Title: Information mosaic effect and discretionary disclosure

Version: May 2025

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Abstract:
This study examines the "mosaic effect" in the context of peer influences on management forecasts. The mosaic effect describes how pieces of information from different sources can be combined to form a more complete picture, enhancing decision-making for managers and well-informed stakeholders. Improvements in information precision among both groups generate two opposing forces influencing managers' strategic disclosure decisions, producing a U-shaped relationship between peer effects and voluntary disclosure. Using linear probability models and addressing the reflection problem, we provide empirical support for the U-shaped relationship using a sample of U.S. firms from 2003 to 2019. Furthermore, we find that as the industry's informational mosaic becomes more complete, voluntary disclosure decisions become less sensitive to peer disclosures, flattening the U-shaped relationship.

Keywords: Peer effect, information mosaic, voluntary disclosure.

Acknowledgments

This work is part of the R+D+i project PID2021-126617NB-I00, funded by MCIN/AEI/10.13039/501100011033.

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1. Introduction

Peer effects refer to the influence that the behavior of a group exerts on the decisions of individual members (Manski, 1993). Among the peer effects studied in the literature on voluntary disclosure[4], the most recent focus has been on the mosaic effect, where disclosures by peers improve the precision of managers' private information and thereby increase voluntary disclosure (Seo, 2021). According to this theory, assembling various pieces of information — much like constructing a mosaic — enhances the precision of private information (Pozen, 2005). Peer disclosures serve as valuable pieces that managers use to complete their informational mosaics, thereby increasing the likelihood of voluntary disclosure (Seo, 2021).

However, the mosaic effect extends beyond managers. Well-informed stakeholders within the same industry also benefit, reducing their need for additional disclosures from managers. As stakeholders independently achieve higher information precision, the informational pressure on managers to disclose weakens. Thus, peer disclosures simultaneously exert two opposing influences on managers' strategic disclosure decisions: a managerial information channel that increases voluntary disclosure, and a stakeholder pressure channel that decreases it.

The interplay of these forces suggests a U-shaped relationship between peer disclosure intensity and managers' voluntary disclosure behavior. Importantly, as industry-wide information availability expands beyond peer disclosures alone — for example, through greater analyst coverage or other external sources —peer effects on disclosure persist but attenuate. This flattening

[4] Another type of peer effect is the transfer or spillover effect, whereby an individual firm's economic situation can be inferred through the information disclosed by other firms within the same group (Baginski and Hinson, 2016; Lin, Mao, and Wang, 2018).

reflects the reduced sensitivity of managers' strategic disclosure decisions to peer behavior in more transparent environments.

This research contributes to the literature in several ways. First, it extends mosaic theory by offering evidence not only of a positive influence of peer disclosures on voluntary disclosure (Seo, 2021), but also of a distinct negative influence that emerges as stakeholders' informational mosaics improve. This dual influence provides a unified explanation for the observed U-shaped relationship between peer disclosure and managerial disclosure decisions, consistent with Verrecchia's (1983, 1990) theoretical predictions.

Identifying this negative influence is particularly meaningful. Prior literature has largely attributed disclosure reductions to opportunistic managerial behavior under spillover or information transfer effects (e.g., Baginski and Hinson, 2016; Lin, Mao, and Wang, 2018; Breuer et al., 2022). In contrast, our framework shows that managers may rationally reduce disclosure when stakeholders possess richer information. As stakeholder information increases — for instance, through improved coverage or within-industry similarity — their reliance on managerial disclosure diminishes. Combined with stronger early-stage reductions in firms' risk premia due to peer disclosures, this strategic withholding becomes not only rational but also comparable in magnitude to the classic mosaic effect (Seo, 2021).

Second, these theoretical insights have practical implications for investors, analysts, and policymakers. A reduction in disclosure should not be automatically interpreted as opportunistic behavior or a free-riding strategy. Instead, it may reflect a rational response to improvements in stakeholders' informational mosaics.

Third, the level of voluntary disclosure may depend on the industry's overall transparency. In industries where public and peer information is already abundant, additional firm-level disclosures may have less marginal value, and managers may rationally withhold further disclosure. In contrast, in less transparent environments, firms may feel greater pressure to contribute to the mosaic.

Finally, peer disclosure is only one among several contributors to stakeholders' information sets. Analyst coverage, correlated fundamentals among firms, and public sources of industry-wide data also shape the informational environment. Nonlinear models, in particular, may better capture how managers adjust their disclosure strategies in response to varying levels of external information. Recognizing these dynamics may help stakeholders more accurately interpret voluntary disclosure behavior, especially in industries with uneven information diffusion.

We build on prior research into peer effects in disclosure (Baginski and Hinson, 2016; Lin, Mao, and Wang, 2018; Breuer et al., 2022; Seo, 2021), while offering a broader conceptual grounding and novel empirical insights. The paper proceeds as follows: Section 2 develops our conceptual framework and hypotheses. Section 3 outlines the empirical methodology. Section 4 presents the results and robustness tests. Section 5 concludes.

2. Theoretical background and hypotheses development

Peer disclosures contribute to completing the focal manager's information mosaic, improving the precision of their private information. According to Verrecchia (1990, Corollaries 1 and 3), this enhancement lowers the manager's disclosure threshold, thereby increasing the likelihood of voluntary disclosure. Specifically, when firm-specific risks are not explicitly priced, withholding information can result in a steeper drop in market value, further incentivizing disclosure. Seo (2021) investigates this mechanism empirically and documents a positive relationship between peer disclosures and voluntary disclosure.

We extend Seo's analysis by incorporating the role of stakeholders' information mosaics and by recognizing that, when firm-specific risks are priced, greater precision in the manager's private information does not necessarily increase the incentive to disclose (Verrecchia, 1990). By addressing these gaps, we uncover a novel dynamic in the relationship between peer disclosures and voluntary disclosure.

Stakeholders, like managers, benefit from peer disclosures, which enhance the precision of their own information mosaics independently of the focal firm's disclosure behavior. As stakeholders become better informed, they rely less on firm-specific disclosures, reducing the external pressure on managers to voluntarily reveal private information (Verrecchia, 1990, Corollaries 2 and 4).

This stakeholder-side dynamic becomes particularly relevant when firm-specific risks are priced. As peer disclosures improve the manager's mosaic, any given disclosure becomes more informative, which lowers uncertainty for stakeholders and reduces the risk premium. A lower risk premium reduces the potential cost of nondisclosure, thereby weakening the manager's incentive to disclose[5]. Likewise, as stakeholders' mosaics become more complete through peer disclosures, the risk premium continues to decline, further diminishing the pressure on managers to voluntarily disclose information.

The magnitude of this risk-based effect depends on the overall level of peer disclosure. When peer disclosure is low, the information environment is less transparent, and stakeholder uncertainty — and therefore the risk premium — is high. Incremental peer disclosures in this range sharply reduce the risk premium due to its convexity[6], producing stronger disincentives for voluntary disclosure. By contrast, when peer disclosure is already high, the informational environment is

[5] As discussed in Verrecchia (1990), Corollaries 1 and 3 do not extend to settings where firm-specific risks are priced.
[6] We note that for CARA and CRRA utility functions, the risk premium is decreasing and convex in the information precision; please, see Appendix A.

more transparent, the risk premium is smaller, and additional peer disclosures reduce it only marginally — resulting in weaker disincentives to disclose.

Figure 1 summarizes the dual-channel mosaic mechanism through which peer disclosures shape voluntary disclosure incentives.

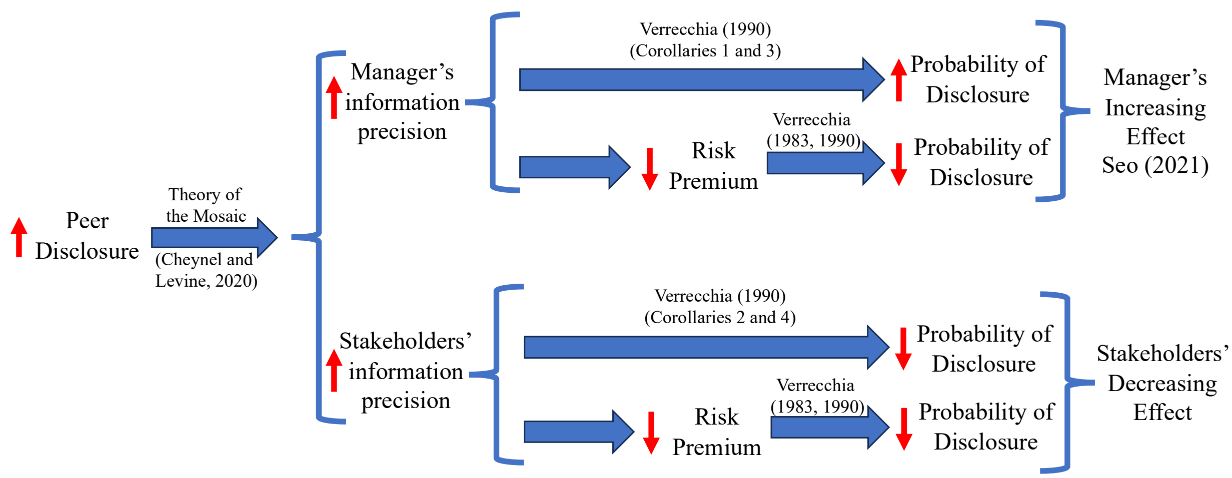

Figure 1: Summary of Peer effects on the probability of disclosure through information mosaics.

Figure 2 illustrates the opposing effects of the manager's mosaic channel (increasing), the stakeholder mosaic channel (decreasing), and the diminishing relevance of the risk premium as peer disclosure increases.

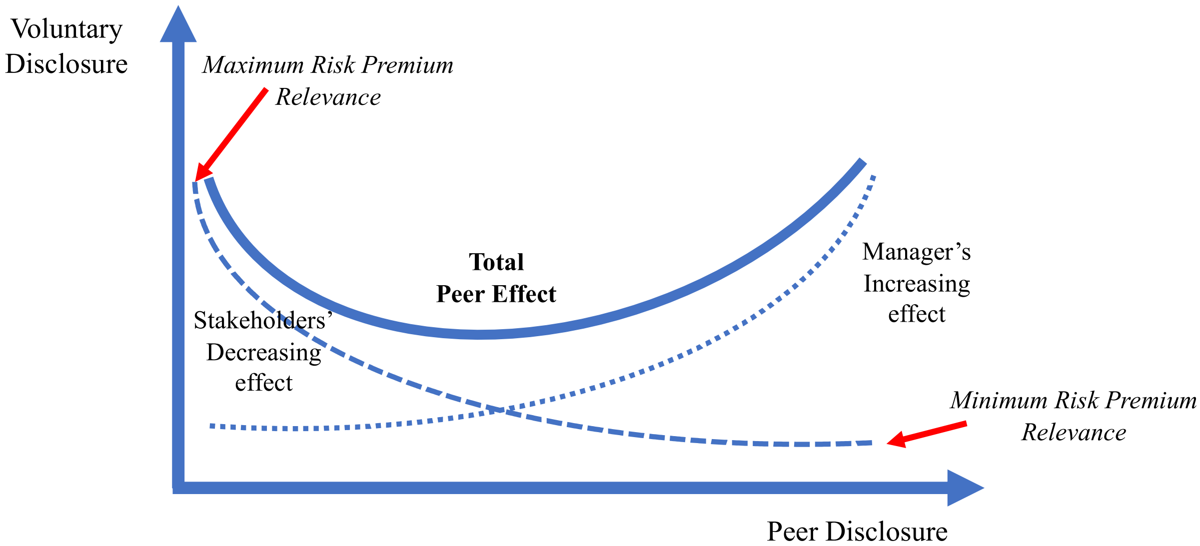

Figure 2: Peer effect influence on Voluntary firm disclosure and its components through information mosaics.

By synthesizing these insights, we propose a U-shaped relationship between peer disclosures and voluntary disclosures. At the lowest levels of peer disclosure and the highest risk premium, peer disclosures not only lead to reduced disclosure pressure from stakeholders, but also to larger adjustments in the risk premium, meaning that incremental peer disclosures are expected to make voluntary disclosure less likely. At higher levels, drawing on evidence from Seo (2021) and considering that peer disclosures engender smaller changes in the risk premium, we expect incremental peer disclosures to increase the likelihood of voluntary disclosure.

Based on these theoretical arguments, we hypothesize:

H1: Individual firms' voluntary disclosure decisions exhibit a U-shaped relationship with industry peer disclosure behavior.

The extent to which stakeholders can complete their informational mosaics depends not only on disclosures from peer firms but also on a range of alternative sources, such as analyst forecasts, institutional ownership reports, and market-based indicators like bid-ask spreads. When these alternative sources provide rich and precise information, stakeholders can build more accurate informational mosaics without relying as heavily on peer disclosures. As a result, the marginal impact of peer disclosure intensity on managers' voluntary disclosure behavior weakens. In other words, improvements in the broader information environment reduce the sensitivity of voluntary disclosure behavior to variations in peer disclosure intensity, thereby flattening the U-shaped relationship.

Figure 3 display this behavior, when total peer effect coexists with other information sources, it seems clear that the impact of peer effect tends to blur losing intensity.

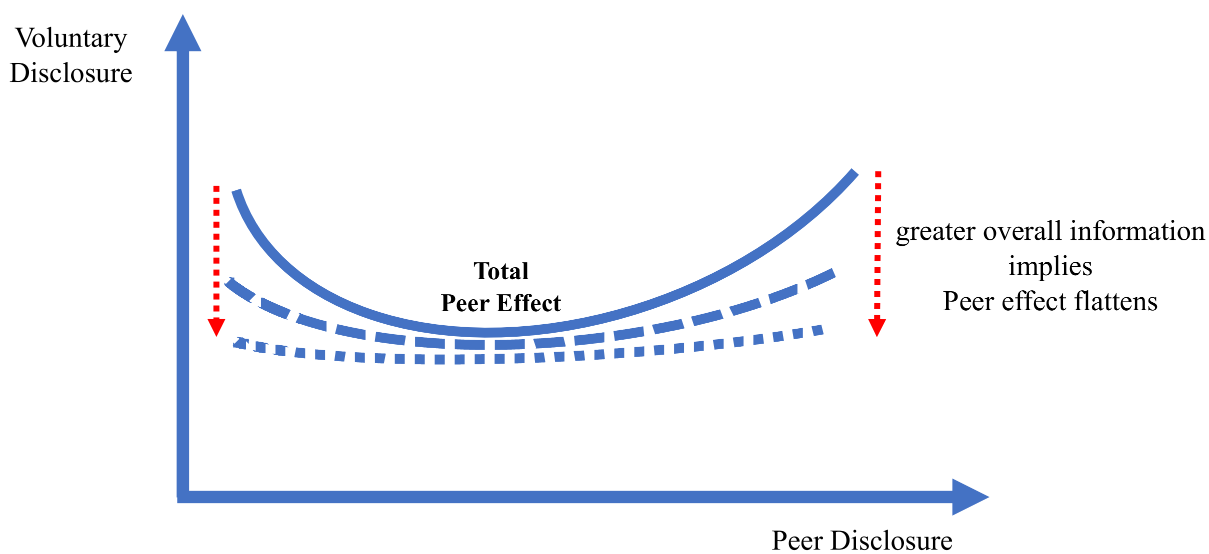

Figure 3: Evolution of Peer effect influence on Voluntary firm disclosure at different levels of overall information

Accordingly, we propose the following hypothesis:

H2: The U-shaped relationship between industry peer disclosure behavior and individual firms' voluntary disclosure decisions is weakened (flatten) in environments characterized by greater overall information availability.

3. Methodology

3.1 Sample

We build our sample starting with all US companies in Compustat, excluding financial firms (SIC code 6000-6999), utilities (SIC code 4900-4999), and public administration (SIC code 9000-9999), for the period from 2003 to 2019. We merge this information with data on firms' quarterly forecasts from the Institutional Brokers Estimate Systems (I/B/E/S) Guidance File, stock returns from CRSP, and data on the analyst coverage and institutional ownership from the I/B/E/S Adjusted Summary File and Thomson Reuters CDA/Spectrum Institutional (13F) Holdings database.[7]

We retain firm-quarter observations where the fiscal quarter-end month is March, June, September, or December, to ensure alignment of disclosure variables, returns, and accounting variables across peers (e.g., Kothari, Li and Short, 2009; Seo, 2021).

Finally, we narrow our sample to firm-quarter observations with non-missing values in all the variables in our empirical analysis. Overall, our sample contains 86,975 firm-quarter observations from 2003 to 2019. All variables in are winsorized at the 1% and 99% level to avoid the influence of outliers.

[7] For the purpose of this study, we assume that firms not appearing in the I/B/E/S Guidance database are non-disclosers. Likewise, if a firm does not appear in the I/B/E/S database in a given quarter, we assume that the number of analysts following it is zero (e.g., Chang, Dasgupta, and Hilary, 2006; Hameed, Morck, Shen, and Yeung, 2015). Finally, if a company does not appear in Thomson Reuters CDA/Spectrum Institutional (13F) Holdings database, we consider the institutional ownership of that firm to be zero (e.g., Bushee and Miller, 2012; Ferreira and Matos, 2008).

3.2 Empirical Model

To test our first hypothesis, we estimate the following equation:

$$\textit{Disclosure}_{i,t} = \beta_0 + \beta_1 * \textit{Peers' Disclosure}_{-i,j,t-1} + \beta_2 * \textit{Peers' Disclosure}^2_{-i,j,t-1}$$
$$+ \sum \mathrm{B}\ \textit{Controls}_{t-1} + \textit{Fixed Effects} + \varepsilon_{i,t} \qquad [1]$$

Equation 1 explains firm *i*'s voluntary disclosure decisions in quarter *t* as a function of the percentage of firm *i*'s industry peers disclosing information in the previous quarter. "$\textit{Disclosure}_{i,t}$" accounts for firm *i*'s voluntary disclosure in quarter t, and takes the value of one if firm *i* discloses at least one quarterly management forecast during quarter t, and zero otherwise.

Our main independent variable is "$\textit{Peers' Disclosure}_{-i,j,t-1}$" which accounts for firm *i*'s peers' voluntary disclosure decisions in quarter t-1. We define "$\textit{Peers' Disclosure}_{-i,j,t-1}$" as the percentage of firms in each industry as defined by the 4-digit Global Industry Classification (hereafter 4GICS), excluding firm *i*, that disclosed at least one management forecast during quarter t-1.[8] We use a lagged measure of our main independent variable to ensure that peers' disclosure decisions are visible to firm *i* before it makes its own voluntary disclosure decision (e.g., Matsumoto et al., 2022).

Following previous research, to test for the existence of a U-shaped relation proposed in our hypothesis, we include the squared of "$\textit{Peers' Disclosure}_{-i,j,t-1}$" in our model. Model 1 also includes a set of variables at both industry and firm-level aiming to control for factors that may influence firm *i*'s voluntary disclosure decisions. Finally, we include firm, year, and quarter fixed effects to control for time-invariant firm-level characteristics and time-variant tendencies and unmeasured common shock affecting firms' voluntary disclosure decisions.

[8] We use the four-digit GICS classification following previous work suggesting that this classification accurately explain cross-industry differences (and capture within-industry similarities) than other taxonomies such as SIC or NAICS classifications (e.g., Wowak, Mannor, Arrfelt and NcNamara, 2016).

3.3 Estimation Method: Two-State Least Squares and Instrumental Variable

A major identification problem in estimating peer effects is the reflection problem, which refers to the difficulty of distinguishing between the peer effects different effects that may influence peer behavior (Manski, 1993). In the context of our study, this problem arises because firms in the same industry may make similar voluntary disclosure decisions simply because they share common characteristics or operate in the same institutional environment. Hence, the estimation of the peer effects proposed in Equation 1 requires a statistical technique that minimizes this identification (or reflection) problem.

In this matter, we estimate model 1 using the methodology pioneered by Leary and Roberts (2014). Specifically, we use a two-stage least squares (2SLS) procedure using firm *i*'s peers' lagged idiosyncratic equity return shock is used as instrumental variable (e.g., Leary and Roberts, 2014; Seo, 2021).[9] This methodology is consistent with previous research exploring the influence of peer effects on individual firms' financial and accounting decisions (e.g., Du and Chen, 2018; Grennan,2019, Tou et al, 2020; Seo 2021, Matsumoto et al, 2022; Li and Wang, 2022; Cave and Lancheros, 2024, Cho et al., 2024; Le and Ramsey, 2024).

Moreover, this methodology poses two major advantages for the purposes of our study. First, idiosyncratic equity returns shocks to different firms within a peer group contain very little common variation (Leary and Roberts, 2014). Common variation constitutes, however, the underlying basis for the information transfer spillover effect. Therefore, if we find a negative influence of peer's behavior on firm i's voluntary disclosure decisions, it is likely to occur due to the mosaic effect described in our theoretical framework, rather than being due to information

[9] Seo (2021) indicates that firms' lagged idiosyncratic equity return shocks are a valid instrumental variable because they are likely to satisfy the relevance and exclusion conditions.

spillover. Second, this method directly allows us to test the quadratic relationship proposed in our theoretical predictions.[10]

Following prior literature, we use the following asset pricing model to isolate the idiosyncratic component of equity returns (e.g., Leary and Roberts, 2014; Seo, 2021):

$$r_{i,t} = \beta_{i,t}^{MKT}(rm_t - rf_t) + \beta_{i,t}^{IND}\left(\overline{r}_{-i,t} - rf_t\right) + \varepsilon_{i,t} \tag{2}$$

where $r_{i,t}$ accounts for firm *i*'s raw return in month t, $(rm_t - rf_t)$ is the excess market return in month t, and $\left(\overline{r}_{-i,t} - rf_t\right)$ represents the excess return on an equally weighted 4GICS industry portfolio (excluding firm *i*'s return). Specifically, we compute our instrument following the next sequential steps (e.g., Seo 2021):

1) For firm *i*, we estimate Equation 2 on a rolling quarterly basis using the stock returns of the past 60 months preceding the fiscal quarter (requiring a minimum of 24 observations).
2) We calculate monthly expected returns by multiplying the factor loadings obtained from step 2 by monthly factor returns in the fiscal quarter.
3) We calculate monthly idiosyncratic returns over the fiscal quarter as the difference between the monthly raw returns and the monthly expected returns calculated in step 2.
4) We compound the monthly idiosyncratic returns over the fiscal quarter to calculate quarterly idiosyncratic returns.
5) We calculate the average of peers' quarterly idiosyncratic returns in each 4GICS industry (excluding firm *i*).

[10] Other methodologies (such as a difference-in-differences models) provide a robust way to test the existence of peer-effects but might not be convenient for testing the existence of non-linear (i.e., quadratic) effects.

6) We lag the variable generated in step 5 two quarters to obtain our instrument (i.e., the instrument leads to peer firms' disclosure, which occurs in t-1). We name this variable "*IND_ Idiosyncratic Returns*$_{-i,j,t-2}$". [11]

We use *IND_ Idiosyncratic Returns*$_{i,j,t-2}$ and its squared term, as instruments in the 2SLS procedure to estimate Equation 1 (i.e., the endogenous variables are *Peers' Disclosure*$_{-i,j,t-1}$ and *Peers' Disclosure*$^{2}_{-i,j,t-1}$).

3.4 Control Variables

We control for a set of factors that previous research indicates may influence firms' voluntary disclosure decisions (e.g., Ajinkya et al., 2005; Balakrishnan et al., 2014b; Boone and White, 2015; Seo 2021). At the firm-level, we control for *"Firm size*$_{t-1}$*"*, which we compute as the natural logarithm of the firms' market capitalization at the end of each quarter (in millions of dollars). *"Leverage*$_{t-1}$*"* accounts for firms' debt-to-assets ratio (i.e., total financial debt /total assets). Past studies suggest that larger and more leveraged firms are more likely to disclose earnings guidance (e.g., Ahmed and Courtis, 1999; Seo 2021). The variable *"Book to Market*$_{t-1}$*"* (i.e., firm's book value of equity divided by firms' market capitalization) controls for individual differences in firms' growth opportunities, which is likely to influence firms' voluntary disclosure decisions (e.g., Vashishtha, 2014; Dong and Zhang 2019).

Prior studies suggest that capital expenditures may influence firms' disclosure decisions since they entail both greater private information and proprietary costs of disclosure (e.g., Boone et al., 2016; Kim et al., 2021). Based on this, we include the variable *"Investment*$_{t-1}$*"*, which accounts for firms' capital expenditures divided by total assets (e.g., Seo, 2021). Given that financial

[11] Appendix B shows a statistical summary of the intermediate results obtained when calculating our instrumental variable. Figures are similar to the intermediate statistics presented by SEO (2021) and Leary and Roberts (2014).

performance may modify the benefits and costs of disclosing information, we include the *"Performance$_{t-1}$"*, which represents firms' return on assets (i.e., income before extraordinary items divided by total assets). Likewise, we include the variable *"Return Shock$_{t-1}$"* to control for firm *i*'s quarterly idiosyncratic stock returns in quarter t-1.

To account for possible differences in firms' voluntary disclosure decisions arising because of the predictability of firms' results, we include the *"R&D$_{t-1}$"* and *"Earnings Volatility$_{t-1}$",* which we calculate as the natural logarithm of firms' research and development expenses (e.g., Ali et al, 2014) and the standard deviation of return on assets for the 20 quarters preceding quarter t (e.g., Seo, 2021), correspondingly.

Since firms owned by institutional investors usually have different information needs than firms owned by individual investors (Bamber and Cheon, 1998; Bushee, Matsumoto and Miller, 2003; Healy, Hutton and Palepu, 1999), we include the variable *"Institutional ownership$_{t-1}$"*. We define this variable as the percentage of firm i's shares owned by institutional investors. Finally, to account for the potential effect of analyst's coverage on firms' voluntary disclosure (Ajinkya, Bhoiraj and Sengupta, 2005; Anilowski, Feng and Skinner, 2007; Healy et al., 1999), we control for the number of analysts following. We refer to this variable as *"Analysts coverage$_{t-1}$"*.

At the industry level, we also include GIC4-industry averages of the above-mentioned control variables to account for incentives to disclose information related with the characteristics and institutional environment of each GIC4 industry (e.g., Seo, 2021). These industry-level variables are labeled with the prefix *"IND_"*. We lag all above-mentioned control variables one period (i.e., they are calculated in t-1) so they precede firm *i*'s disclosure decisions in time t. Table 1 provides a summary of the definitions of all the variables included in our models.

4. Results

4.1 Statistical Summary and Correlations

Table 2 displays the descriptive statistics of the variables included in our empirical models. Statistics indicate that around 26% of the companies in our sample provide quarterly guidance and 13% of the firms in the average industry disclosed information during the previous quarter (with a minimum of zero and a maximum of 38%). The statistics of the rest of the variables suggest that our sample has enough variability to generalize our results.

Table 3 presents the Pearson's pairwise correlation among the variables in our analysis. Consistent with prior research (e.g., Seo, 2021), *"$Disclosure_{i,t}$"* is significantly and positively related to *"Peers' $Disclosure_{–i,j,t-1}$"* ($r=0.485$; $p\text{-value}<0.05$). Table 3 does not show any high pairwise correlation between our controls and our main independent variable, and hence, we do not expect to find severe multicollinearity problems in our estimations.[12] For the sake of readability, we do not offer insights on the pairwise correlations between our control variables.

TABLE 2 about here

TABLE 3 about here

4.2 U-shape relation between Peers' $Disclosure_{–i,j,t-1}$ and $Disclosure_{it,}$

We test Hypothesis 1, which predicts a U-shaped relationship between the endogenous variable (*$Disclosure_{i,t}$*) and the main independent variable (*Peers' $Disclosure_{–i,j,t-1}$*), following Equation [1].

Table 4 reports the results from two-stage least squares (2SLS) regressions with firm-level clustered standard errors.[13] In Model 1, we examine the linear effect of *Peers' $Disclosure_{–i,j,t-1}$* on

[12] Consistent with this notion, the Variance Inflation Factor of the variables in our models is low (i.e., VIF of "Peers' Disclosure–i,j,t-1" is 2.2 and the largest individual VIF of the model is 4.24).
[13] Similar to recent research on voluntary disclosure (e.g., Seo, 2021; Kim, Taylor and Verrecchia, 2021), we use a linear probability model as opposed to a non-linear model such as probit or logit to avoid the incidental parameters problem arising due to the use of firm and time fixed effects (e.g., Ai and Norton, 2003).

Disclosure$_{i,t}$. Consistent with Seo (2021), the estimated coefficient is positive and statistically significant (p-value < 0.001).

In Model 2, we add the squared term of *Peers' Disclosure*$_{-i,j,t-1}$. The coefficient on the quadratic term is positive and significant (p-value < 0.05), indicating a convex effect. This result provides initial support for the U-shaped relationship proposed in our theoretical framework. However, as emphasized by Haans, Pieters, and He (2016) and Lind and Mehlum (2010), three additional conditions must be satisfied to formally support the existence of a U-shaped relationship.

First, the influence of disclosure behavior of industry peers on the voluntary disclosure decisions of individual firms must be negative at the lowest level of peers' disclosures. We formally test this condition by assessing whether β_1 + (2*β_2* MIN*Peers' Disclosure*$_{-i,j,t-1}$) is negative and significant.

Second, the influence of the disclosure behavior of industry peers on the voluntary disclosure decisions of individual firms must be positive at the highest level of peers' disclosures. We formally test this condition by assessing whether β_1 + (2*β_2* MAX*Peers' Disclosure*$_{-i,j,t-1}$) is positive and significant.

Finally, the turning point of the quadratic function must be located well within the data range of *Peers' Disclosure*$_{i,t-1}$ in our sample. To test this condition, we calculate the 95% interval of the turning point of the function (i.e., $-\beta_1 / 2\beta_2$)..

These three additional tests are presented in the lower panel of Table 4. Results indicate that the slope of the quadratic function at the lowest level of *Peers' Disclosure*$_{-i,j,t-1}$ is negative and significant (p-value < 0.10) while the slope at the highest level of *Peers' Disclosure*$_{-i,j,t-1}$ is positive and significant (p-value < 0.05). Likewise, the confidence interval for the turning point (i.e., [0.122, 0.189]) is within the range of *Peers' Disclosure*$_{-i,j,t-1}$. Overall, consistent with our theoretical prediction, this evidence supports the existence of a U-shape relationship between *Peers' Disclosure*$_{-i,j,t-1}$ and *Disclosure*$_{i,t}$.

Figure 4 presents a graphical representation of these results. Table 4 also presents the Kleibergen-Paap rk Wald F statistic, which provides insights about the strength of the instrumental variable used in the 2SLS model. In Models 1 and 2, the statistic is well above the commonly accepted threshold of 10 (e.g., Staiger and Stock, 1997) and the critical values indicated by Stock and Yogo (2005) for models with two endogenous variables and two instruments. These findings suggest that our instruments are not weak.

TABLE 4 about here

FIGURE 4 about here

4.3 Moderation Analysis

In this subsection, we test Hypothesis 2. Given the U-shaped relationship between *Disclosure*$_{i,t}$ and our main independent variable, *Peers' Disclosure*$_{-i,j,t-1}$, we explore how this relationship flattens or steepens depending on different moderators that represent the completeness of the information mosaic. As mentioned in H2, we expect the U-shape to flatten as firm i's informational environment enables market agents to make more accurate predictions of firm i's outcomes. We test this notion with the following model:

$$\begin{aligned} \textit{Disclosure}_{i,t} = {} & \beta_0 + \beta_1 * \textit{Peers' Disclosure}_{-i,j,t-1} + \beta_2 * \textit{Peers' Disclosure}^2_{-i,j,t-1} + \beta_3 * \textit{Moderator}_{t-1} + \\ & \beta_4 * \textit{Peers' Disclosure}_{-i,j,t-1} * \textit{Moderator}_{t-1} + \beta_5 * \textit{Peers' Disclosure}^2_{-i,j,t-1} * \textit{Moderator}_{t-1} + \\ & \sum B\ \textit{Controls}_{t-1} + \textit{Fixed Effects} + \varepsilon_{i,t} \end{aligned} \quad [3]$$

Testing whether the U-shaped relationship found in our main analysis steepens or flattens depending on the moderating variable can be assessed by analyzing the sign and significance of β_5 from Equation [3]. Specifically, the U-shaped function will steepen (flatten) when β_5 is positive (negative) and statistically significant (Haans et al., 2016). Similar to the empirical model used to test H1, we estimate Equation [3] using a two-stage least squares (2SLS) procedure, where *Peers' Disclosure*$_{-i,j,t-1}$, *Peers' Disclosure*$^{2}_{-i,j,t-1}$, and their cross-products with *Moderator*$_{t-1}$ are treated as exogenous variables, and *IND_ Idiosyncratic Returns*$_{i,j,t-2}$, *IND_ Idiosyncratic Returns*$_{i,j,t-2}^{2}$, and their corresponding interactions with *Moderator*$_{t-1}$ are used as instruments.

For the purposes of this analysis, *Moderator*$_{t-1}$ may account for six different proxies that previous studies have linked to differences in firms' informational environment: firm size, institutional ownership, bid-ask spread, accuracy of analysts' forecasts, dispersion of analysts' forecast, and a measure of the overall uncertainty in firm's informational environment.

First, we compute firm size as firms' market capitalization in *t-1*. The amount of information available tends to be larger for larger firms and hence, larger firms may present a less uncertain informational environment (e.g., Collins et al., 1987; Zhang 2006). Therefore, we would expect the U-shape to flatten as firms' size increases.

Second, firms with larger institutional ownership (computed as the percentage of firm *i*'s shares owned by institutional investors) tend to produce richer public information (both by managers and analysts), and show lower information asymmetries as well as higher liquidity (e.g., Boone and White, 2015). Based on this notion, we expect the U-shape to flatten as the degree of firms' institutional ownership increases. The quarterly average of the daily bid-ask spread (i.e., ask minus bid divided by the average of the two (e.g., Chung and Zang, 2014)) aims to capture the information asymmetries existing in firm i's informational environment.

Third, a higher bid-ask spread indicates more information asymmetries and therefore, we expect the U-shape to steepen in firms with a higher bid-ask spread.

Fourth, the accuracy and dispersion of analysts' forecasts are factors that may be related to the level of information that market agents have about firm *i* (e.g., Barron et al., 1998). We compute the accuracy and dispersion of analysts' forecasts in the following way:

$$Accuracy_{i,t} = \left(\frac{\left|\mathrm{MEANEST}_{i,t} - \mathrm{EPS}_{i,t}\right|}{Price_{i,t-1}}\right) x - 100$$

$$Dispersion_{i} = \left(\frac{\mathrm{Std\ dev\ (EST}_{i,t})}{Price_{i,t-1}}\right) x\ 100$$

Accuracy is the mean forecast error (i.e., mean analysts' EPS forecast minus actual EPS) in quarter *t* divided by the stock price at the beginning of quarter *t* x -100. Higher values of accuracy correspond to situations in which analysts' forecast errors are smaller. Dispersion is computed as the standard deviation of analysts' forecasts in quarter *t* divided by the stock price at the beginning of quarter *t* x 100 (e.g., Lang and Lundholm, 1996, Cohen and Lys, 2003; Behn et al., 2008; Lim, Lim, and Lobo 2013; Gul et al. 2013).

A higher accuracy (dispersion) suggests that firm *i*'s informational environment may be less (more) uncertain. Therefore, we expect the U-shape to flatten (steepen) as the accuracy (dispersion) of analysts' forecasts increases.

Finally, we proxy the overall uncertainty in firm *i*'s informational environment using the measure of the overall uncertainty proposed originally by Barron et al. (1998). We calculate this variable in the following way (e.g., Lehavy et al., 2011):

$$Overall\ Uncertainty = \left(1 - \frac{1}{\#Analysts_{i,t}}\right) * \left(\frac{\mathrm{Std\ dev\ (EST}_{i,t})}{Price_{i,t-1}}\right) - \frac{\left(\mathrm{MEANEST}_{i,t} - \mathrm{EPS}_{i,t}\right)^{2}}{Price_{i,t-1}}$$

We expect the U-shape to steepen as firms' information environments are characterized by greater uncertainty. To explore the heterogeneity of effects, we partition firms based on the quartile-median values of the moderators.[14]

TABLE 5 about here

Table 5 presents the results of our moderation analysis. Models 1 and 2 indicate that the U-shaped relationship between "$Disclosure_{i,t}$" and "$Peers' \ Disclosure_{-i,j,t-1}$" tends to be flatter for larger firms (β_5=-21.466, p-value < 0.001) and for firms with lower bid-ask spreads (β_5=9.520, p-value < 0.05), respectively. These results provide support for H2.

In a similar fashion, and consistent with H2, Model 3 shows that the U-shaped relationship explored in H1 is flatter for firms with higher institutional ownership (β_5=-6.221, p-value < 0.034). Regarding the accuracy and dispersion of analysts' forecasts, Models 4 and 5 indicate that the U-shaped relationship between "$Disclosure_{i,t}$" and "$Peers' \ Disclosure_{-i,j,t-1}$" is flatter when analysts' forecasts are more accurate (β_5=-13.390, p-value < 0.001) and when analysts' forecasts are less dispersed (β_5=12.994, p-value<0.001). These findings are consistent with H2.

Finally, the results of Model 6 suggest that firms operating in an information environment characterized by higher overall uncertainty exhibit a steeper U-shaped relationship between peers' disclosure and firm *i*'s voluntary disclosure decisions (β_5=14.973, p-value < 0.001). This result also supports H2.

Figure 5 presents a graphical representation of all the moderation effects analyzed in this subsection. Overall, the results of our moderation analysis suggest that, as predicted in H2, the U-shaped relationship between "$Disclosure_{i,t}$" and "$Peers' \ Disclosure_{-i,j,t-1}$" is flatter for firms with a

[14] We first divide the sample into quartiles and then we compute the median of each quartile.

less uncertain information environment or, according to the mosaic theory, greater completeness of the information mosaic.

TABLE 5 about here

FIGURE 5 about here

4.4 Robustness Tests

An important assumption for the reflection problem to exist is that all peers within a group have the same set of peers over the time span of the study (e.g., Aghamolla and Thakor, 2022). This assumption is more likely to hold when peers are identified based on static industry classification, such as the 4-digit GICS. Under such conditions, a conventional panel data regression model cannot identify peer effects, and more robust methodologies are required (such as the approach proposed by Leary and Roberts). Conversely, the reflection problem is less likely to be a material issue if peers are identified using a non-static industry classification in which firms' peers vary over time.

Based on this idea, we estimate a conventional panel data model using the two-digit "text-based network industry classifications" (TNIC), in which each firm has its own distinct and evolving set of competitors (Hoberg and Phillips, 2016).

The model includes firm, year, and quarter fixed effects, as well as the full set of control variables used in our main analysis. Table 6 presents the results of the analysis testing for the existence of a U-shaped relationship between *Peers' Disclosure*$_{-i,j,t-1}$ and *Disclosure*$_{i,t}$ using the TNIC classification. Consistent with our main analysis, Model 2 confirms the existence of a U-shaped relationship between "*Disclosure*$_{i,t}$" and "*Peers' Disclosure*$_{-i,j,t-1}$".

Table 7 presents the results of our moderation analysis using the alternative TNIC industry classification. Models 1-7 show that the interaction terms between the moderators and *Peers'*

Disclosure$_{-i,j,t-1}$ are significant and suggest a moderating effect consistent with our main findings. From our perspective, these results suggest that the methodology employed to test H1 adequately overcomes the reflection problem and provides a reasonable identification strategy for peer effects on voluntary disclosure.[15]

TABLE 6 about here

TABLE 7 about here

5. Conclusions

This study extends prior research on peer disclosure influences (Baginski and Hinson, 2016; Lin, Mao, and Wang, 2018) by adopting a mosaic theory perspective (Seo, 2021; Cheynel and Levine, 2020). In incomplete information environments, both managers and external decision-makers construct their information mosaics using disclosures from peer firms. This dual-channel mechanism gives rise to two opposing forces linking peer and managerial disclosure, ultimately resulting in a U-shaped relationship.

Our analysis provides empirical support for a previously unrecognized negative peer effect on voluntary disclosure, while also providing evidence that aligns with and extends existing theoretical prediction. Peer disclosures enhance the precision of stakeholders' private information and reduce the associated risk premium. As a result, managers face diminished pressure to disclose. These dynamics go beyond the traditional "free-riding" interpretation and evidence that a single framework—mosaic theory—can account for both positive and negative disclosure incentives.

[15] In untabulated results we also added the quarterly change in revenues to the models as a control variable. Controlling for this factor does not modify the results of our analysis.

From a methodological standpoint, our findings underscore the importance of nonlinear modeling in analyzing voluntary disclosure decisions. Standard linear models may introduce bias by misestimating the direction or strength of peer influences across varying levels of industry transparency. Moreover, peer disclosure is only one of many sources through which stakeholders construct their mosaics. As alternative information channels—such as analyst coverage—expand, the marginal influence of peer disclosure weakens. This highlights that managerial disclosure incentives are shaped by the broader informational environment.

Our findings also yield practical insights. As peer disclosures improve stakeholders' informational position, their reliance on firm-specific guidance declines. This shift reduces the marginal benefit of voluntary disclosure for managers. As a result, managers may rationally choose to withhold disclosure even as peer disclosures increase—a dynamic driven not by information transfer per se, but by the way peer disclosures enrich the broader informational mosaic available to investors.

From stakeholders' perspective, such as institutional investors or board members, non-disclosure should be interpreted in the context of industry-level information precision. At lower levels of peer disclosure, a firm's silence may reflect an efficient response to reduced informational demand rather than an intentional signal of opacity. Similarly, analysts should interpret reduced disclosure in low-disclosure settings with caution. When a firm refrains from disclosing while its peers increase disclosures, this may reflect optimal behavior, rather than diminished transparency.

Lastly, policymakers and standard setters should recognize that more peer disclosure does not always lead to more firm-level disclosure. If the goal is to increase voluntary disclosure, strengthening other sources of investor information—such as promoting analyst activity or enhancing institutional transparency—can moderate the negative peer effect at low levels of peer transparency, although it may also dampen the positive effect at higher levels. Thus, disclosure regulation should consider the dynamic, non-linear effects of peer transparency when designing incentives or mandates.

Finally, while our study identifies a rational mechanism through which peer disclosures may reduce firm-level disclosure, earlier work has emphasized opportunistic motivations such as free-riding behavior (Baginski and Hinson, 2016; Breuer et al., 2022). Future research should aim to disentangle these competing explanations. Specifically, when managers withhold information, what share of the effect reflects strategic adaptation to reduced external demand, and what share reflects an agency-based effort to obscure? Clarifying this distinction would help deepen our understanding of how transparency, discretion, and market incentives interact.

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Table 1. Variable definitions

Variable	Definition
Disclosure$_{i,t}$	1 if firm *i* provides any types of management guidance for the current quarter and 0 otherwise.
Peers' Disclosure$_{-i,j,t-1}$	Percentage of firms disclosing any types of management guidance (excluding firm i) in quarter t-1. Calculated for each four-digit GICS industry.
Firm Size$_{t-1}$	Natural logarithm of firm *i*'s market capitalization (in million USD) in quarter *t-1*.
Book to market$_{t-1}$	Firm *i*'s Book to market ratio (i.e. firms market capitalization plus long-term debt divided by firm total asset) in quarter *t-1*.
Leverage$_{t-1}$	Firm *i*'s Debt-equity ratio (i.e. total liabilities divided by Stockholders' equity) in quarter *t-1*.
Investment$_{t-1}$	Firm *i*'s capital expenditures divided by total assets in quarter *t-1*.
Performance$_{t-1}$	Firm *i*'s ROA ratio (i.e. income before extraordinary items divided by total assets) in quarter -1*t*.
Return Shock$_{t-1}$	Firm i's quarterly idiosyncratic stock returns in quarter t-1.
R&D$_{t-1}$	Natural logarithm firm *i*'s research and development expenses in quarter *t-1*.
Earnings Volatility$_{t-1}$	Standard deviation of firm *i*'s return on assets for the 20 quarters preceding quarter t.
Analysts Coverage$_{t-1}$	Number of analysts following firm *i* in quarter *t*.
Institutional Ownership$_{t-1}$	Percentage of firm *i*'s stock owned by institutional investors in quarter *t*.
Industry Averages$_{t-1}$	Models include GIC4-industry averages of the above-mentioned control variables to account for incentives to disclose information related with the characteristics of each GIC4 industry. These industry-level variables are labeled with the prefix "IND_".
Bid-Ask Spread$_{t-1}$	Quarterly average daily bid-ask spread (i.e., ask minus bid divided by the average of the two).
Accuracy$_{t-1}$	Absolute value of mean forecast error (i.e., mean analysts' EPS forecast minus actual EPS) in quarter t divided by the stock price at the beginning of quarter t x -100
Dispersion$_{t-1}$	Standard deviation of analysts' forecasts in quarter t divided by the stock price at the beginning of quarter t x 100
Overall Uncertainty$_{t-1}$	$\left(1-\frac{1}{\#\,Analysts_{i,t}}\right)*\left(\frac{\text{Std dev}\left(\text{EST}_{i,t}\right)}{Price_{i,t-1}}\right)-\frac{\left(\text{MEANEST}_{i,t}-\text{EPS}_{i,t}\right)^2}{Price_{i,t-1}}$ Where $\#\,Analysts$ accounts for the number of analysts following firm *i* in quarter *t*, Std dev $\left(\text{EST}_{i,t}\right)$ is the standard deviation of analysts' EPS forecasts of firm *i* in quarter *t*, $\text{MEANEST}_{i,t}$ is the mean analysts' EPS forecast of firm *i* in quarter *t*, $\text{EPS}_{i,t}$ is the actual EPS of firm *i* in quarter *t*, and $Price_{i,t-1}$ is firm *i*'s stock price at the beginning of quarter *t*.

Notes: All continuous variables winsorized at 1% and 99% level.

Table 2. Summary of Statistics

Variable	*n*	*Mean*	*S.D.*	*Min*	*0.25*	*Median*	*0.75*	*Max*
Disclosure$_{i,t}$	86,975	0.26	0.44	0	0	0	1	1
Peers' Disclosure$_{-i,j,t-1}$	86,975	0.13	0.11	0	0.04	0.11	0.18	0.38
Firm Size$_{t-1}$	86,975	7.12	1.67	0.27	5.92	7.01	8.2	10.83
Book to Market$_{t-1}$	86,975	0.51	0.45	0.02	0.24	0.4	0.64	5.21
Leverage$_{t-1}$	86,975	0.22	0.19	0	0.03	0.2	0.35	0.81
Investment$_{t-1}$	86,975	2.97	3.85	0	0.73	1.64	3.51	22.01
Performance$_{t-1}$	86,975	0	0.05	-0.42	0	0.01	0.02	0.12
Return Shock$_{t-1}$	86,975	-0.01	0.2	-0.56	-0.13	-0.02	0.08	0.84
R&D$_{t-1}$	86,975	0.01	0.03	0	0	0	0.02	0.14
Earnings Volatility$_{t-1}$	86,975	0.03	0.04	0	0.01	0.02	0.04	0.41
Analysts Coverage$_{t-1}$	86,975	9	6.21	0	4	7	13	24
Institutional Ownership$_{t-1}$	86,975	0.72	0.25	0	0.59	0.79	0.91	1
IND_Size$_{t-1}$	86,975	5.83	0.67	3.97	5.36	5.88	6.29	7.46
IND_Book to Market$_{t-1}$	86,975	4.78	27.95	0.27	0.53	0.68	0.9	253.15
IND_Leverage$_{t-1}$	86,975	0.21	0.07	0.07	0.15	0.21	0.26	0.47
IND_Investment$_{t-1}$	86,975	2.73	2.12	0.02	1.43	2.08	3.11	11.39
IND_Performance$_{t-1}$	86,975	-0.02	0.06	-0.92	-0.03	-0.01	0	0.17
IND_R&D$_{t-1}$	86,975	0.02	0.02	0	0	0.01	0.02	0.08
IND_Earnings Volatility$_{t-1}$	86,975	0.08	0.1	0.01	0.04	0.06	0.09	1.15
IND_Analysts Coverage$_{t-1}$	86,975	4.79	1.63	0.97	3.62	4.53	5.57	8.52
IND_Institutional Ownership$_{t-1}$	86,975	0.35	0.09	0	0.28	0.34	0.41	0.53
IND_Idiosyncratic Returns$_{-i,j,t-2}$"	86,975	-0.01	0.02	-0.04	-0.02	-0.01	0	0.04

Table 2 shows the number of observations, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum of all the variables included in our analysis. Variable definitions are presented in Table 1.

Table 3. Correlations (Part A)

	Variable	1	2	3	4	5	6	7	8	9	10
1	*Disclosure*$_{i,t}$	1									
2	*Peers' Disclosure*$_{-i,j,t-1}$	0.4846*	1								
3	*Firm Size*$_{t-1}$	0.0002	-0.1523*	1							
4	*Book to Market*$_{t-1}$	-0.0165*	0.0200*	-0.3193*	1						
5	*Leverage*$_{t-1}$	-0.1585*	-0.2812*	0.1809*	0.0390*	1					
6	*Investment*$_{t-1}$	-0.0515*	-0.0796*	0.0325*	0.0463*	0.0863*	1				
7	*Performance*$_{t-1}$	0.0893*	0.0675*	0.3299*	-0.0771*	0.0052	0.0503*	1			
8	*Return Shock*$_{t-1}$	-0.0005	-0.0094*	0.0715*	-0.1230*	0.0062	-0.0174*	0.0556*	1		
9	*R&D*$_{t-1}$	0.0276*	0.0676*	-0.2269*	-0.1933*	-0.2625*	-0.1496*	-0.5257*	-0.0128*	1	
10	*Earnings Volatility*$_{t-1}$	-0.0034	0.0588*	-0.3051*	-0.0251*	-0.1281*	-0.0340*	-0.3662*	-0.0202*	0.3934*	1
11	*Analysts Coverage*$_{t-1}$	0.0782*	-0.0378*	0.7152*	-0.1518*	0.1094*	0.1307*	0.1628*	-0.0147*	-0.0942*	-0.1560*
12	*Institutional Ownership*$_{t-1}$	0.1046*	0.0321*	0.3381*	-0.0854*	0.0570*	-0.0194*	0.2248*	0.0078*	-0.1619*	-0.2290*
13	*IND_Size*$_{t-1}$	-0.2361*	-0.3595*	0.2338*	-0.0540*	0.2294*	0.1385*	0.0468*	0.0374*	-0.1213*	-0.0898*
14	*IND_Book to Market*$_{t-1}$	0.0083*	-0.0011	0.0022	0.0271*	0.0266*	0.0498*	0.0260*	0.001	-0.0538*	-0.0250*
15	*IND_Leverage*$_{t-1}$	-0.3138*	-0.5989*	0.1834*	0.1309*	0.3900*	0.2789*	0.1131*	0.0140*	-0.4197*	-0.2124*
16	*IND_Investment*$_{t-1}$	-0.0803*	-0.1285*	0.0852*	0.1430*	0.1622*	0.6096*	0.0852*	0.0208*	-0.2439*	-0.0879*
17	*IND_Performance*$_{t-1}$	-0.0361*	-0.0691*	0.0928*	0.1315*	0.1279*	0.2274*	0.1744*	0.0124*	-0.3344*	-0.1460*
18	*IND_R&D*$_{t-1}$	0.0583*	0.0955*	-0.1201*	-0.1604*	-0.2178*	-0.2152*	-0.3100*	-0.0132*	0.6298*	0.2990*
19	*IND_Earnings Volatility*$_{t-1}$	0.0384*	0.0451*	-0.0482*	-0.0154*	-0.0413*	0.0374*	-0.0516*	-0.0193*	0.0857*	0.0692*
20	*IND_Analysts Coverage*$_{t-1}$	-0.0567*	0.0013	0.1126*	0.0622*	0.0825*	0.1194*	0.0144*	0.0215*	-0.0140*	-0.0135*
21	*IND_Institutional Ownership*$_{t-1}$	-0.0994*	-0.1167*	0.0961*	-0.0063	0.0565*	-0.0423*	-0.0170*	0.0342*	0.0497*	-0.0449*
22	*IND_Idiosyncratic Returns*$_{-i,j,t-2}$"	-0.1138*	-0.1933*	0.0543*	-0.0436*	0.0521*	0.0119*	-0.0406*	0.0261*	0.0369*	-0.0337*

Table 3. Correlations (Part B)

	Variable	11	12	13	14	15	16	17	18	19	20	21	22
11	*Analysts Coverage$_{t-1}$*	1											
12	*Institutional Ownership$_{t-1}$*	0.2931*	1										
13	*IND_Size$_{t-1}$*	0.1565*	0.0465*	1									
14	*IND_Book to Market$_{t-1}$*	0.0071*	-0.0080*	-0.0252*	1								
15	*IND_Leverage$_{t-1}$*	0.0792*	-0.0170*	0.4617*	0.0748*	1							
16	*IND_Investment$_{t-1}$*	0.1420*	-0.0412*	0.2646*	0.0639*	0.4404*	1						
17	*IND_Performance$_{t-1}$*	0.0868*	0.0041	0.2548*	0.0689*	0.3686*	0.3692*	1					
18	*IND_R&D$_{t-1}$*	-0.0423*	-0.0481*	-0.2058*	-0.0844*	-0.6336*	-0.3432*	-0.5328*	1				
19	*IND_Earnings Volatility$_{t-1}$*	-0.0152*	-0.0565*	-0.1351*	-0.0069*	-0.0759*	0.0322*	-0.1149*	0.1506*	1			
20	*IND_Analysts Coverage$_{t-1}$*	0.2074*	0.0554*	0.7179*	-0.0275*	0.1164*	0.2223*	0.2165*	-0.0444*	-0.1547*	1		
21	*IND_Institutional Ownership$_{t-1}$*	0.0673*	0.1474*	0.5370*	-0.0540*	0.0663*	-0.0307*	0.0280*	0.0792*	-0.2196*	0.6091*	1	
22	*IND_Idiosyncratic Returns$_{-i,j,t-2}$”*	0.0116*	0.0383*	0.2296*	-0.0368*	0.0890*	0.0192*	-0.0006	0.0547*	-0.0976*	0.1241*	0.2341*	1

Table 3 presents Pearson's pairwise correlations among the variables used in our analysis. Variable definitions are presented in Table 1. *significant at 5% level.

Table 4. *U-shape relationship between Peers' Disclosure*$_{-i,j,t-1}$ and *Disclosure*$_{i,t}$

Variables	DV: *Disclosure*$_{i,t}$	
	Model 1	*Model 2*
Peers' Disclosure$_{-i,j,t-1}$	1.991***	-6.090*
	(0.000)	(0.062)
Peers' Disclosure$_{-i,j,t-1}^2$		19.561**
		(0.031)
Firm Size$_{t-1}$	0.013*	0.016**
	(0.069)	(0.035)
Book to Market$_{t-1}$	-0.006	0.004
	(0.529)	(0.655)
Leverage$_{t-1}$	0.020	0.019
	(0.441)	(0.469)
Investment$_{t-1}$	0.002**	0.001
	(0.015)	(0.105)
Performance$_{t-1}$	0.126***	0.061
	(0.001)	(0.257)
Return Shock$_{t-1}$	-0.001	0.003
	(0.853)	(0.591)
R&D$_{t-1}$	0.116	-0.017
	(0.497)	(0.931)
Earnings Volatility$_{t-1}$	-0.137	-0.166*
	(0.108)	(0.070)
Analysts Coverage$_{t-1}$	0.002**	0.004***
	(0.024)	(0.003)
Institutional Ownership$_{t-1}$	0.050***	0.062***
	(0.002)	(0.001)
IND_Size$_{t-1}$	-0.007	-0.022
	(0.755)	(0.301)
IND_Book to Market$_{t-1}$	0.000	0.000
	(0.213)	(0.168)
IND_Leverage$_{t-1}$	0.292	0.486*
	(0.168)	(0.093)
IND_Investment$_{t-1}$	-0.004**	0.009
	(0.016)	(0.198)
IND_Performance$_{t-1}$	0.038	0.081*
	(0.153)	(0.051)
IND_R&D$_{t-1}$	1.454***	-0.480
	(0.008)	(0.560)
IND_Earnings Volatility$_{t-1}$	0.046	0.051
	(0.183)	(0.139)
IND_Analysts Coverage$_{t-1}$	0.003	0.031**
	(0.705)	(0.042)
IND_Institutional Ownership$_{t-1}$	-0.168	-0.020
	(0.435)	(0.908)
Constant	No	No
Firm Fixed Effects	Yes	Yes
Year and Quarter Fixed Effects	Yes	Yes
Observations	86,975	86,975
Number of Firms	3,254	3,254
Strength of the Instrument		
Kleibergen-Paap rk Wald F statistic:	269.3	17.57
Conditions for U-Shape (p-value)		
C1: (β1 + (2β2 XMin) <0)	N/A	0.064*
C2: (β1 + (2β2 XMax) >0)	N/A	0.015**
C3: (β2>0 and significant)	N/A	0.031**
C4: (95% CI ∈ Data Range)	N/A	[0.122,0.189]
U-Shape Overall Result	N/A	Yes

Table 4 shows second-stage results from two stage least squares (2SLS) models with firm-level clustered errors. Table presents coefficients and P-values (below). The dependent variable in all models is "$Disclosure_{i,t}$". Table 4 presents one-tailed P-values for the predicted effects (i.e., coefficients of "$Peers'\ Disclosure_{-i,j,t-1}$" and "$Peers'\ Disclosure_{-i,j,t-1}{}^2$", and conditions testing the existence of a U-shape), and two-tailed P-values otherwise. Variable definitions are presented in Table 1. *, **, *** correspond to 10%, 5%, and 1% significance level.

Table 5. *Moderation Analysis*

	Moderator					
	Firm Size$_{t-1}$	*Bid-Ask Spread$_{t-1}$*	*Institutional Ownership$_{t-1}$*	*Accuracy$_{t-1}$*	*Dispersion$_{t-1}$*	*Overall Uncertainty$_{t-1}$*
VARIABLES	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Peers' Disclosure$_{-i,j,t-1}$	-25.147***	-11.683**	-9.304**	-6.259	-7.833*	-10.758
	(0.000)	(0.045)	(0.015)	(0.147)	(0.075)	(0.137)
Peers' Disclosure$_{-i,j,t-1}^2$	81.775***	37.309**	29.300**	20.482*	23.561**	32.790*
	(0.000)	(0.023)	(0.010)	(0.081)	(0.042)	(0.098)
Moderator	-0.089***	-1.742**	-0.250*	-0.003***	0.295**	26.967***
	(0.000)	(0.048)	(0.065)	(0.001)	(0.011)	(0.009)
Peers' Disclosure x Moderator	2.706***	64.420**	6.963**	0.061**	-10.895***	-923.772***
	(0.000)	(0.034)	(0.020)	(0.011)	(0.001)	(0.004)
Peers' Disclosure^2 x Moderator	-8.810***	-247.789**	-20.286**	-0.156**	34.564***	2,908.524***
	(0.001)	(0.017)	(0.015)	(0.024)	(0.001)	(0.006)
Constant	No	No	No	No	No	No
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year and Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86,975	86,968	86,975	68,864	69,122	69,103
Number of Firms	3,254	3,254	3,254	2,742	2,740	2,740

Table 6 shows second-stage results from Two Stage Least Squares (2SLS) models with firm-level clustered errors. Table 5 presents coefficients and p-values (below). The dependent variable in all models is "*Disclosure$_{i,t}$*". P-values are one-tailed for the predicted effect of Hypothesis 2 (i.e., "*Peers' Disclosure$_{-i,j,t-1}^2$ X Moderator*"), and two-tailed otherwise. Variable definitions are presented in Table 1. *, **, *** correspond to 10%, 5%, and 1% significance level.

Table 6. *U-shape relationship between Peers' Disclosure*$_{-i,j,t-1}$ and *Disclosure*$_{i,t}$ *using alternative industry classification(TNIC)*

VARIABLES	*Model 1*	*Model 2*
Peers' Disclosure$_{-i,j,t-1}$	0.663***	-0.126**
	(0.001)	(0.044)
Peers' Disclosure$_{-i,j,t-1}^2$		1.245***
		(0.001)
Constant		Yes
Control Variables		Yes
Firm Fixed Effects		Yes
Year and Quarter Fixed Effects		Yes
Observations	74,392	74,392
Number of Firms	3,129	3,129
Conditions for U-Shape (p-value)		
C1: (β1 + (2β2 XMin) <0)	N/A	0.044**
C2: (β1 + (2β2 XMax) >0)	N/A	0.001***
C3: (β2>0 and significant)	N/A	0.001**
C4: (95% CI ∊ Data Range)	N/A	[0.010, 0.092]
U-Shape Overall Result	N/A	Yes

Table 6 shows panel data OLS models identifying peers using the using the two-digit "text-based net- work industry classifications" (or TNIC), in which each firm has its own set of distinct competitors that may change over time (Hoberg and Phillips, 2016). Models estimated with firm-level clustered errors. Table 6 presents coefficients and p-values (below). The dependent variable in all models is "*Disclosure*$_{i,t}$". Table 6 presents one-tailed P-values for the predicted effects (i.e., coefficients of "*Peers' Disclosure*$_{-i,j,t-1}$" and "*Peers' Disclosure*$_{-i,j,t-1}^2$", and conditions testing the existence of a U-shape), and two-tailed P-values otherwise. Variable definitions are presented in Table 1. *, **, *** correspond to 10%, 5%, and 1% significance level.

Table 7. *Moderation analysis using alternative industry classification*

	Moderator					
	Firm Size$_{t-1}$	*Bid-Ask Spread$_{t-1}$*	*Institutional Ownership$_{t-1}$*	*Accuracy$_{t-1}$*	*Dispersion$_{t-1}$*	*Overall Uncertainty$_{t-1}$*
VARIABLES	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Peers' Disclosure$_{-i,j,t-1}$	-1.064***	-0.164*	-0.898***	-0.073	0.158*	0.131
	(0.001)	(0.054)	(0.000)	(0.400)	(0.093)	(0.156)
Peers' Disclosure$_{-i,j,t-1}^2$	2.169***	1.368***	1.832***	1.245***	0.939***	0.982***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Moderator	-0.017***	-0.023	-0.137***	-0.000**	0.110***	9.324***
	(0.006)	(0.916)	(0.000)	(0.047)	(0.000)	(0.000)
Peers' Disclosure x Moderator	0.127***	2.152	1.018***	0.005***	-2.114***	-166.335***
	(0.002)	(0.284)	(0.000)	(0.003)	(0.000)	(0.000)
Peers' Disclosure^2 x Moderator	-0.123**	-6.221**	-0.782**	-0.008***	2.666***	204.924***
	(0.035)	(0.036)	(0.019)	(0.002)	(0.000)	(0.000)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year and Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,392	74,363	74,392	59,962	59,974	59,970
Number of Firms	3,129	3,129	3,129	2,734	2,732	2,732

Table 6 shows panel data OLS models identifying peers using the using the two-digit "text-based net- work industry classifications" (or TNIC), in which each firm has its own set of distinct competitors that may change over time (Hoberg and Phillips, 2016). All models estimated with firm-level clustered errors. Table 6 presents coefficients and p-values (below). The dependent variable in all models is "*Disclosure$_{i,t}$*". P-values are one-tailed for the predicted effect of Hypothesis 2 (i.e., "*Peers' Disclosure$_{-i,j,t-1}^2$ X Moderator*"), and two-tailed otherwise. Variable definitions are presented in Table 1. *, **, *** correspond to 10%, 5%, and 1% significance level.

Figure 4. Effect of "*Peers' Disclosure*$_{-i,j,t-1}$" on "*Disclosure*$_{i,t}$"

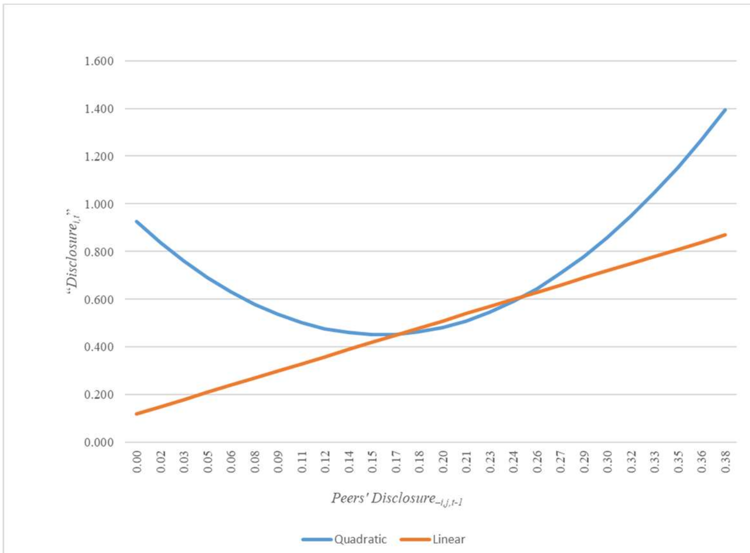

Figure 4 presents a graphical representation of the relation between "*Peers' Disclosure*$_{-i,j,t-1}$" and "*Disclosure*$_{i,t}$" estimated in Models 1 and 2 of Table 4.

Figure 5. Moderation Analysis

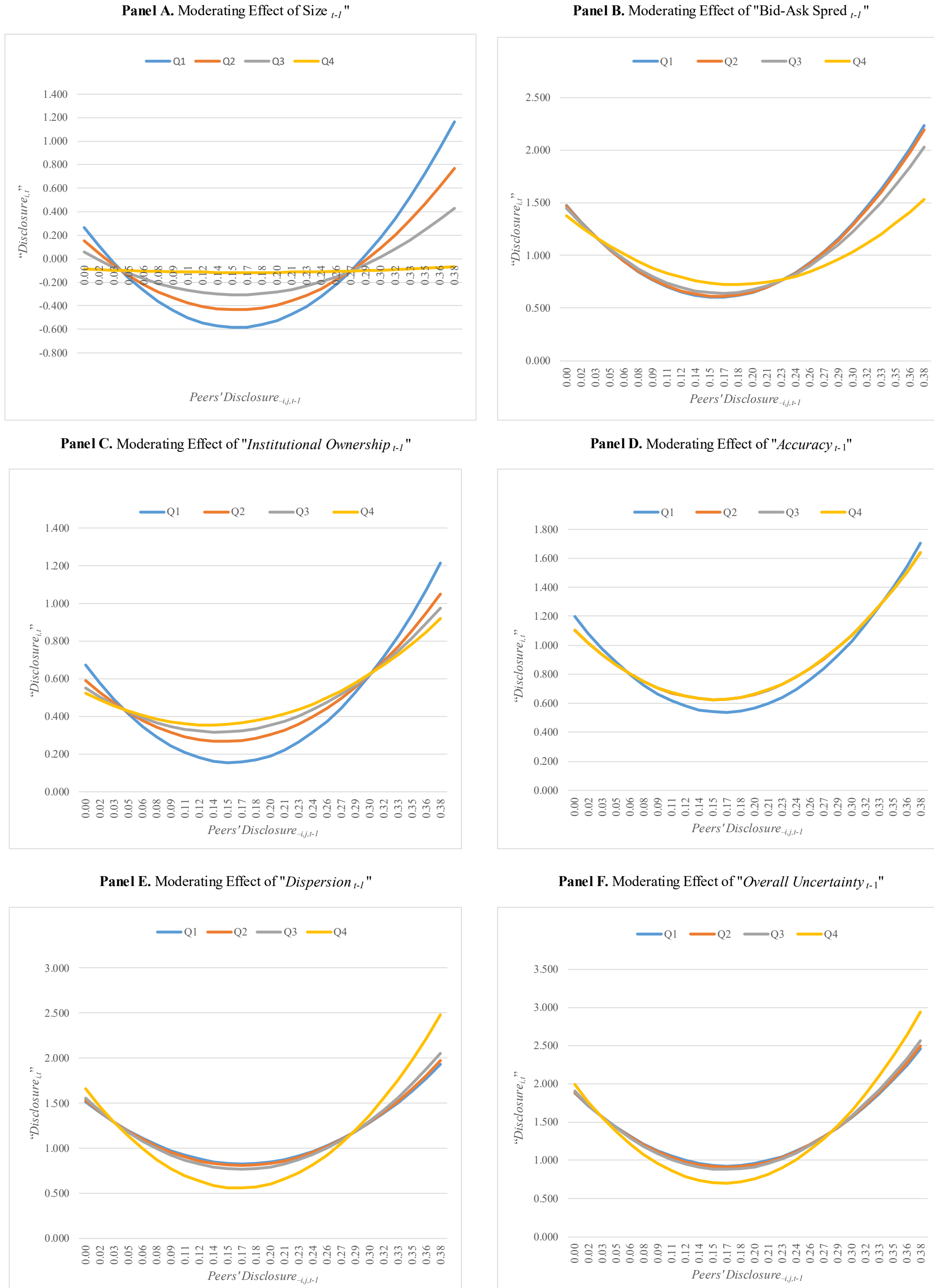

Figure 5 presents a graphical representation of the relation between "*Peers' Disclosure*$_{-i,j,t-1}$" and *Disclosure*$_{i,t}$" moderated by "*Size*$_{t-1}$" (Panel A), "*Bid-Ask Spread*$_{t-1}$" (Panel B), "*Institutional Ownership*$_{t-1}$" (Panel C), "*Accuracy*$_{t-1}$" (Panel D) , "*Dispersion*$_{t-1}$" (Panel E), and "*Overall Uncertainty*$_{t-1}$" (Panel F). Graphs correspond to estimations presented in Models 1-6 of Table 5.

Appendix A: Risk Premium for CARA and CRRA Utility Functions

An individual has Gaussian prior information about a payoff (precision t) and receives a Gaussian signal (precision s). After combining the prior information and the signal, the posterior precision of the belief about the payoff is $\tau = t + s$

We compute the risk premium, defined as the difference between the expected value of the payoff and the certainty equivalent (CE) under a given function:

$$\text{Risk Premium (RP)} = \text{E}[X] - \text{CE}$$

A. CARA utility function

The CARA (Constant Absolute Risk Aversion) utility function is defined as:

$$u(c) = -\text{e}^{-\alpha c}$$

Where $\alpha > 0$ is the coefficient of absolute risk aversion.

Certainty Equivalent (CE) for CARA

The certainty equivalent is the value of a certain payoff that provides the same utility as the expected utility of the uncertain payoff (we are normalizing the wealth to zero; it is not important for the point we want to make):

$$u(\text{CE}) = \mathbb{E}[u(X)]$$

For the CARA utility function:

$$-e^{-\alpha\text{CE}} = \mathbb{E}[-e^{-\alpha X}]$$

Thus:

$$\text{CE} = \mu_{\text{posterior}} - \frac{\alpha}{2}\frac{1}{\tau}$$

Where $\mu_{\text{posterior}}$ is the posterior mean of the payoff.

Risk Premium for CARA

The risk premium is the difference between the expected value of the payoff (equal to $\mu_{\text{posterior}}$) and the certainty equivalent:

$$\text{Risk Premium (RP)} = \text{E}[X] - \text{CE}$$

Substituting the CE relative to the CARA utility:

$$\text{RP} = \mu_{\text{posterior}} - \left(\mu_{\text{posterior}} - \frac{\alpha}{2}\frac{1}{\tau}\right)$$

Simplifying:

$$\text{RP} = \frac{\alpha}{2}\frac{1}{\tau}$$

Which is decreasing and convex with respect to τ.

B. CRRA utility function

The CRRA (Constant Relative Risk Aversion) utility function is defined as:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma}, \quad \gamma \neq 1$$

Where $\gamma > 0$ is the coefficient of relative risk aversion.

Certainty Equivalent (CE) for CRRA

Recall that:

$$u(\text{CE}) = \mathbb{E}[u(X)]$$

For the CRRA utility function:

$$\frac{\text{CE}^{1-\gamma}}{1-\gamma} = \mathbb{E}\left[\frac{X^{1-\gamma}}{1-\gamma}\right]$$

To simplify, we approximate the right-hand side using a second-order Taylor expansion around $\mu_{\text{posterior}}$:

$$\mathbb{E}[X^{1-\gamma}] \approx \mu_{\text{posterior}}^{1-\gamma}\left(1 + \frac{(1-\gamma)(-\gamma)}{2}\frac{\frac{1}{\tau}}{\mu_{\text{posterior}}^{2}}\right)$$

Using this approximation, the certainty equivalent for CRRA utility is:

$$\mathrm{CE} \approx \mu_{\mathrm{posterior}} - \frac{\gamma}{2}\frac{1}{\mu_{\mathrm{posterior}}\tau}$$

Risk Premium for CRRA

The risk premium is the difference between the expected value of the payoff (equal to $\mu_{\mathrm{posterior}}$) and the certainty equivalent:

$$\mathrm{RP} = \mathrm{E}[X] - \mathrm{CE}$$

Substituting the CE relative to the CRRA utility:

$$\mathrm{RP} = \mu_{\mathrm{posterior}} - \left(\mu_{\mathrm{posterior}} - \frac{\gamma}{2}\frac{1}{\mu_{\mathrm{posterior}}\tau}\right)$$

Simplifying:

$$\mathrm{RP} \approx \frac{\gamma}{2}\frac{1}{\mu_{\mathrm{posterior}}\tau}$$

Which is also decreasing and convex with respect to τ.

Appendix B. Return Shock Construction (summary of statistics)

	Mean	SD	Q1	Median	Q3
Regression Summary					
Alpha	0.005	0.018	-0.004	0.004	0.013
Beta (Market)	0.155	0.945	-0.279	0.139	0.638
Beta (Industry)	0.860	0.793	0.350	0.758	1.234
Adjusted R-squared	0.236	0.180	0.091	0.208	0.354
Quarterly Decomposition					
Raw Return	0.033	0.295	-0.099	0.014	0.133
Idiosyncratic Return	-0.006	0.259	-0.121	-0.018	0.080
Expected Return	0.043	0.180	-0.034	0.034	0.106
Industry (GIC4) Quarterly Average Idiosyncratic return	-0.007	0.021	-0.017	-0.006	0.003

This table, Appendix B, shows mean, standard deviations, 25th percentile, median, and 75th percentile of the intermediate steps to calculate firms and GIC4 idiosyncratic returns.