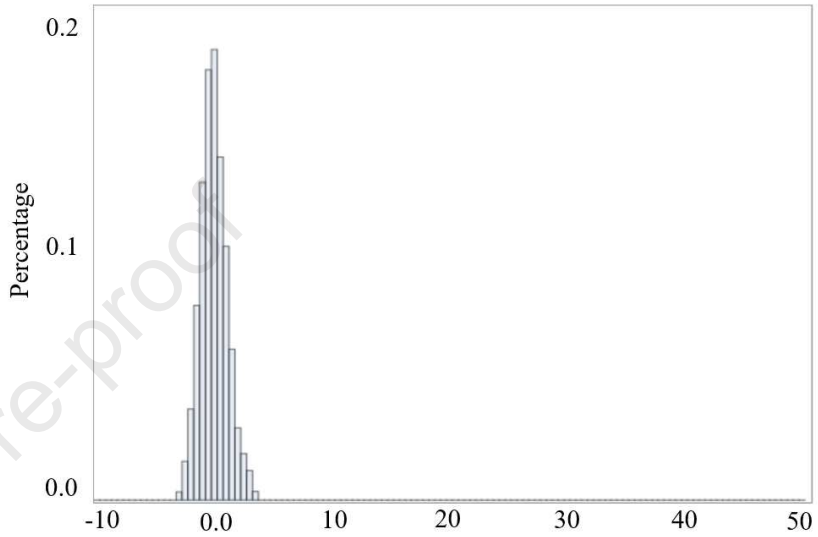


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Table 1
Idiosyncratic Returns

This table reports descriptive statistics for the idiosyncratic returns over the sample period between 2002 and 2014. Panel A presents the estimation results of the firm-specific factor loading regression

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT}(rm_t - rf_t) + \beta_{i,t}^{IND}(\bar{r}_{-i,t} - rf_t) + \eta_{i,t}$$

where $r_{i,t}$ is the raw return for firm *i* over month *t*, $(rm_t - rf_t)$ is the excess market return over month *t*, and $(\bar{r}_{-i,t} - rf_t)$ is the excess return on an equal-weighted peer group portfolio excluding firm *i*'s return over month *t*. Peer group is defined using the six-digit GICS industry. The regression is firm-specific and estimated on a rolling quarterly basis using the past 60 monthly stock returns preceding the fiscal quarter (a minimum of 24 monthly observations is required). Expected returns are calculated using the estimated factor loadings and realized factor returns. Idiosyncratic returns are computed as the difference between raw returns and expected returns. Panel B presents the empirical distribution of pairwise correlation coefficients and *t*-statistics of the sample firms' stock returns with their industry peers' stock returns over the sample period.

Panel A Return shock construction

Variables	Mean	Std	Q1	Median	Q3
Regression summary					
Alpha	0.003	0.017	-0.005	0.004	0.012
Beta (Market)	0.218	0.847	-0.240	0.175	0.679
Beta (Industry)	0.795	0.618	0.373	0.749	1.164
Adjusted R-squared	0.256	0.179	0.113	0.232	0.375
Quarterly Decomposition					
Raw Return	0.038	0.308	-0.102	0.019	0.142
Idiosyncratic Return	-0.001	0.275	-0.125	-0.019	0.085
Expected Return	0.041	0.164	-0.036	0.039	0.114

Panel B Intra-industry pairwise correlation coefficients of stock returns

Variables	Mean	Std	Q1	Median	Q3
Corr. Coeff. (Raw Return)	0.216	0.180	0.104	0.187	0.296
Corr. Coeff. (Idiosyncratic Return)	-0.004	0.043	-0.014	-0.001	0.010
t-statistics (Raw Return)	13.676	10.664	6.115	11.806	19.170
t-statistics (Idiosyncratic Return)	-0.031	1.249	-0.819	-0.098	0.691

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Table 2
Descriptive Statistics

This table reports descriptive statistics for the main variables of the sample firm-quarter observations with available information over the sample period between 2002 and 2014. All ratios are winsorized at the 1st and 99th percentiles. Peer firm averages are constructed as the average of all firms within an industry-quarter combination, excluding the firm *i*'s observation. Industries are defined by the six-digit GICS industry. All variables are defined in Appendix A.

Variables	N	Mean	STD	Q1	Median	Q3
MF FREQ$_{i,t}$	181,089	0.501	0.738	0.000	0.000	1.000
MF BD FREQ$_{i,t}$	181,089	0.221	0.504	0.000	0.000	0.000
MF NEU FREQ$_{i,t}$	181,089	0.097	0.319	0.000	0.000	0.000
MF GD FREQ$_{i,t}$	181,089	0.183	0.460	0.000	0.000	0.000
Size$_{i,t-1}$	181,089	6.193	2.075	4.665	6.102	7.589
Market-to-Book$_{i,t-1}$	181,089	1.790	1.316	1.036	1.312	1.988
R&D$_{i,t-1}$	181,089	0.012	0.028	0.000	0.000	0.011
Return on Assets$_{i,t-1}$	181,089	-0.006	0.057	-0.004	0.005	0.017
Earnings Volatility$_{i,t-1}$	181,089	0.034	0.054	0.006	0.015	0.039
Leverage$_{i,t-1}$	181,089	0.209	0.211	0.025	0.156	0.323
Investment$_{i,t-1}$	181,089	1.027	1.571	0.081	0.479	1.249
Coverage$_{i,t-1}$	181,089	1.451	0.955	0.693	1.386	2.197
INSTOWN$_{i,t-1}$	181,089	0.496	0.333	0.177	0.523	0.800
Return Shock$_{i,t-1}$	181,089	-0.001	0.276	-0.126	-0.020	0.085
P_MF FREQ$_{-i,j,t}$	181,089	0.501	0.301	0.256	0.500	0.728
P_Return Shock$_{-i,j,t-1}$	181,089	-0.001	0.033	-0.017	-0.003	0.012
Fluidity$_{i,t-1}$	157,088	7.880	3.697	5.129	7.330	10.012
CSM$_{i,t-1}$	151,837	-0.099	5.790	-1.352	-0.038	1.201
CF Vol$_{i,t-1}$	165,003	0.044	0.049	0.015	0.028	0.053
Ret Vol$_{i,t-1}$	181,089	0.031	0.024	0.017	0.025	0.038
Ext Fin Dep$_{i,t-1}$	163,794	1.350	59.729	-5.698	-0.922	1.241
Equity Issue$_{i,t+1}$	181,089	0.080	0.272	0.000	0.000	0.000
Debt Issue$_{i,t+1}$	181,089	0.200	0.400	0.000	0.000	0.000

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Table 3
Correlations

Panel A presents Pearson correlations for the main variables. Panel B presents correlations for the stock return variables. Significance at the 1% level is bolded. Panel C reports partial correlations between peer idiosyncratic return shocks in period *t-1* in column 1 ($P\_Return\ Shock_{-i,j,t-1}$) or peer idiosyncratic return shocks in period *t* in column 2 ($P\_Return\ Shock_{-i,j,t}$) and firm-specific characteristics in period *t-1*. All variables are defined in Appendix A. All ratios are winsorized at the 1st and 99th percentiles. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A Pearson correlations among main variables

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	$MF\ FREQ_{i,t}$												
(2)	$Size_{i,t-1}$	**0.35**											
(3)	$Market\text{-}to\text{-}Book_{i,t-1}$	**0.05**	**0.13**										
(4)	$R\&D_{i,t-1}$	**-0.05**	**-0.18**	**0.46**									
(5)	$Return\ on\ Assets_{i,t-1}$	**0.16**	**0.31**	**-0.21**	**-0.56**								
(6)	$Earnings\ Volatility_{i,t-1}$	**-0.10**	**-0.27**	**0.33**	**0.47**	**-0.46**							
(7)	$Leverage_{i,t-1}$	**0.07**	**0.12**	**-0.11**	**-0.16**	**-0.02**	**-0.06**						
(8)	$Investment_{i,t-1}$	**0.09**	**0.13**	**0.10**	**-0.08**	**0.08**	**0.01**	**0.09**					
(9)	$Coverage_{i,t-1}$	**0.43**	**0.72**	**0.12**	**-0.04**	**0.18**	**-0.16**	**0.06**	**0.13**				
(10)	$INSTOWN_{i,t-1}$	**0.40**	**0.46**	**0.06**	**-0.09**	**0.20**	**-0.17**	**0.09**	**0.10**	**0.60**			
(11)	$Return\ Shock_{i,t-1}$	**-0.01**	**-0.01**	**0.09**	**0.02**	**0.01**	**0.03**	0.00	**-0.01**	**-0.06**	**-0.05**		
(12)	$P\_MF\ FREQ_{-i,j,t}$	**0.37**	**0.13**	**0.08**	**0.02**	**0.07**	**0.03**	**0.06**	**0.13**	**0.16**	**0.22**	0.00	
(13)	$P\_Return\ Shock_{-i,j,t-1}$	**-0.01**	0.01	**0.02**	**0.02**	**-0.02**	**0.02**	-0.01	**0.02**	**0.01**	**-0.01**	**-0.02**	**-0.02**

Panel B Correlations among the stock return variables

	Variables	(1)	(2)	(3)	(4)	(5)
(1)	$P\_Return_{-i,j,t-1}$					
(2)	$Return_{i,t-1}$	**0.46**				
(3)	$P\_Return\ Shock_{-i,j,t-1}$	**0.43**	**0.10**			
(4)	$Return\ Shock_{i,t-1}$	**0.02**	**0.84**	**-0.02**		
(5)	$Return_{i,t}$	**0.09**	**0.03**	0.00	**-0.01**	
(6)	$Return\ Shock_{i,t}$	**0.01**	**-0.05**	**0.01**	**-0.02**	**0.84**

Panel C Partial correlations between peer idiosyncratic return shocks and firm characteristics

	P_Return Shock$_{-i,j,t-1}$	*P_Return Shock*$_{-i,j,t}$
Independent Variables	(1)	(2)
Size$_{i,t-1}$	-0.000	0.001***
	(-1.307)	(5.710)
Market-to-Book$_{i,t-1}$	-0.000	-0.000
	(-1.640)	(-0.365)
R&D$_{i,t-1}$	-0.011	-0.018**
	(-1.555)	(-2.470)
Return on Assets$_{i,t-1}$	-0.005*	-0.007***
	(-1.807)	(-2.604)
Earnings Volatility$_{i,t-1}$	0.004	-0.002
	(1.215)	(-0.602)
Leverage$_{i,t-1}$	0.001	0.001
	(1.405)	(1.470)
Investment$_{i,t-1}$	0.000	0.000*
	(0.906)	(1.901)
Coverage$_{i,t-1}$	0.000*	-0.000
	(1.748)	(-0.910)
INSTOWN$_{i,t-1}$	0.000	-0.000
	(0.118)	(-0.054)
Peer Firm Averages	Yes	Yes
Own Firm Return Shock	Yes	Yes
Firm and Quarter FE	Yes	Yes
Number of Observations	181,089	181,089
Adjusted R-squared	0.148	0.146

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Table 4
Two-way dependent sorts: Peer idiosyncratic return shocks or peer firm disclosure

This table presents the average frequency of management forecasts for 25 groups in each panel. The 25 groups are formed by the intersection of quintiles based on peer idiosyncratic return shocks (i.e., the instrument, *P_Return Shock*$_{-i,j,t-1}$) and the average frequency of peer firm management forecasts (i.e., peer firm disclosure, *P_MF FREQ*$_{-i,j,t}$). In Panel A, all firm-quarter observations are first sorted into quintiles based on *P_Return Shock*$_{-i,j,t-1}$ as denoted in the first column. Next, each quintile is further (conditionally) sorted into quintiles based on *P_MF FREQ*$_{-i,j,t}$ as denoted in the top rows. The "High - Low" column provides the mean difference of the average frequency of management forecasts between the 5th and the 1st quintile of *P_MF FREQ*$_{-i,j,t}$. The "All" row reports the average frequency of management forecasts for each *P_MF FREQ*$_{-i,j,t}$ quintile. In Panel B, all firm-quarter observations are first sorted into quintiles based on *P_MF FREQ*$_{-i,j,t}$ as denoted in the first column. Next, each quintile is further (conditionally) sorted into quintiles based on *P_Return Shock*$_{-i,j,t-1}$ as denoted in the top rows. The "High - Low" column provides the mean difference of the average frequency of management forecasts between the 5th and the 1st quintile of *P_Return Shock*$_{-i,j,t-1}$. The "All" row reports the average frequency of management forecasts for each *P_Return Shock*$_{-i,j,t-1}$ quintile. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A The relation between peer firm disclosure and own firm disclosure

P_Return Shock$_{-i,j,t-1}$ (Instrument)	*P_MF FREQ*$_{-i,j,t}$ (Peer Firm Disclosure)					
	Low	2	3	4	High	High - Low
1	0.189	0.415	0.562	0.707	0.841	0.652***
2	0.082	0.318	0.500	0.705	0.860	0.778***
3	0.070	0.229	0.489	0.685	0.856	0.786***
4	0.062	0.256	0.462	0.708	0.864	0.802***
2	0.211	0.368	0.544	0.673	0.852	0.641***
All	0.124	0.317	0.512	0.696	0.855	0.731***

Panel B The relation between the instrument and own firm disclosure

P_MF FREQ$_{-i,j,t}$ (Peer Firm Disclosure)	*P_Return Shock*$_{-i,j,t-1}$ (Instrument)					
	Low	2	3	4	High	High - Low
1	0.118	0.099	0.091	0.093	0.109	-0.009
2	0.345	0.325	0.335	0.337	0.351	0.006
3	0.506	0.513	0.499	0.494	0.524	0.018
4	0.677	0.717	0.705	0.727	0.666	-0.011
5	0.852	0.849	0.865	0.871	0.853	0.001
All	0.499	0.501	0.499	0.505	0.500	0.001

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Table 5
IV estimate: Peer effects in corporate disclosure decisions

Panel A reports the estimation result from OLS in column 1 and the estimation results from 2SLS in column 2 and 3 where the endogenous variable is the average frequency of peer firm management forecasts, and the instrument is peer firm idiosyncratic return shocks. The dependent variable is denoted in the top row of each column. A 95% confidence set for the IV coefficient that is robust to weak instruments is provided below the *t*-statistic of *P_MF FREQ*$_{-i,j,t}$. Panel B reports the second-stage estimation results from various robustness tests using 2SLS. Panel C presents the second-stage estimation results from over-identified 2SLS and LIML, where the endogenous variable is *P_MF FREQ*$_{-i,j,t}$. Panel D reports the estimation results from 2SLS using the customer-supplier relationship. In this analysis, peer firms for firm *i* are defined as the subset of firms in the same industry as firm *i* with at least one customer firm that satisfies the following three criteria: (1) the customer is in an industry different from firm *i*, (2) the customer is not a customer of firm *i*, and (3) the customer accounts for at least 10% of the peer firm's sales. The instrumental variable is the average idiosyncratic return shocks to such customers, and the endogenous variable is the average frequency of the peer firms' management forecasts. All variables are defined in Appendix A. The table presents the heteroscedasticity-corrected Cragg-Donald (1993) statistic testing for weak instruments (First-Stage F-statistic), and *t*-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A IV estimate

	MF FREQ$_{i,t}$	*P_MF FREQ*$_{-i,j,t}$	*MF FREQ*$_{i,t}$
Independent Variables	(1)	(2)	(3)
	OLS	2SLS	
		First-Stage	Second-Stage
P_MF FREQ$_{-i,j,t}$	0.555***		1.011***
	(20.095)		(3.451)
[95% confidence set]			[0.466, 1.603]
P_Return Shock$_{-i,j,t-1}$		-0.154***	
		(-13.451)	
Return Shock$_{i,t-1}$	-0.010**	-0.006***	-0.007
	(-2.250)	(-5.145)	(-1.599)
Size$_{i,t-1}$	0.102***	0.021***	0.092***
	(14.971)	(10.001)	(10.002)
Market-to-Book$_{i,t-1}$	-0.012***	-0.006***	-0.009**
	(-3.298)	(-5.132)	(-2.365)
R&D$_{i,t-1}$	0.178	0.143***	0.113
	(1.107)	(3.551)	(0.673)
Return on Assets$_{i,t-1}$	0.386***	-0.031***	0.399***
	(8.760)	(-2.591)	(8.759)
Earnings Volatility$_{i,t-1}$	-0.251***	-0.005	-0.248***
	(-3.141)	(-0.197)	(-3.067)
Leverage$_{i,t-1}$	0.145***	0.017*	0.137***
	(5.144)	(1.934)	(4.747)
Investment$_{i,t-1}$	0.007***	-0.001*	0.007***
	(3.533)	(-1.951)	(3.729)
Coverage$_{i,t-1}$	0.064***	-0.003	0.066***
	(8.408)	(-1.320)	(8.460)
INSTOWN$_{i,t-1}$	-0.010	-0.049***	0.012
	(-0.386)	(-5.864)	(0.429)
P_Size$_{-i,j,t-1}$	-0.020	0.076***	-0.054**
	(-1.565)	(11.565)	(-2.178)
P_Market-to-Book$_{-i,j,t-1}$	-0.006	-0.024***	0.006
	(-0.492)	(-6.092)	(0.440)
P_R&D$_{-i,j,t-1}$	1.763**	0.974***	1.305

	(2.329)	(2.718)	(1.562)
P_Return on Assets$_{-i,j,t-1}$	-0.025	1.637***	-0.784
	(-0.095)	(18.759)	(-1.375)
P_Earnings Volatility$_{-i,j,t-1}$	0.352	-0.780***	0.717
	(0.860)	(-6.216)	(1.544)
P_Leverage$_{-i,j,t-1}$	0.148*	0.283***	0.020
	(1.687)	(5.642)	(0.158)
P_Investment$_{-i,j,t-1}$	-0.010	-0.028***	0.003
	(-1.158)	(-7.424)	(0.234)
P_Coverage$_{-i,j,t-1}$	-0.021	0.257***	-0.139*
	(-0.731)	(24.451)	(-1.701)
P_INSTOWN$_{-i,j,t-1}$	-0.300***	-0.082***	-0.265***
	(-4.790)	(-3.032)	(-3.970)
First-Stage F-statistic		314.889	
Firm and Quarter FE	Yes	Yes	
Number of Observations	181,089	181,089	
Adjusted R-squared	0.541	0.536	

Panel B Robustness tests

	MF FREQ$_{i,t}$			
Independent Variables	(1)	(2)	(3)	(4)
P_MF FREQ$_{-i,j,t}$	1.011***	0.996***	1.012***	0.985***
	(3.409)	(3.141)	(3.104)	(2.924)
First-Stage F-statistic	307.656	276.187	252.999	247.247
Firm-Specific Characteristics	Y	Y	Y	Y
Peer Firm Averages	Y	Y	Y	Y
Raw Returns in period *t-1* and period *t*	Y	N	N	Y
Additional Control Variables	N	Y	N	Y
Contemporaneous Control Variables	N	N	Y	Y
Firm and Quarter FE	Yes	Yes	Yes	Yes
Number of Observations	181,089	178,880	181,089	173,625
Adjusted R-squared	0.536	0.538	0.537	0.539

Panel C Over-identified 2SLS and LIML

	MF FREQ$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
P_MF FREQ$_{-i,j,t}$ (2SLS)	-1.489	1.992	1.285***	1.011***	1.175***
	(-0.385)	(1.514)	(3.283)	(3.451)	(4.182)
P_MF FREQ$_{-i,j,t}$ (LIML)					1.176***
					(4.178)
First-stage instrument					
P_Return Shock$_{-i,j,t-4}$	0.011				-0.011
	(1.115)				(-1.203)
P_Return Shock$_{-i,j,t-3}$		-0.035***			-0.082***
		(-2.961)			(-7.806)
P_Return Shock$_{-i,j,t-2}$			-0.107***		-0.101***
			(-9.692)		(-9.793)
P_Return Shock$_{-i,j,t-1}$				-0.154***	-0.149***
				(-13.451)	(-13.271)
Over-identification test					
Hasen J Statistic					1.065

					(0.786)
First-Stage F-statistic	1.885	16.864	161.543	314.889	137.358
Firm-Specific Characteristics	Yes	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes	Yes
Firm and Quarter FE	Yes	Yes	Yes	Yes	Yes
Number of Observations	180,191	180,206	180,590	181,089	179,825
Adjusted R-squared	0.862	0.862	0.863	0.863	0.532

Panel D Customer-Supplier relationship

	$P\_MF\ FREQ_{-i,j,t}$	$MF\ FREQ_{i,t}$
Independent Variables	(1)	(2)
	First-stage	Second-stage
$P\_MF\ FREQ_{-i,j,t}$		0.627**
		(2.349)
$P\_Customer\ Return\ shock_{-i,j,t-1}$	0.076***	
	(6.317)	
$P\_Raw\ Return_{-i,j,t-1}$	-0.155***	0.002
	(-14.097)	(0.040)
First-Stage F statistic	59.753	
Firm-Specific Characteristics	Yes	
Peer Firm Averages	Yes	
Firm and Quarter FE	Yes	
Number of Observations	138,033	
Adjusted R-squared	0.480	

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Table 6
Peer effects in future disclosures

This table presents the second-stage estimation results from 2SLS where the endogenous variable is the average frequency of peer firm management forecasts, and the instruments are peer idiosyncratic return shocks in quarter *t* and quarter *t-1*. The dependent variable is denoted in the top row of each column. $MF\ FREQ_{i,t+1}$, $MF\ FREQ_{i,t+2}$, and $MF\ FREQ_{i,t+3}$ is defined as the frequency of firm *i*'s management forecasts in quarter *t*, quarter *t+1*, and quarter *t+3*, respectively. All variables are defined in Appendix A. The table presents the heteroscedasticity-corrected Cragg-Donald (1993) statistic testing for weak instruments (First-Stage F-statistic), and *t*-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	$MF\ FREQ_{i,t+1}$	$MF\ FREQ_{i,t+2}$	$MF\ FREQ_{i,t+3}$
Independent Variables	(1)	(2)	(3)
$P\_MF\ FREQ_{-i,j,t}$	0.640**	0.483*	0.063
	(2.510)	(1.916)	(0.253)
First-Stage F-statistic	244.325	244.325	244.325
Firm-Specific Characteristics	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes
Firm and Quarter FE	Yes	Yes	Yes
Number of Observations	181,089	181,089	181,089
Adjusted R-squared	0.534	0.529	0.523

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Table 7
Cross-sectional analyses: Environmental uncertainty

This table reports second-stage results from 2SLS where the two endogenous variables are the average frequency of management forecasts (*P_MF FREQ*$_{-i,j,t}$) and the interaction between *P_MF FREQ*$_{-i,j,t}$ and *High Uncertainty*$_{i,t-1}$, and the two instruments are peer idiosyncratic return shocks (*P_Return Shock*$_{-i,j,t-1}$) and the interaction between *P_Return Shock*$_{-i,j,t-1}$ and *High Uncertainty*$_{i,t-1}$. *High Uncertainty*$_{i,t-1}$ in column 1 is based on the product market fluidity and is an indicator equal to one if the product market fluidity for firm *i* in quarter *t-1* exceeds the sample median and zero otherwise. In column 2, *High Uncertainty*$_{i,t-1}$ is based on the Competitive Strategic Measure (CSM) and equal to one if the absolute value of CSM exceeds the sample median and zero otherwise. CSM is defined as the coefficient of correlation between the ratio of the change of a firm's profits to the change of its sales, and the change in the combined sales of its rivals (i.e., a cross-partial derivative of firm value with regards to peer firms' strategic actions as measured by changes in sales). *High Uncertainty*$_{i,t-1}$ in column 3 is based on the cash flow volatility and equal to one if the cash flows volatility for firm *i* as of the beginning of quarter *t* is above the sample median and zero otherwise. Cash flows volatility is measured using seasonally-adjusted quarterly operating cash flows divided by lagged total assets using the last 20 quarterly observations preceding quarter *t* (a minimum of 12 observations is required). In column 4, the conditioning variable is based on the stock return volatility, which is measured as the standard deviation of firm *i*'s daily stock returns in quarter *t-1*, and equal to one if the stock return volatility is above the sample median and zero otherwise. All variables are defined in Appendix A. The table presents the heteroscedasticity-corrected Cragg-Donald (1993) statistic testing for weak instruments (First-Stage F-statistic), and *t*-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	MF FREQ$_{i,t}$			
Independent Variables	(1)	(2)	(3)	(4)
	Fluidity	CSM	CF Vol	Ret Vol
P_MF FREQ$_{-i,j,t}$	1.052***	0.484	0.646*	0.533
	(3.169)	(1.151)	(1.758)	(1.458)
High Uncertainty$_{i,t-1}$	-0.559**	-0.612***	-0.352*	-0.528***
	(-2.308)	(-2.715)	(-1.845)	(-2.796)
P_MF FREQ$_{-i,j,t}$ × *High Uncertainty*$_{i,t-1}$	1.121**	1.175***	0.622*	1.078***
	(2.312)	(2.651)	(1.714)	(2.756)
First-Stage F-statistic	49.991	49.729	108.568	64.39
Firm-Specific Characteristics	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Firm and Quarter FE	Yes	Yes	Yes	Yes
Number of Observations	157,088	151,726	164,939	181,089
Adjusted R-squared	0.493	0.496	0.520	0.488

Table 8
Cross-sectional analyses: Capital market benefits and peer effects

This table reports the second-stage estimation results from 2SLS where the two endogenous variables are the average frequency of management forecasts (*P_MF FREQ*$_{-i,j,t}$) and the interaction between *P_MF FREQ*$_{-i,j,t}$ and a conditioning variable in each column, and the two instruments are peer idiosyncratic return shocks (*P_Return Shock*$_{-i,j,t-1}$) and the interaction between *P_Return Shock*$_{-i,j,t-1}$ and the conditioning variable in each column. In column 1, the conditioning variable is *High Ext Fin Dep*$_{i,t-1}$ and based on the external financing dependence for firm *i* in quarter *t-1*. *Ext Fin Dep*$_{i,t-1}$ is computed as capital expenditures less operating cash flows divided by capital expenditures in quarter *t-1*. *High Ext Fin Dep*$_{i,t-1}$ is an indicator equal to one if *Ext Fin Dep*$_{i,t-1}$ exceeds the sample median and zero otherwise. In column 2, the conditioning variable is *Equity Issue*$_{i,t+1}$, which is an indicator equal to one if firm *i*'s net equity issuance in quarter *t+1* exceeds one percent of total assets and zero otherwise. In column 3, the conditioning variable is *Debt Issue*$_{i,t+1}$, which is an indicator equal to one if firm *i*'s net debt issuance in quarter *t+1* exceeds one percent of total assets and zero otherwise. All variables are defined in Appendix A. The table presents the heteroscedasticity-corrected Cragg-Donald (1993) statistic testing for weak instruments (First-Stage F-statistic), and *t*-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	MF FREQ$_{i,t}$		
	(1)	(2)	(3)
P_MF FREQ$_{-i,j,t}$	0.369	0.910***	1.045***
	(0.874)	(3.069)	(3.409)
High Ext Fin Dep$_{i,t-1}$	-0.602***		
	(-3.272)		
P_MF FREQ$_{-i,j,t}$ × *High Ext Fin Dep*$_{i,t-1}$	1.152***		
	(3.213)		
Equity Issue$_{i,t+1}$		-0.392**	
		(-2.378)	
P_MF FREQ$_{-i,j,t}$ × *Equity Issue*$_{i,t+1}$		0.827**	
		(2.441)	
Debt Issue$_{i,t+1}$			0.092
			(0.461)
P_MF FREQ$_{-i,j,t}$ × *Debt Issue*$_{i,t+1}$			-0.171
			(-0.419)
First-Stage F-statistic	67.243	154.572	63.026
Firm-Specific Characteristics	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes
Firm and Quarter FE	Yes	Yes	Yes
Number of Observations	161,613	181,089	181,089
Adjusted R-squared	0.485	0.531	0.535

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Table 9
Does peer firm disclosure induce disclosure of bad news?

This table presents the second-stage result from 2SLS where the endogenous variable is the average frequency of peer firm management forecasts and the instrument is peer idiosyncratic return shocks. The top row denotes the dependent variable used in each column. *MF BD* $FREQ_{i,t}$, *MF NEU* $FREQ_{i,t}$, and *MF GD* $FREQ_{i,t}$ is defined as the frequency of firm *i*'s management forecasts in quarter *t* that contain bad, neutral, and good news, respectively. All variables are defined in Appendix A. The table presents the heteroscedasticity-corrected Cragg-Donald (1993) statistic testing for weak instruments (First-Stage F-statistic), and *t*-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	MF BD $FREQ_{i,t}$	*MF NEU* $FREQ_{i,t}$	*MF GD* $FREQ_{i,t}$
Independent Variables	(1)	(2)	(3)
P_MF $FREQ_{-i,j,t}$	0.632***	0.123	0.256
	(2.767)	(0.728)	(1.062)
First-Stage F-statistic	314.889	314.889	314.889
Firm-Specific Characteristics	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes
Firm and Quarter FE	Yes	Yes	Yes
Number of Observations	181,089	181,089	181,089
Adjusted R-squared	0.267	0.131	0.224

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Table 10
Peer effects in other disclosure decisions

This table reports the second-stage results from 2SLS. In column 1, the endogenous variable is the peer firm average frequency of firm-initiated press releases, and the instrument is peer idiosyncratic return shocks. The dependent variable is denoted in the top row of each column. *PR* $FREQ_{i,t}$ is defined as the frequency of firm-initiated press release of firm *i* in quarter *t*. In columns 2-4, the endogenous variable is the peer firm average frequency of 8-K filings, and the instruments are peer idiosyncratic return shocks in quarter *t-1*, *t-2*, and *t-3*. *8K* $FREQ_{i,t}$, *Vol8K* $FREQ_{i,t}$, and *Man8K* $FREQ_{i,t}$ is defined as the frequency of firm *i*'s total, voluntary, and mandatory 8-K filings in quarter *t*, respectively. The table presents the heteroscedasticity corrected Cragg-Donald (1993) statistic testing for weak instruments (First-Stage F-statistic), and *t*-statistics robust to heteroskedasticity and within-firm dependence are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	PR $FREQ_{i,t}$	*8K* $FREQ_{i,t}$	*Vol8K* $FREQ_{i,t}$	*Man8K* $FREQ_{i,t}$
Independent Variables	(1)	(2)	(3)	(4)
P_PR $FREQ_{-i,j,t}$	1.324**			
	(2.343)			
P_8K $FREQ_{-i,j,t}$		0.544	1.186***	0.060
		(1.497)	(3.224)	(0.190)
First-Stage F-statistic	84.665	117.787	117.787	117.787
Firm-Specific Characteristics	Yes	Yes	Yes	Yes
Peer Firm Averages	Yes	Yes	Yes	Yes
Firm and Quarter FE	Yes	Yes	Yes	Yes
Number of Observations	101,221	180,066	180,066	180,066
Adjusted R-squared	0.664	0.540	0.474	0.327

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Research Highlights

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- Industry-peer disclosures induce firm disclosure, suggesting that they are a complement to a firm's information environment.
- Peer effects are more pronounced when a firm's strategic uncertainty is higher.
- Peer effects are stronger when a firm's dependence on external financing is greater.

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