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International Review of Financial Analysis 84 (2022) 102357

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Internal information quality and financial policy peer effects

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ARTICLE INFO

Keywords:
Internal information quality
Financial policy
Peer effects

ABSTRACT

This paper investigates how firms' internal information quality (IIQ) influences the peer effects of their financial policies. Using earnings announcement speed and insider trading profitability difference as measurements, we find that when IIQ is low, firms are more likely to change their leverage following a similar change made by peer firms in the same industry. Our further analysis shows that this mimicking behavior hurts firms' operating performance, and is more prevalent when firms are also characterized by poor corporate governance. Overall, our results indicate that poor information quality could amplify the agency problem, therefore leading to stronger peer effects in corporate financial policies.

1. Introduction

It has long been known that the actions and endorsements of some agents often influence others' behavior (Bikhchandani, Hirshleifer, & Welch, 1998). A recent strand of literature also discovered that when peer firms change their financing, investment, or dividend policies, firms tend to follow and adjust their own policies accordingly (Bustamante & Frésard, 2020; Foucault & Fresard, 2014; Francis, Hasan, & Kostova, 2016; Graham & Harvey, 2001; Grennan, 2019). This is known as “peer effects”. In this study, we investigate how firms' internal information quality (IIQ) influences peer effects on their financial policies.

Gallemore and Labro (2015) define the IIQ as “accessibility, usefulness, reliability, accuracy, quantity, and signal-to-noise ratio of the data and knowledge collected, generated, and consumed within an organization”. IIQ is important for corporate decision-making for two reasons. First, the quality of internal information will influence the quality of corporate decisions and their outcomes (Gallemore & Labro, 2015). Low IIQ can prevent firms from making optimal corporate decisions. Second, the quality of internal information influences the efficacy of monitoring (Harp & Barnes, 2018; Laux, Lóránth, & Morrison, 2018). In organizations characterized by poor IIQ, monitoring is more costly and agency costs are exacerbated.

Peer effects in corporate financial policy are closely related to a firm's internal information quality. First, according to Bikhchandani et al. (1998)'s observational learning model, if a firm is confident about the precision of its self-collected information, it will rely less on the information generated by external sources. Consequently, firms' reliance on the signals implied by peer firms' financial policy will be influenced by their IIQ. Secondly, a firm's IIQ will impact its corporate governance as information plays a crucial role in corporate monitoring (Laux et al., 2018). Since the quality of internal control is also related to the peer effects of corporate policies (Fairhurst & Nam, 2020), IIQ could potentially influence leverage peer effects through the corporate governance channel.

To understand the effect of IIQ on financial policy peer effects, following Gallemore and Labro (2015) and Chen, Martin, Roychowdhury, Wang, and Billett (2018), we adopt two internal information quality measurements to test the moderating effects of internal information quality on firms' mimicking behavior. The first measurement is earnings announcement speed (EAS), which is the number of days between the earnings announcement date and fiscal year-end, divided by 365. Intuitively, effective internal information-sharing mechanisms should enable firms to quickly integrate information from different parts of the organization. Therefore, a more efficient internal information system should be able to narrow the time gap between the earnings announcement date and fiscal year-end date (Gallemore & Labro, 2015). The second measurement is the difference in insider trading profitability (Dret), which is the difference between the trading profit on their own company's stock achieved by divisional managers and top managers. Higher Dret indicates a more severe information asymmetry between managers at different levels and implies poorer internal information quality possessed by top managers (Chen et al., 2018). By using these two measurements, we find that, when internal information quality is low (high EAS and high Dret), firms' capital structure is more likely to

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https://doi.org/10.1016/j.irfa.2022.102357
Received 5 April 2022; Received in revised form 21 June 2022; Accepted 30 August 2022
Available online 5 September 2022

move in line with the capital structure of their industry peer firms. This effect is both statistically and economically significant. For a firm with IIQ ranked top 25% of the sample, a one standard deviation increase in peer leverage would, on average, lead to a 1.81% or 0.97% increase in the firm's own leverage depending on which measure we are using.[1] However, for firms with IIQ in the bottom 25%, the same increase in peer leverage would lead to a leverage increase of 3.35% (EAS) or 1.38% (Dret).[2] These numbers indicate 85% increase in the value of EAS or 42% increase in the value of Dret, compared with firm with IIQ ranked top 25% of the sample. Our robustness tests adopting different leverage measurements (market leverage or book leverage) and industry classification (both SIC and TNIC) confirm these findings.

Our findings are unlikely to suffer from reverse causality- Firms' internal information quality is unlikely to be driven by peer effects on their financial policy. However, we still need to address the potential endogeneity issue caused by unobservable omitted variables that simultaneously drive both firms' IIQ and leverage peer effects. We adopt a difference-in-difference test to mitigate this concern. In 2004, Section 404 of the Sarbanes-Oxley Act (SOX404) was enacted. The Act mandates firms to evaluate the adequacy of their internal controls and to disclose material weaknesses. To avoid reputational loss due to the disclosure of material internal control weaknesses, firms have incentives to improve their internal information quality. Since the enactment of the Act is exogenous to the decision of the firm, we can exploit this shock and design difference-in-difference tests to validate our findings.[3] Consistent with the main conjecture, firms that experience a distinct improvement in internal information quality (disclosed a material weakness in 2004 and revised it in the year after) significantly reduce mimicking behavior after the event.

We investigate two potential motivations that drive firms to mimic the capital structure of their peers. First, firms can acquire information both internally and externally. When internal information quality is poor, we expect firms to be more reliant on external sources of information. One important external information source is industry peers (Leary & Roberts, 2014). Considering peer firms are not likely to reveal all the information in their possession to the market, actual corporate decisions may convey implied signals that the firms of interest use in their decision-making. Since the signal that the focal firm receives originated from its peers, they are likely to make similar decisions to those made by their peers. Therefore we can observe a peer effect in financial policies. This behavior is consistent with the prediction of the information cascade model by Bikhchandani, Hirshleifer, and Welch (1992) and Bikhchandani et al. (1998). We call this the *information acquisition channel*.

On the other hand, poor internal information quality will reduce the monitoring efficacy of the board of directors and weaken corporate governance (Harp & Barnes, 2018; Laux et al., 2018). An inefficient internal information system will make it harder for boards to detect managers' self-interested behavior. Also, firm performance is frequently measured against peer firms. Therefore, incompetent CEOs could simply follow the decisions made by their peers to “play it safe” so that they could attribute any potential failure to industry-level shocks rather than to their lack of competence (Scharfstein & Stein, 1990). Therefore, stronger peer effects in corporate policies may also imply the presence of severe agency problems (Fairhurst & Nam, 2020). With poor internal information quality, monitoring becomes more costly and agency costs can be amplified, resulting in stronger peer effects in firms' financial policy. We call this the *agency cost channel*.

We conduct further tests to investigate which of these two potential channels is the main driver of our findings. First, the information acquisition channel implies that peer mimicking provides an important channel through which firms can learn new information. Peers' actions may contain information about market trends and investment opportunities (Foucault & Fresard, 2014; Leary & Roberts, 2014). As suggested by Larcker, So, and Wang (2013) and El-Khatib, Fogel, and Jandik (2015), the quality of information acquired by firms' headquarters is critical for firms' performance.[4] Therefore, following peers should improve the firm's information set and eventually be positively reflected in the firm's performance. On the contrary, agency issues are value-destroying to the shareholders. Scharfstein and Stein (1990) suggest that it is inefficient for firms to mimic peers' investment, but it can protect managers' reputations. If the amplified peer effects are the results of amplified agency costs associated with poor IIQ, we should expect a negative impact of peer effects on the firm's performance. To investigate these predictions, we follow Fairhurst and Nam (2020) and identify firms that are subject to stronger leverage peer effect as mimickers and other firms as non-mimickers. Then we look at the performance of these firms under different levels of IIQ. Our results show that the performance of mimickers is significantly worse when they operate in a poor IIQ environment. Compared with the average performance of non-mimickers, mimickers' return on equity (ROE) is 51.3% lower while return on assets (ROA) is 40.7% worse when IIQ is low. These results indicate that on average when IIQ is poor, the stronger peer effects in leverage are value-destroying. Therefore, the agency cost channel, rather than the information acquisition channel, is more likely to be the main driver of the amplified peer effect.

The tests of firm performance provide indirect evidence on the potential channel of our main findings. However, to further verify our claim that our main findings can be attributed to the *agency cost channel*, we conducted further tests. The previous literature has long established that effective corporate governance can significantly mitigate agency costs. Therefore, for a well-governed firm with effective monitoring in place, we expect the agency cost amplified by the poor IIQ to be moderate. In other words, if strong leverage peer effects are indeed the results of agency costs, we should observe that the effects would only be significant for firms without strong corporate governance. To test this hypothesis, we use the takeover index and CEO-Chair duality as proxies to further divide our samples into well-governed firms and poorly-governed firms before estimating our baseline regression in each of the subsamples. Our results show that stronger peer effects in leverage are mainly driven by firms without good corporate governance, and confirm our hypothesis that our main findings are driven by the agency cost channel.

We also conduct a battery of robustness checks to further mitigate various potential concerns with our findings. First, although the contemporaneous specification of our baseline model could limit the time for firms to respond to other firms (Leary & Roberts, 2014), one may argue that this would also amplify the potential reverse causality issue. While we believe the two stage least squares (2SLS) estimation approach can largely mitigate this concern, we also conducte further tests by using lagged independent variables. Second, to further control for potential omitted variable issues, we conducted further tests by replacing the industry fixed effects with stricter firm fixed effects and high dimensional fixed effects in the panel regressions. Third, to make sure that our results are robust to different proxies, we conducted further

[1] The standard deviation of estimated peer leverage ratio is 0.089 for EAS sample and 0.080 for Dret sample. Based on the standard deviation of estimated peer leverage, the 1.81% is calculated as $0.089 \times (0.099 \times 2.035 + 0.002)$, while the 0.97% is calculated as $0.080 \times (-0.091 \times 0.295 + 0.149)$.

[2] Based on the standard deviation of estimated peer leverage, the 3.35% is calculated as $0.089 \times (0.184 \times 2.035 + 0.002)$, while the 1.38% is calculated as $0.080 \times (0.083 \times 0.295 + 0.149)$.

[3] A similar approach has been applied in previous studies, such as Gallemore and Labro (2015) and Huang et al. (2020).

[4] Larcker et al. (2013) argue that firm with higher level of board net work centrality earning higher risk-adjusted stock return. Similarly, El-Khatib et al. (2015) find firms with higher CEO net work centrality are associated with more value creating acquisition deals.

tests using alternative internal information quality proxies, book leverage, and an alternative peer definition. Lastly, to mitigate the concerns that our results might be driven by the size, financial distress, cash flow volatility, or the idea that IIQ is a proxy for corporate governance, we conduct further tests by including interaction terms between IIQ and relative size, *Z*-score, industry level cash flow volatility and corporate governance proxies to our baseline model. Our results remain robust to all these additional tests.

Our paper contributes to the literature in several ways. First, it enriches the recent literature studying peer effects in corporate policies. The extant studies focus mainly on identifying the existence of peer effects in firm behaviors such as financial policies (Leary & Roberts, 2014), dividend policies (Grennan, 2019), investment policies (Bustamante & Frésard, 2020), trade credit policy (Gyimah, Machokoto, & Sikochi, 2020), or innovation (Machokoto, Gyimah, & Ntim, 2021). However, we focus on identifying the background mechanisms that drive the peer effects. We find that low quality of internal information increase peer mimicking, and these effects are more pronounced in firms with higher agency costs. Our findings also support previous literature that the peer effects are related to corporate governance level and are value-destroying (Fairhurst & Nam, 2020).[5]

Second, our paper contributes to the studies that investigate the influence of information quality on corporate decision-making. Some pioneering work has been done in this area. For example, Gallemore and Labro (2015) find that firms with good internal information quality enjoy a lower effective tax rate. Heitzman and Huang (2019) argue that when IIQ is high, corporate investments are more sensitive to internal signals. Huang, Lao, and McPhee (2020) find that higher IIQ could have a positive effect on innovation. However, to the best of our knowledge, our study is the first to investigate the effect of IIQ on the peer effects of corporate policies, and it provides new insights into the real effects of internal information quality.

The paper proceeds as follows. Section 2 presents the methodology and variable definitions. Section 3 displays the sample used in this study and empirical results. Section 4 describes the further analysis and robustness checks. Section 5 provides conclusions and implications.

2. Research design and variable definition

2.1. Research design

Following Leary and Roberts (2014), we estimate the leverage peer effects by applying the model below:

$$Leverage_{it} = \alpha + \beta Peer\ Leverage_{-ijt} + \gamma Controls_{-ijt-1} + \delta Controls_{it-1} + \rho\mu_j + \varphi\nu_t + \varepsilon_{it} \tag{1}$$

The dependent variable $Leverage_{it}$ indicates the leverage ratio of firm *i*, in year *t*. $Peer\ Leverage_{-ijt}$ is the average leverage ratio of all the firms in industry *j* with the same 3-digit industry SIC code, excluding firm *i*, at year *t*. $Controls_{it-1}$ indicates a set of firm characteristics which are determinants of the firm's capital structure and $Controls_{-ijt-1}$ indicates the average value of these characteristics for industry peers. The terms μ_j and ν_t are the industry and year fixed effects, respectively. In this model, the value of β indicates the reaction of a firm's leverage in response to the change in the average peer leverage. A positive and statistically significant β, therefore, indicates the existence of peer effects in that firms will change their leverage in the same direction as changes made by peer firms in the same industry.

To identify the incremental effect of internal information quality on the peer effect in financial policy, we extend Leary and Roberts's model by including internal information quality proxies and their interaction with peer leverage into the model (1):

$$Leverage_{it} = \alpha + \beta_1 Peer\ Leverage_{-ijt} \times IIQ_{it} + \beta_2 Peer\ Leverage_{-ijt} + \beta_3 IIQ_{it} + \gamma Controls_{-ijt-1} + \delta Controls_{it-1} + \rho\mu_j + \varphi\nu_t + \varepsilon_{it} \tag{2}$$

where IIQ_{it} indicates a proxy for internal information quality. In this augmented model, β_3 will capture the effect of internal information quality on firm leverage, while the coefficient of interaction term (β_1) will identify the incremental effect of internal information quality on the leverage peer effect. A similar approach has been adopted by other studies, such as Francis et al. (2016).

2.2. Identification of peer mimicking

The identification of peer effects is not straightforward. According to Manski (1993) and Leary and Roberts (2014), correlation between the characteristics of a firm and its peers can also be caused by other factors. For example, a common shock to an industry may cause all the firms in that industry to simultaneously change their financial policy, and therefore leads to a positive correlation between their leverage. This challenge arises when we try to identify the effect of group characteristics on the group member firms and it is essentially an endogeneity problem that needs to be addressed.

To address this concern, we follow Leary and Roberts (2014) and adopt a 2SLS approach to estimate the model. Specifically, before we run the second stage regression that identifies the peer effect, we use peer equity shock, which is measured by the idiosyncratic component of stock return, as an instrumental variable (IV) to extract the fitted value of peer leverage. The construction of this IV is based on the following augmented market model:

$$r_{ijt} = \alpha_{ijt} + \beta^M_{ijt}(rm_t - rf_t) + \beta^{IND}_{ijt}\left(\overline{r}_{-ijt} - rf_t\right) + \eta_{ijt} \tag{3}$$

$$\widehat{r}_{ijt} = \widehat{\alpha}_{ijt} + \widehat{\beta}^M_{ijt}(rm_t - rf_t) + \widehat{\beta}^{IND}_{ijt}\left(\overline{r}_{-ijt} - rf_t\right)$$

$$Equity\ shock = r_{ijt} - \widehat{r}_{ijt}$$

In Eq. (3), the r_{ijt} is the stock return of firm *i* in industry *j* in month *t*. $(rm_t - rf_t)$ is the market excess return. $\left(\overline{r}_{-ijt} - rf_t\right)$ is the excess return of an equally weighted portfolio consisting of all firm *i*'s peer firms in industry *j*. η_{ijt} refers to the idiosyncratic part of firm *i*'s stock returns. Model (3) is then estimated annually for each firm with a 60-month (minimum 24-month) rolling window. For instance, to estimate the coefficient β^M_{ijt} and β^{IND}_{ijt} for a firm in 2010, we need at least 24 monthly stock return observations for this firm from January 2005 to December 2009. We then calculate the firm's equity shock by extracting the idiosyncratic part of this firm's stock return using Eq. (3). Specifically, we first estimate the expected stock return $\widehat{r}_{ijt}$ for each firm in each month using the rolling estimation method introduced above. Then, we calculate the idiosyncratic return by deducting the expected value of stock return from its actual value. Finally, we compound the monthly idiosyncratic stock returns to obtain the annually equity return shock. The detailed estimation results of model (3) are reported in appendix B.

The validity of equity return shock as an instrumental variable rests on two grounds. First, a firm's stock return is known to be an important determinant of capital structure (Loughran & Ritter, 1995; Marsh, 1982). Therefore, the IV satisfies the relevance condition. Second, when estimating the idiosyncratic return, the common factors that influence the return of the entire market and the return of specific industry have been absorbed by the two independent variables: $(rm_t - rf_t)$ and $\left(\overline{r}_{-ijt} - rf_t\right)$. Since η_{ijt} is net of these common factors, it captures the variation of return that is independent of the market or industry-wide shock, and the exclusion condition is also satisfied (Leary & Roberts, 2014).

[5] Our results stay robust after controlling for several corporate governance measurements.

Table 1
Summary statistics.

	Nobs	Mean	SD	P1	P25	P50	P75	P99
Dependent variables								
Market Leverage	100,745	0.268	0.246	0	0.051	0.209	0.429	0.915
Book Leverage	100,745	0.236	0.197	0	0.069	0.214	0.352	0.878
Main independent variables								
EAS	91,984	0.146	0.062	0.047	0.099	0.137	0.184	0.332
Dret	25,223	−0.006	0.226	−0.854	−0.091	−0.003	0.083	0.725
Peer market leverage	100,745	0.268	0.141	0.038	0.153	0.251	0.359	0.684
Peer book leverage	100,745	0.236	0.098	0.047	0.166	0.226	0.289	0.540
Control variables								
Size (Log(sales))	100,745	5.342	2.191	−0.122	3.832	5.266	6.826	10.601
MTB	100,745	1.360	1.166	0.286	0.690	0.982	1.556	7.295
Prof	100,745	0.107	0.148	−0.588	0.068	0.126	0.182	0.389
Tang	100,745	0.311	0.224	0.009	0.135	0.260	0.441	0.893
Equity shock	100,745	−0.008	0.531	−0.842	−0.327	−0.093	0.173	2.362
Peer size	100,745	5.339	1.295	2.699	4.352	5.166	6.212	8.825
Peer MTB	100,745	1.356	0.605	0.511	0.908	1.220	1.662	3.312
Peer Prof	100,745	0.107	0.066	−0.110	0.071	0.116	0.152	0.245
Peer Tang	100,745	0.311	0.178	0.062	0.182	0.262	0.397	0.770
Peer equity shock	100,745	−0.010	0.152	−0.408	−0.090	−0.024	0.055	0.576
Other variables								
ROA	100,745	0.005	0.166	−0.917	−0.004	0.042	0.080	0.248
ROE	100,357	−0.008	0.515	−3.055	−0.005	0.053	0.100	2.360
Takeover	66,049	0.170	0.086	0.045	0.102	0.152	0.224	0.416
Entrenched	23,599	0.467	0.499	0	0	0	1	1
Restatement	26,372	0.103	0.304	0	0	0	0	1
Weakness	25,592	0.067	0.251	0	0	0	0	1
Size_rel	100,745	1.008	0.385	−0.028	0.768	0.995	1.231	2.159
Z-score	97,946	1.621	2.516	−12.465	1.064	2.055	2.895	5.738

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965 to 2017 with non-missing data for all firm characteristics. All variables are winsorized at 1st and 99th level and defined in Appendix A. Peer firm average variables are calculated as the mean value of all firms within the industry-year excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. Firm specific variables denote firm *i*'s variable in year *t*. For the main independent variables, EAS stands for earnings announcement speed. Dret is the difference in insider trading profitability between divisional managers and top managers in last three years. Restatement is an indicator variable which equal to one if firm disclose an unintentional restatement in the current year and zero otherwise. Weakness is an indicator variable equal to one if firm reports a material weakness in the current year and zero otherwise.

2.3. Internal information quality measurements

We use two variables to measure a firm's internal information quality. The first is earnings announcement speed, which is the number of days between the firm's fiscal year-end and earnings announcement date, divided by 365. Intuitively, a higher value of *EAS* indicates that a firm takes more time to prepare the financial statements and indicates a lower internal information quality. EAS is widely used as a proxy for a firm's internal information quality (Gallemore & Labro, 2015; Heitzman & Huang, 2019; Huang et al., 2020). Jennings, Seo, and Tanlu (2013) argue that firms with better internal information systems can report earnings information more quickly. Gallemore and Labro (2015) also argue that an accounting system that eliminates manual intervention, reduces redundancy, and streamlines reporting can also improve the efficiency of financial disclosure and accelerate the earnings announcement speed.

The second variable we use to measure internal information quality is the difference between the insider trading profitability for divisional managers and top managers, *Dret*.[6] Chen et al. (2018) suggest that the disparity between the profitability of insider trading for different levels of managers reflects the asymmetry of information within the management hierarchy. Higher trading profitability of the divisional managers (*higher Dret*) not only indicates their information advantage over top managers but also reveals an obstructed information acquired from different divisions and business units, the obstructed information transmission will amplify the difficulties faced by top managers in accessing the information on the firm's financial health and limit their ability to make strategic decisions.

For robustness checks, we also adopt two alternative indicators to measure a firm's internal information quality. The first one is *Restatement*- a dummy variable that equals one if firms report any restatement due to unintentional errors and zero otherwise. Those unintentional errors arise mainly because of basic accounting errors. Such restatements indicate the information reported is unreliable or inaccurate, which also suggests poor internal information quality (Gallemore & Labro, 2015; Heitzman & Huang, 2019). The second variable is *Weakness*- a dummy variable that equals one if firms disclose a material weakness in internal controls in the current year and zero otherwise. According to Feng, Li, and McVay (2009) and Gallemore and Labro (2015), firms with material weakness are more likely to decide their strategy based on untimely or even inaccurate financial information. In principle, firms which disclose a material weakness in the current year are more likely to face lower internal information quality.

2.4. Control variables

To eliminate the possibility that our findings are driven by heterogeneity in firms' basic characteristics, we include a set of control variables in the model. These variables include firm size (log*(sales)*) market to book ratio, profitability (*EBITDA/ Total Assets*), and asset tangibility (*Net PP&E/ Total Assets*). In addition to the firms' characteristics, the

[6] Chen et al. (2018) treated the CEO, CFO and COO as top managers and other lower-level managers as divisional managesr. Detailed definitions are provided in Appendix A.

Table 2
Baseline Regression-OLS results.

	(1)	(2)	(3)
VARIABLES	Market leverage	Market leverage	Market leverage
EAS × Peer leverage		1.066***	
		(6.713)	
Dret × Peer leverage			0.162***
			(2.737)
EAS		0.683***	
		(14.519)	
Dret			0.001
			(0.040)
Peer leverage	0.164***	−0.008	0.133***
	(8.791)	(−0.296)	(4.492)
Peer Size	−0.005*	−0.003	0.001
	(−1.784)	(−1.180)	(0.339)
Peer MTB	0.008**	0.006*	−0.004
	(2.549)	(1.853)	(−0.801)
Peer Prof	0.102***	0.033	0.088**
	(3.525)	(1.132)	(2.029)
Peer Tang	0.019	−0.004	−0.024
	(0.761)	(−0.141)	(−0.573)
Equity shock	−0.022***	−0.017***	−0.017***
	(−18.907)	(−15.305)	(−8.256)
Firm Size	0.012***	0.028***	0.014***
	(12.779)	(25.682)	(9.132)
Firm MTB	−0.058***	−0.049***	−0.044***
	(−47.650)	(−40.926)	(−28.759)
Firm Prof	−0.297***	−0.268***	−0.195***
	(−30.343)	(−27.259)	(−13.241)
Firm Tang	0.188***	0.204***	0.158***
	(14.875)	(15.645)	(8.157)
Constant	0.222***	0.044**	0.099**
	(13.606)	(2.418)	(2.530)
Industry/ Year fixed effects	Yes	Yes	Yes
Observations	100,745	91,984	25,223
Adjusted R^2	0.339	0.393	0.386

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965 to 2017 with non-missing data for all firm characteristics. All variables are defined in Appendix A. The table displays OLS estimated coefficients and t-statistics, clustered at firm level, in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. Column (1) displays how peers' leverage influence firm's leverage, while columns (2) and (3) show the moderating effect of IIQ on peer effects. Columns (2) and (3) measure firms' internal information quality using earnings announcement speed (EAS) and the difference in insider trading profitability between divisional managers and top managers (Dret), respectively. ***, ** and* indicate statistical significance level at 1%, 5% and 10% level, respectively

average values of these characteristics for peer firms are also included in the model.

3. Sample selection and empirical findings

3.1. Sample selection and descriptive statistics

Our analysis is focused on a large sample of listed firms in the US. To construct our sample, we extract accounting data and earnings announcement data from the Compustat database, stock price data from the CRSP database, and insider trading data from Thomson Financial. In addition, we download data about firms' restatements and internal control weakness from Audit Analytics. Consistent with Leary and Roberts (2014), all financial firms (SIC code from 6000 to 6999), utilities (SIC code from 4900 to 4999), and government entities (SIC code greater than or equal to 9000) are excluded. For additional tests, the CEO duality information comes from the ExecuComp database, and the takeover index data comes from Dr. Stephen McKeon's webpage.[7] All variable definitions are given in detail in Appendix A.

Due to differences in data availability, our samples for the two main internal information quality proxies span two different periods - *EAS* is available from 1965 to 2017, while *Dret* is available from 1989 to 2017.[8] Table 1 presents summary statistics for our sample. Our full sample contains 100,745 firm-year observations with non-missing data for all firm characteristic variables. All variables are presented after winsorizing at the 1st and 99th percentiles. Variables without "peer" in the name refer to the characteristics of a single firm, while the variables starting with "peer" stand for average characteristics of firms within the same 3-digit SIC industry, excluding the firm in question. The summary statistics in our tables are very similar to the ones reported in previous papers, such as Leary and Roberts (2014), Gallemore and Labro (2015), and Chen et al. (2018).

3.2. Internal information quality and financial policy peer effects

In this section, we investigate the impact of firms' IIQ on their capital structure peer effects. First, we estimate model (1) to identify the existence and magnitude of the leverage peer effect. Column (1) of Table 2 shows that average peer leverage is positive and significantly related to firms' leverage, indicating the existence of leverage peer effects. Then we estimate model (2) with the interaction terms between IIQ and peer leverage. In columns (2) and (3), the coefficients of both interaction terms, *EAS* × *peer leverage,* and *Dret* × *peer leverage*, are positive and statistically significant. The result indicates that as IIQ deteriorates (when *EAS* or *Dret* are higher), an increase in average peer leverage has a stronger positive impact on firms' leverage. This is consistent with our main conjecture that lower internal information quality will enhance the firm's propensity to mimic peer behavior.

As discussed in section 2.2, the positive correlation between firm leverage and peer firms' leverage might also be driven by the "reflection-problem" or the "self-selection" issue. In other words, the OLS estimation of leverage peer effect might be subject to an endogeneity problem. To address this issue, following Leary and Roberts (2014), we use the instrumental variable approach introduced in section 2.2 to estimate the model. Specifically, we run a 2SLS regression for Eq. (2). In the first stage, we use peer equity shock as the instrumental variable. In the second stage, we replace the peer leverage with its fitted value obtained from the first stage model. A similar approach has been adopted in related research (Fairhurst & Nam, 2020; Francis et al., 2016; Leary & Roberts, 2014).

The results of our 2SLS estimation are presented in Table 3. In columns (1) and (2), we first check how peers' leverage influences a firm's financing decisions. Consistent with previous studies (e.g., Leary & Roberts, 2014), we find that peer equity shock is a negative and statistically significant predictor of peer leverage in the first-stage regressions. In addition, the coefficient of fitted peer leverage in the second-stage regression is positive and statistically significant. These results confirm our finding of the leverage peer effects in our OLS regression. Columns (3)–(6) present estimation result including the interaction between IIQ and peer leverage. In columns (4) and (6), we find positive and statistically significant coefficients for the interaction between IIQ and peer leverage (*EAS*× *Peer leverage* and *Dret*× *Peer leverage*). The coefficients of the interaction terms are also economically significant. A one standard deviation increase in peer leverage would lead to a 1.81% increase in firms' leverage for a firm with 25% EAS while the same change in peer leverage will induce a 3.35% increase in

[7] https://pages.uoregon.edu/smckeon/

[8] Our *Dret* sample covers a shorter period because the insider trading data is only available after 1989. Our results are staying robust if the *EAS* sample also starts from 1989.

Table 3
Baseline regression- Two stage least squares results.

	(1)	(2)	(3)	(4)	(5)	(6)
	First stage	Second stage	First stage	Second stage	First stage	Second stage
VARIABLES	Peer leverage	Market leverage	Peer leverage	Market leverage	Peer leverage	Market leverage
EAS × Peer leverage				2.035***		
				(8.042)		
Dret × Peer leverage						0.295***
						(3.082)
EAS			0.036***	0.416***		
			(4.915)	(6.151)		
Dret					0.005**	−0.029
					(2.273)	(−1.473)
Peer leverage		0.348***		0.002		0.149
		(3.804)		(0.019)		(0.709)
Peer equity shock	−0.043***		−0.038***		−0.033***	
	(−19.639)		(−6.664)		(−8.186)	
Peer equity shock × EAS			−0.022			
			(−0.630)			
Peer equity shock × Dret					−0.002	
					(−0.110)	
Peer Size	0.012***	−0.007**	0.012***	−0.005	0.015***	0.001
	(8.455)	(−2.439)	(8.386)	(−1.605)	(5.321)	(0.209)
Peer MTB	−0.078***	0.023***	−0.078***	0.019**	−0.072***	−0.003
	(−46.698)	(2.837)	(−45.582)	(2.166)	(−28.695)	(−0.178)
Peer Prof	−0.392***	0.176***	−0.387***	0.094*	−0.289***	0.093
	(−28.599)	(3.729)	(−27.718)	(1.917)	(−12.639)	(1.234)
Peer Tang	0.197***	−0.017	0.203***	−0.032	0.226***	−0.026
	(12.777)	(−0.557)	(12.601)	(−0.981)	(8.694)	(−0.401)
Equity shock	−0.001***	−0.021***	−0.001***	−0.017***	−0.001	−0.017***
	(−3.166)	(−18.562)	(−3.051)	(−14.900)	(−1.028)	(−8.224)
Firm Size	−0.000	0.012***	0.000	0.028***	0.000	0.014***
	(−0.824)	(12.875)	(1.364)	(25.685)	(0.796)	(9.143)
Firm MTB	0.000	−0.058***	0.001*	−0.049***	−0.000	−0.044***
	(1.481)	(−47.754)	(1.955)	(−41.129)	(−0.554)	(−28.761)
Firm Prof	0.007***	−0.298***	0.008***	−0.272***	−0.000	−0.194***
	(2.664)	(−30.435)	(3.305)	(−27.534)	(−0.051)	(−13.214)
Firm Tang	0.007**	0.187***	0.005*	0.205***	0.008	0.158***
	(2.206)	(14.822)	(1.668)	(15.825)	(1.501)	(8.141)
Constant	0.312***	0.165***	0.300***	0.034	0.270***	0.097
	(36.958)	(5.048)	(34.184)	(0.945)	(14.724)	(1.425)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,745	100,745	91,984	91,984	25,223	25,223
Adjusted R^2	0.734	0.337	0.739	0.391	0.768	0.385

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965 to 2017 with non-missing data for all firm characteristics. All variables are defined in Appendix A. The table displays 2SLS estimated coefficients and t-statistics, clustered at firm level, in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. Columns (1) and (2) display how peers' leverage influence firm's leverage, while columns (3)–(6) show the moderating effects of IIQ on peer effects. In columns (3) and (4), firm's internal information quality is measured by earnings announcement speed (EAS). Columns (5) and (6) measure firms' internal information quality using Dret variable, which indicates the difference in insider trading profitability between divisional managers and top managers. ***, ** and* indicate statistical significance level at 1%, 5% and 10% level, respectively

leverage for a firm with 75% EAS.[9] For the Dret sample, a one standard deviation increase in peer leverage would lead to a 0.97% increase of firms' leverage for a firm with 25% Dret while the same change in peer leverage will induce a 1.38% increase in leverage for a firm with 75% Dret.[10] These results indicate that poor IIQ would amplify the peer effects of firm leverage.

3.3. *Endogeneity and identification*

3.3.1. *Difference-in-difference approach*

Although our findings are unlikely to be driven by reverse causality, because leverage peer effects should not be a driver of a firm's information quality, it is still reasonable to expect that some omitted factors could simultaneously influence both internal information quality and the leverage peer effects. To address this endogeneity concern, following Gallemore and Labro (2015) and Huang et al. (2020), we designed a difference-in-difference test by exploiting the enactment of the Sarbanes-Oxley Act (SOX) as an exogenous shock to firms' internal information quality.

Section 404 of SOX requires firms to evaluate their internal controls on financial reporting and to disclose if there is a material weakness. Since the disclosure of material weakness sends a negative signal to the market, firms are incentivized to improve their internal information quality. Therefore, the enactment of SOX 404 could be used as a shock

[9] The standard deviation of estimated peer leverage ratio is 0.089 for EAS sample and 0.080 for Dret sample. Based on the standard deviation of estimated peer leverage, the 1.81% is calculated as 0.089 × (0.099 × 2.035 + 0.002), while the 0.97% is calculated as 0.080 × (−0.091 × 0.295 + 0.149).

[10] Based on the standard deviation of estimated peer leverage, the 3.35% is calculated as 0.089 × (0.184 × 2.035 + 0.002), while the 1.38% is calculated as 0.080 × (0.083 × 0.295 + 0.149).

for our identification (Gallemore & Labro, 2015).[11]

In our difference-in-difference design, following Gallemore and Labro (2015) and Huang et al. (2020), we defined firms that disclosed material weaknesses in the year 2004 but revised it in the following years as treated firms, and all other firms with Audit Analytics database coverage as control firms. A dummy variable "*Treated*" is then generated to indicate the treated firms and to capture the difference in characteristics between two sets of firms. We also treat three years before the enactment (2001, 2002, and 2003) as the pre-event period and three years after the enactment (2005, 2006, and 2007) as the post-event period, and generated a dummy variable "*Post*" to indicate the post-event change of leverage of all firms. The interaction term "*Treated*× *Post*" identifies the incremental effect of the SOX 404 enactment on the treated firms' leverage. To capture the impact of SOX 404 enactment on the financial policy peer effect, we follow the design of Edmans, Jayaraman, and Schneemeier (2017) and Jayaraman and Wu (2019) by interacting the "*Treated*× *Post*" with the fitted peer leverage obtained by estimate the first-stage regression of our 2SLS model and generate a triple interaction term $Peer\ Leverage_{-it} \times Treated \times Post$.[12] Since treated firms are expected to improve their internal information quality as a result of SOX 404 enactment, our hypothesis predicts a negative coefficient on the triple interaction term: the leverage peer effect of the treated firms would become less prominent after the event. After adding the same set of control variables as used in the baseline model and fixed effects, our full model can be displayed as follows:

$$\begin{aligned} Leverage_{it} &= \alpha + \beta_1 Peer\ Leverage_{-ijt} \times Treated \times Post + \beta_2 Peer\ Leverage_{-ijt} \\ &\times Treated + \beta_3 Peer\ Leverage_{-ijt} \times Post + \beta_4 Treated \times Post \\ &+ \beta_5 Peer\ Leverage_{-ijt} + \beta_6 Treated + \gamma Controls_{-ijt-1} \\ &+ \delta Controls_{it-1} + \rho\mu_j + \varphi\nu_t + \varepsilon_{it} \end{aligned} \tag{4}$$

Table 4 presents the results of our difference-in-difference tests. Columns (1) and (2) of Panel A display the results with industry fixed effects and firm fixed effects, respectively. Since the SOX-404 enactment event would lead to an improvement of IIQ, we would expect weaker peer effects of the financial policy after the SOX-404 enactment, if the peer effects on financial policy are indeed amplified by low IIQ. Consistent with our prediction, in both columns, the coefficients β_1 of the triple interaction term $Peer\ Leverage_{-ijt} \times Treated \times Post$ in Eq. (4) are negative and statistically significant.

We then apply the propensity score matching (PSM) procedure to mitigate the influence brought by heterogeneity in firm-specific characteristics between treated and control firms. Considering that the number of treated firms is small, we match each of them with three control firms in the year before the event (the year 2003).[13] Panel B displays the difference of firm-specific characteristics between treated firms and control firms after the matching. We can see that the differences in the average value of all the matching variables are statistically insignificant, showing that the matching procedure largely eliminates the heterogeneity between treated and control firms. Panel C presents the difference-in-difference test results using the matched sample. The coefficient β_1 on the triple interaction term is still negative and statistically significant. These findings indicate that the influence of peer firms' leverage on the treated firms' leverage is significantly weaker after the enactment of SOX 404 and support our main conjecture that the peer effect on firm leverage weakens when internal information quality

Table 4
Difference-in-difference tests.

Panel A. Difference in difference tests

	(1)	(2)
VARIABLES	Market leverage	Market leverage
Post × Treated × Peer leverage	−0.594**	−0.471**
	(−2.220)	(−2.179)
Post × Treated	0.068	0.091*
	(1.117)	(1.851)
Post × Peer leverage	−0.407***	−0.486***
	(−7.098)	(−8.132)
Treated × Peer leverage	−0.003	0.275
	(−0.009)	(0.899)
Peer leverage	0.407*	0.385*
	(1.674)	(1.787)
Treated	−0.010	
	(−0.148)	
Constant	0.013	−0.070
	(0.159)	(−0.863)
First stage instrument	−0.039***	−0.040***
	(−6.818)	(−10.07)
Control variables	Yes	Yes
Industry fixed effects	Yes	No
Firm fixed effects	No	Yes
Year fixed effects	Yes	Yes
Observations	10,856	10,856
Adjusted R^2	0.400	0.773

Panel B. Summary statistics after PSM

Variable	Average Treated	Average Controls	Difference	T-statistics
Size	5.774	5.927	−0.153	−0.54
MTB	1.232	1.155	0.077	0.53
Prof	0.066	0.09	−0.025	−1.14
Tang	0.297	0.329	−0.033	−0.85
Equity shock	0.026	0.12	−0.094	0.9

Panel C. Difference in difference tests after PSM

	(1)	(2)
VARIABLES	Market leverage	Market leverage
Post × Treated × Peer leverage	−0.795**	−0.519*
	(−2.492)	(−1.832)
Post × Treated	0.094	0.076
	(1.260)	(1.263)
Post × Peer leverage	−0.241	−0.166
	(−1.225)	(−0.871)
Treated × Peer leverage	−0.125	0.187
	(−0.303)	(0.523)
Peer leverage	2.186**	1.492**
	(2.448)	(2.118)
Treated	0.006	
	(0.068)	
Constant	−0.466*	−0.308
	(−1.675)	(−1.060)
First stage instrument	−0.029*	−0.034***
	(−1.802)	(−2.901)
Control variables	Yes	Yes
Industry fixed effects	Yes	No
Firm fixed effects	No	Yes
Year fixed effects	Yes	Yes
Observations	1123	1123
Adjusted R^2	0.555	0.755

This table displays the impact of SOX 404 adoption on firms' financial policy peer effects. The application of SOX 404 is treated as an exogenous shock for firm's internal information quality. Post is an indicator variable equal to one for post-event years (2005, 2006 and 2007), and zero for pre-event years (2001, 2002 and 2003). Treated is an indicator variable equal to one if a firm reports material weakness in 2004 which was revised in the following year, and zero

[11] A similar strategy has also been adopted by Huang et al. (2020) and McGuire, Rane, and Weaver (2018)

[12] We use the fitted peer leverage to alleviate the endogeneity concern in identifying leverage peer effect. The test using peer leverage variable directly, yields very similar findings.

[13] We also try 1-to-1 match and 1-to-2 match methods, but the matched control firms have higher differences in some characteristics for treated firms, compared with all the control firms in the full sample.

otherwise. The sample includes all nonfinancial, nonutility firms with material weakness data from Audit Analytics. Panel A displays the difference-in-difference tests results with peer leverage estimated by instrumental variable. Panels B and C display results employing propensity score matching (PSM). All treated firms are matched with three control firms with similar characteristics in the year before the event (2003). Panel B presents the statistics of firm specific characteristics after PSM. Panel C displays the 2SLS regression results after the propensity score matching. Panels A and C display 2SLS estimated coefficients and t-statistics, clustered at firm level in parentheses. Industries are defined by the three-digit SIC code. All the variables are defined in Appendix A. ***, ** and* indicate statistical level at 1%, 5% and 10% level, respectively

improves.

3.3.2. Lagged explanatory variables and firm fixed effects

To be consistent with the existing studies, such as (Fairhurst & Nam, 2020; Francis et al., 2016; Leary & Roberts, 2014), we used a contemporaneous setting in our baseline model. While the contemporaneous model is a stricter setting to test peer mimicking as it allows less time for firms to react (Leary and Roberts (2014), it is also more likely to be contaminated by the common omitted factors that lead to the endogeneity problem. A dynamic model with lagged independent variables could partially alleviate this concern, therefore, in this section, we adopt a robustness check by using lagged estimated peer leverage and internal information quality proxies in our tests.

Panel A of Table 5 presents the results of our baseline model estimated by using lagged explanatory variables. Consistent with the baseline results, the coefficients of the interaction term are still positive and statistically significant. The results could, at least partially, mitigate the concern that the results are driven by firms' co-movement in response to the contemporaneous shock.

Our baseline model has already incorporated several firm characteristics and industry fixed effects. To further alleviate the concern that omitted time-invariant factors may also drive our findings, we also conducted a test including firm fixed effects. Compared with industry fixed effects, firm fixed effects can better control for unobserved factors that may influence our results. In panel B of Table 5, we present the results of baseline tests after replacing industry fixed effects with the firm fixed effects. The positive and statistically significant coefficients of the interaction terms (*EAS/ Dret× Peer leverage*) provide evidence that our results are not driven by time-invariant fixed effects.

4. Potential mechanisms and further analysis

In this section, we explore the effects of, and potential channels for peer mimicking under poor internal information quality.

4.1. Information acquisition vs. agency cost

After documenting the amplified financing policy peer effects under poor internal information quality, we shift our focus to an attempt to identify the potential mechanisms that drive the effect. Firms are likely to mimic the behavior of their product market peers because they believe that peer firms have better information. Consequently, when a firm observes that peer firms change their leverage, they may assume that this would also be a good option for them too, therefore they adjust their own capital structure following the lead of their peers. This hypothesis is consistent with the informational cascade model developed by Bikhchandani et al. (1998), which predicts that decision-makers are

Table 5
Robustness Checks.

Panel A. Lagged independent variables

	(1)	(2)
VARIABLES	Market leverage	Market leverage
$EAS_{t-1} \times$ Peer $leverage_{t-1}$	2.075***	
	(7.569)	
$Dret_{t-1} \times$ Peer $leverage_{t-1}$		0.199**
		(2.073)
EAS_{t-1}	0.243***	
	(3.253)	
$Dret_{t-1}$		−0.017
		(−0.871)
Peer $leverage_{t-1}$	−0.387***	0.071
	(−8.300)	(1.544)
Constant	0.298***	−0.006
	(13.384)	(−0.130)
First stage instrument	−0.038***	−0.033***
	(−6.665)	(−8.187)
Control variables	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	80,824	21,716
Adjusted R^2	0.375	0.387

Panel B. Firm fixed effect

	(1)	(2)
VARIABLES	Market leverage	Market leverage
EAS × Peer leverage	1.517***	
	(6.966)	
Dret × Peer leverage		0.176**
		(2.065)
EAS	0.349***	
	(5.765)	
Dret		−0.010
		(−0.596)
Peer leverage	−0.004	0.077
	(−0.049)	(0.422)
Constant	−0.025	0.060
	(−0.839)	(1.159)
First stage instrument	−0.033***	−0.029***
	(−6.141)	(−7.251)
Control variables	Yes	Yes
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	91,984	25,223
Adjusted R^2	0.709	0.739

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965 to 2017 with non-missing data for all firm characteristics. The variables are defined in Appendix A. The table displays 2SLS estimated coefficients and t-statistics, clustered at firm level in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. Panel A lagged all main independent variables by one period. Panel B displays the results including firm fixed effects. ***, ** and* indicate statistical significance level at 1%, 5% and 10% level, respectively

Table 6
Internal information quality, mimicking and future profitability.

	High EAS		High Dret		Low EAS		Low Dret	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	ROE_{t+1}	ROA_{t+1}	ROE_{t+1}	ROA_{t+1}	ROE_{t+1}	ROA_{t+1}	ROE_{t+1}	ROA_{t+1}
Mimicker	−0.013**	−0.004**	−0.022**	−0.006**	−0.005	−0.000	−0.004	−0.001
	(−2.280)	(−2.130)	(−2.475)	(−2.009)	(−1.588)	(−0.189)	(−0.467)	(−0.422)
Leverage	−0.262***	−0.037***	−0.334***	−0.027***	−0.133***	−0.026***	−0.269***	−0.023***
	(−14.788)	(−9.527)	(−8.374)	(−3.182)	(−9.766)	(−9.091)	(−7.384)	(−2.927)
Size	0.041***	0.014***	0.031***	0.015***	0.016***	0.007***	0.018***	0.012***
	(17.845)	(21.866)	(11.489)	(14.224)	(15.196)	(17.594)	(7.910)	(12.437)
MTB	0.011***	−0.003**	0.009***	0.007***	0.007***	0.008***	0.010***	0.009***
	(4.352)	(−2.075)	(2.803)	(4.166)	(3.900)	(7.770)	(3.781)	(5.868)
Current ROE/ROA	0.436***	0.573***	0.313***	0.580***	0.523***	0.614***	0.374***	0.584***
	(25.828)	(48.956)	(7.205)	(28.544)	(17.290)	(37.433)	(9.039)	(27.824)
Constant	−0.017	−0.022***	−0.128***	−0.070	0.039***	−0.017***	−0.106***	−0.061***
	(−0.898)	(−4.859)	(−3.289)	(−1.502)	(3.455)	(−5.753)	(−5.300)	(−7.395)
Industry/ Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,412	36,596	9801	9829	44,131	44,228	11,854	11,887
Adjusted R^2	0.261	0.412	0.175	0.446	0.265	0.427	0.180	0.436

The sample includes all nonfinancial, nonutility firms from CRSP-Compustat Merged database from 1965 to 2017 with non-missing data for all firm characteristics. All variables are defined in Appendix A. The table displays OLS regression estimated coefficients and t-statistics clustered at firm level in parentheses. The table displays the heterogeneity of firm mimicking behavior's influence on their future profitability for firms with different levels of internal information quality. The dependent variables are firm's ROE and ROA in year t + 1. The *Mimicker* variable is an indicator variable equal to one if firms are treated as mimicker in the current year and zero otherwise. Columns (1)–(4) indicate mimicking behavior's influence on future profitability for low internal information quality firms, while columns (5)–(8) indicate the influence for high internal information quality firms. ***, ** and* indicate statistical significance level at 1%, 5% and 10% level, respectively.

likely to follow the behaviors of their peers as long as they believe their peers' decisions contain new information. Banerjee (1992)'s herding model also implies that uninformed individuals will be more likely to follow predecessors.[14] Similar arguments are also supported by more recent literature. For example, Foucault and Fresard (2014) suggest that firms will learn from their peers' stock prices when making investment decisions because peers' stock prices contain useful information about future demand in the industry. We define this potential explanation as "*the information acquisition channel*".

On the other hand, firms may also mimic the behavior of their product market peers due to agency problems. For example, managers are concerned about their reputation in the labor market. A "follow the herd" strategy enables them to attribute their failure to uncontrollable systematic risk, instead of lack of competence (Bolton & Scharfstein, 1990). Therefore, when corporate governance is weak, managers would be more likely to choose to optimize their career outcome by ignoring their private information and mimicking the behavior of their peers. Also, good internal information quality is essential for shareholders to mitigate agency problems. Low internal information quality reduces the efficacy of the board of directors' monitoring and amplifies the agency problem (Harp & Barnes, 2018; Laux et al., 2018). Therefore, a low IIQ environment would enable managers to ignore private information and choose to follow peers' decisions. We define this explanation the "*the agency cost channel*".

Although both the information acquisition and agency cost hypothesis predict that with low internal information quality, firms are more likely to mimic the financial policy of their product market peers, the implications of the two hypotheses are different. If mimicking behavior reflects managers' incentives to learn, then the consequence of such learning should in general be positively reflected in the firms' future performance. On the other hand, if mimicking is the consequence of amplified agency cost, then the firms' performance would be likely to suffer.

To improve our understanding of this issue, we classify firms as mimickers and non-mimickers and investigate the difference in their performance under different levels of information quality. Specifically, we follow the approach taken by Belsley, Kuh, and Welsch (2005, p. 13-14) and use DFBETA statistics as the basis of the mimicker classification. DFBETA describes how the coefficient estimates change if an observation is excluded. In this study, for each firm-year observation, DFBETA is the difference between the coefficient of *peer leverage* estimated using all data and the coefficient estimated by deleting this observation (Belsley et al., 2005). Essentially, the leverage of firms that follow their peers' financial policy more closely should exhibit a higher correlation with the peer leverage. Therefore, deleting this observation should lead to a significant change in coefficient estimates, and the difference between the coefficient estimates with and without this observation will be high. On the other hand, firms that do not follow their peers contribute less to the overall goodness of fit of the model, by excluding them, the difference between the coefficients will be small. This approach has also been used by Fairhurst and Nam (2020) and following their specification, we define a firm as a mimicker in year *t* if its DFBETA value falls in the top tercile of the industry-year observations and as a non-mimicker otherwise.

Next, to test the heterogeneity of firms' performance with different levels of internal information quality (IIQ), we split our sample into a high IIQ group and a low IIQ group using the level of internal information quality in the current year. The high IIQ group contains firms whose internal information quality is above the median level of the industry-year, and the low IIQ group contains firms with IIQ below the median. Then we run the following regression for each subsample:

$$Profitability_{t+1} = \alpha + \beta Mimicker_t + \gamma Controls_{it} + \rho\mu_j + \varphi\nu_t + \varepsilon_{it} \quad (5)$$

We measure a firm's future profitability using return on equity (*ROE)* and return on asset *(ROA)* in year *t* + *1*. $Mimicker_t$ is an indicator variable equals one if the firm is a mimicker and zero otherwise. Firm size, market to book ratio, leverage ratio, and the current year's profitability are included to control for firm-specific characteristics. Industry and year fixed effects are also included.

Table 6 displays the regression results of Eq. (5). In this table,

[14] In Banerjee's (1992) model, all individuals can observe the choices of their predecessors, and they know that their predecessors have their own signals. However, they do not know the contents of their predecessor's signals and have no idea of whether the signals are correct. Also, they do not know how the predecessors make their decisions (based on their own signals or mimicking others).

Table 7
Internal information quality, agency costs and peer effects.

	High EAS		Low EAS		High EAS		Low EAS	
	Entrenched CEO	Not entrenched CEO	Entrenched CEO	Not entrenched CEO	Low takeover index	High takeover index	Low takeover index	High takeover index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage	Market leverage
Peer leverage	1.178*	0.366	0.331	0.056	0.536**	0.347	0.221	0.347
	(1.867)	(0.770)	(1.388)	(0.129)	(2.204)	(1.364)	(1.131)	(1.603)
Constant	−0.162	−0.032	0.040	0.118	0.025	0.175**	0.148**	0.263***
	(−0.895)	(−0.312)	(0.552)	(1.423)	(0.315)	(2.042)	(2.258)	(3.528)
First stage instrument	−0.023***	−0.039***	−0.039***	−0.026***	−0.045***	−0.045***	−0.039***	−0.044***
	(−3.078)	(−4.195)	(−5.629)	(−3.118)	(−9.407)	(−8.806)	(−7.569)	(−8.694)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/ Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5003	5105	7543	5877	18,015	14,541	18,489	15,004
Adjusted R^2	0.465	0.465	0.513	0.474	0.353	0.365	0.410	0.418

The sample includes all nonfinancial, nonutility firms in US market with non-missing data of CEO duality in Execucomp database or non-missing data with takeover index from Stephen McKeon's personal webpage. All variables are defined in Appendix A. The table displays 2SLS estimated coefficients and t-statistics clustered at firm level in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by the three-digit SIC code. All control variables are lagged by one period to be consistent with related studies. The table displays the heterogeneity in firm's internal information quality's influence on financial policy peer effects for firms with different level of corporate governance. Column (1)–(2) and (5)–(6) present the influence of corporate governance for firms with bad internal information quality. Column (3)–(4) and (7)–(8) present the influence of corporate governance for firms with good internal information quality. A CEO is defined as entrenched if he/she is also the chairman of the board. A firm is defined as high (low) takeover index firm if its takeover index value is above (below) the median level within the industry-year. ***, ** and* indicate statistical significance level at 1%, 5% and 10% level, respectively

columns (1)–(4) present the effect of mimicking behavior on firms' future profitability for the low IIQ group, while columns (5)–(8) present the influence for firms in the high IIQ group. The negative and statistically significant coefficient of *Mimicker* in the first four columns indicates thatwhen suffering from low IIQ, firms that are more accustomed to mimic are usually worse performers. This effect is also economically significant, compared to the average ROE_{t+1} (−0.076) and ROA_{t+1} (−0.027) of low IIQs (high *EAS*) firms, mimickers' ROE and ROA are 51.3% and 40.7% lower.[15] Our results indicate that mimicking behavior is value-destroying, contradicting the prediction of the information acquisition hypothesis while agreeing with the prediction of the agency cost hypothesis.

4.2. Agency problem and peer effects

So far, our empirical tests show that with poor IIQ, mimicking peer firms' corporate financial policy would impair shareholder value and lead to worse future performance. To further investigate whether such effects can be directly attributed to the amplified agency cost, we exploit the cross-sectional heterogeneity of firms' corporate governance and conduct further analysis. If the amplified peer effect caused by low IIQ is comes from agency costs, we expect that better corporate governance can mitigate the effect.[16]

We choose two proxies to measure a firm's corporate governance level: *Takeover index* and *CEO entrenchment*. The *Takeover index* measures the effectiveness of state law in encouraging hostile takeovers (Cain, McKeon, & Solomon, 2017). By integrating the information of takeover law legislation at the state level with several key characteristics of the firm, the takeover index could positively predict the likelihood of hostile takeover and therefore measure the effectiveness of the market for corporate control Cain et al. (2017) This measurement has been widely used as a corporate governance proxy in recent studies (Atanassov & Liu, 2020; Boulton & Campbell, 2016; Fairhurst & Nam, 2020; Ferris, Javakhadze, & Rajkovic, 2017). Our second proxy for corporate governance is a dummy variable that indicates the presence of an entrenched CEO. Following Baginski, Campbell, Hinson, and Koo (2018), we define a CEO as entrenched if she is also the chair of the board. When the CEO also serves as the board chair, the monitoring role of the board could be partially compromised, and the shareholders' interests could suffer (Rechner & Dalton, 1991).

Our objective is to identify the effect of corporate governance in mitigating the agency cost associated with leverage peer effects. To do so, we first split our sample into two subsets: low IIQ firms with *EAS* above the industry median and high IIQ firms with below industry median *EAS*. Then we further split each subsample based on the quality of corporate governance. We classify the firms with independent CEOs (CEOs that are not serving as chair of the board) or with an above industry median takeover index as well-governed firms and other firms as poorly governed firms. This procedure gives us four samples: high IIQ firms with poor corporate governance, high IIQ firms with good corporate governance, low IIQ firms with poor corporate governance, and low IIQ firms with good corporate governance. Then we estimated the baseline model for each subsample.

Table 7 displays our estimation results. Within the four groups of firms, we find that when IIQ is low (columns 1, 2, 5, and 6), the coefficients of peer leverage are positive and statistically significant only when firms exhibit weak corporate governance, this applies with both measures of governance quality, CEO duality (column 1) and takeover index (column 5). These findings confirm our conjecture that prominent financial policy peer effects are likely to be the consequence of severe agency problems. Meanwhile, we also find that when the IIQ is high (columns 3, 4, 7, and 8), even though the estimated coefficients of peer leverage for weak corporate governance firms (columns 3 and 7) are still larger than the well-governed firms (columns 4 and 8), it is not

[15] For firms with Dret above the median (low IIQ), mimickers on average earn 43.3% and 56.8% lower ROE_{t+1} and ROA_{t+1} respectively, compared with non-mimickers.

[16] A large strand of literature has long argued that effective corporate governance can mitigate agency costs.(Cain et al., 2017; John, Knyazeva, & Knyazeva, 2015; Morellec, Nikolov, & Schürhoff, 2018)

Table 8
Further robustness checks.

Panel A. Alternative IIQ measurements

	(1)	(2)
VARIABLES	Market leverage	Market leverage
Restatement × Peer leverage	0.149***	
	(2.899)	
Weakness × Peer leverage		0.221***
		(2.699)
Restatement	0.009	
	(0.846)	
Weakness		0.019
		(1.271)
Peer leverage	0.052	−0.016
	(0.206)	(−0.064)
Constant	0.175*	0.025
	(1.725)	(0.648)
First stage instrument	−0.028***	−0.027***
	(−7.141)	(−7.018)
Control variables	Yes	Yes
Industry/ Year fixed effects	Yes	Yes
Observations	26,372	25,592
Adjusted R^2	0.389	0.396

Panel B. Alternative leverage measurements

	(1)	(2)
VARIABLES	Book leverage	Book leverage
EAS × Peer leverage	1.910***	
	(3.847)	
Dret × Peer leverage		0.295*
		(1.736)
Peer leverage	0.086	0.403
	(0.362)	(0.837)
EAS	0.249**	
	(2.124)	
Dret		−0.052
		(−1.403)
Constant	0.017	0.075
	(0.379)	(0.992)
First stage instrument	−0.014***	−0.013***
	(−3.078)	(−3.800)
Control variables	Yes	Yes
Industry/ Year fixed effects	Yes	Yes
Observations	91,984	25,223
Adjusted R^2	0.251	0.297

Panel C. Alternative industry classification (TNIC)

	(1)	(2)
VARIABLES	Market leverage	Market leverage
EAS × Peer leverage	2.766***	
	(11.706)	
Dret × Peer leverage		0.315***
		(3.970)
Peer leverage	0.009	0.427*
	(0.044)	(1.746)
EAS	0.284***	
	(2.632)	
Dret		−0.033**
		(−2.171)
Constant	0.001	0.299***
	(0.018)	(5.001)
First stage instrument	−0.018***	−0.020***
	(−3.314)	(−5.438)
Control variables	Yes	Yes
Industry/ Year fixed effects	Yes	Yes

(continued on next page)

Table 8 (*continued*)

Panel C. Alternative industry classification (TNIC)

VARIABLES	(1) Market leverage	(2) Market leverage
Observations	58,236	24,903
Adjusted R^2	0.375	0.374

Panel D. High dimensional fixed effects

VARIABLES	(1) Market leverage	(2) Market leverage
EAS × Peer leverage	0.609*	
	(1.870)	
Dret × Peer leverage		0.172*
		(1.778)
Peer leverage	−0.013	−0.012
	(−0.114)	(−0.057)
EAS	0.585***	
	(6.810)	
Dret		−0.013
		(−0.676)
Constant	−0.070*	−0.015
	(−1.921)	(−0.297)
First stage instrument	−0.033***	−0.034***
	(−6.138)	(−7.017)
Control Variables	Yes	Yes
Firm fixed effects	Yes	Yes
Industry× Year fixed effects	Yes	Yes
Observations	91,984	25,223
Adjusted R^2	0.722	0.758

Panel E. Additional controls

VARIABLES	(1) Market leverage	(2) Market leverage	(3) Market leverage	(4) Market leverage	(5) Market leverage	(6) Market leverage	(7) Market leverage	(8) Market leverage
EAS × Peer leverage	1.863***		1.203***		2.340***		4.775***	
	(6.735)		(4.712)		(7.958)		(7.816)	
Dret × Peer leverage		0.294***		0.328***		0.289***		0.153*
		(3.074)		(3.482)		(3.014)		(1.828)
Peer leverage	0.091	0.404*	0.471***	0.346*	0.032	0.576***	−0.196	0.289
	(0.735)	(1.800)	(4.466)	(1.674)	(0.246)	(2.752)	(−1.021)	(1.232)
Size_rel	0.072***	0.136***						
	(3.517)	(5.323)						
Size_rel × Peer leverage	−0.053	−0.513***						
	(−1.196)	(−5.711)						
Z-score			0.012***	0.007**				
			(6.262)	(2.388)				
Z-score × Peer leverage			−0.151***	−0.148***				
			(−15.224)	(−8.671)				
Takeover					−0.010	0.136*		
					(−0.158)	(1.830)		
Takeover × Peer leverage					−0.724***	−1.350***		
					(−3.178)	(−4.049)		
Entrenched							−0.004	0.004
							(−0.404)	(0.527)
Entrenched × Peer leverage							−0.011	−0.049
							(−0.234)	(−1.224)
EAS/ Dret	0.463***	−0.029	0.524***	−0.037*	0.497***	−0.028	−0.238*	0.008
	(6.459)	(−1.467)	(7.836)	(−1.888)	(6.672)	(−1.466)	(−1.796)	(0.434)
First stage instrument	−0.046***	−0.054***	−0.026***	−0.033***	−0.035***	−0.035***	−0.024*	−0.027***
	(−3.749)	(−3.509)	(−3.898)	(−6.025)	(−3.689)	(−3.745)	(−1.886)	(−3.523)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry/ Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,984	25,223	89,474	24,464	66,049	19,581	23,528	15,363
Adjusted R^2	0.392	0.386	0.415	0.409	0.394	0.391	0.452	0.448

The sample includes all nonfinancial, nonutility firms from the CRSP-Compustat Merged database from 1965 to 2017 with non-missing data for all firm characteristics. The table displays 2SLS estimated coefficients and t-statistics clustered at firm level in parentheses. The peer firm average variables are calculated as the mean value of all firms within the industry excluding firm *i*'s observation. Industries are defined by three-digit SIC codes, except panel in C. All control variables are lagged by one period to be consistent with related studies. Panel A displays results using *Restatement* and *Weakness* as IIQ proxies. *Restatement* and *Weakness* are two indicator variables equal to one if a firm reports an unintentional restatement (weakness) and zero otherwise. Panel B shows baseline tests using book leverage as leverage measurement. Panel C shows baseline tests using the TNIC classification as the peer group definition. Panel D displays baseline tests using high dimensional fixed effects model. Panel E displays baseline tests by adding additional control variables. ***, ** and* indicate statistical significance level at 1%, 5% and 10% level, respectively.

statistically significant. These results show that agency cost-related peer mimicking is much less severe when the IIQ is high.

4.3. Further robustness checks

We conduct a battery of further tests to ensure our results are robust. First, to make sure that our findings are not unique to the measures we use for internal information quality, we employ two alternative internal information quality proxies following Gallemore and Labro (2015). The first proxy is *Restatement*, which is an indicator variable which equals one if firms disclose a restatement because of unintentional error and zero otherwise. The second one is *Weakness*, which is also an indicator variable which equals one when firms disclose a material weakness and a zero otherwise. Panel A of Table 8 presents the results of using these two proxies for Eq. (2). The coefficients of the interaction terms (*Restatement*× *Peer leverage* and *Weakness*× *Peer leverage*) are both positive and statistically significant, confirming our main findings that firms which suffer from bad internal information qualityare more willing to

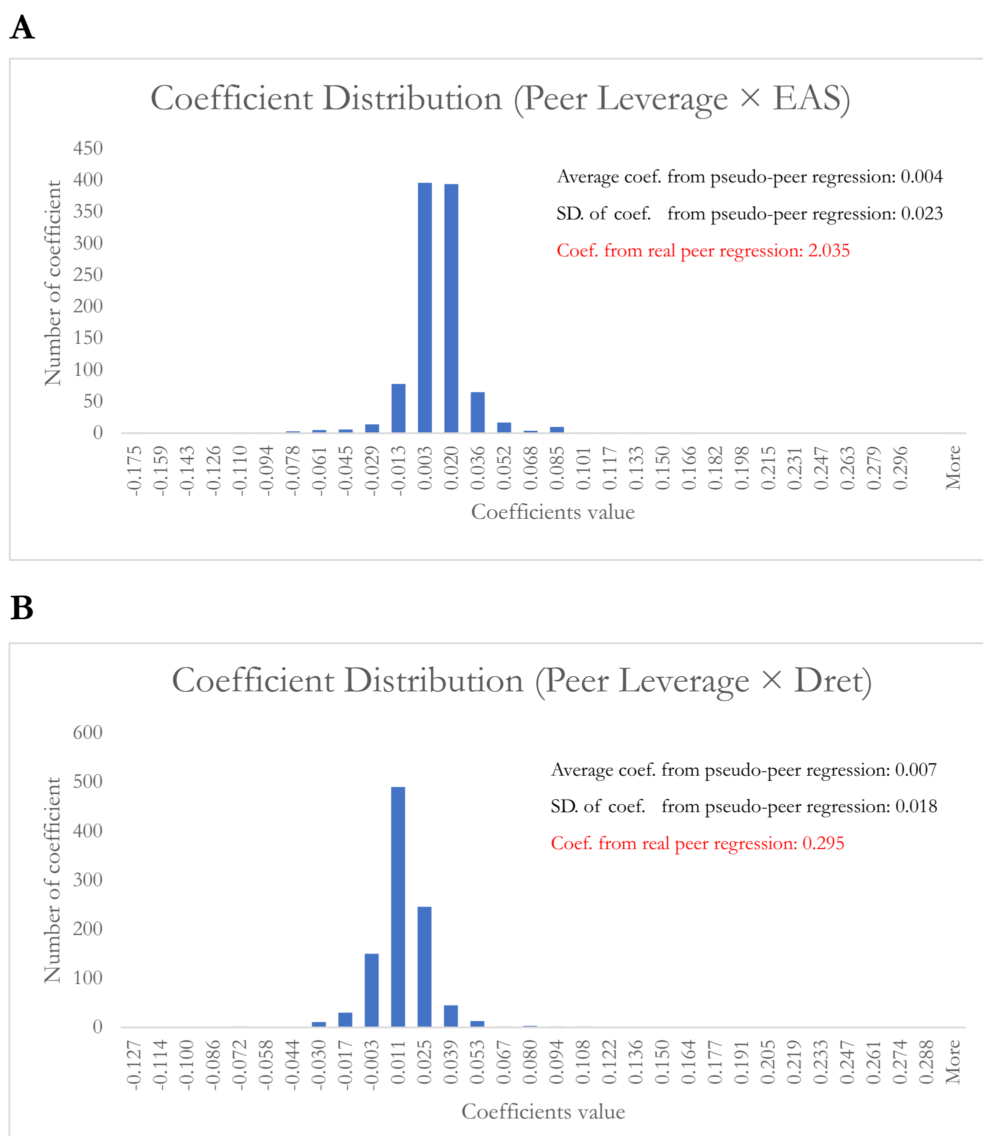

Fig. 1. Placebo tests: coefficient distribution.
The figure presents the distrbution of coefficients from the placebo tests (section 4.3). For each firm with n peers, we randomly selected n firms from entire market as its pseudo-peer firms and use the average leverage of pseudo-peers to conduct our baseline regression- Eq. (2). We repeated this process 1000 times and reported the distribution of the coeffients (β_1 in Eq. (2)) in the figures.The horizental-asix in the figure is the coefficient value and the vertical-asix refers to the number of coefficients in this value range.

adjust their leverage by following their industry peer firms.

Second, since the market value of equity is used to calculate market leverage, one may argue that the identified leverage peer effect might simply reflect the co-movement of the market value of equity of firms in the same industry. Although the use of instrumental variable analysis in our main analysis should alleviate this concern, the use of book leverage could further address this issue as its construction will not rely on the market value of equity. Panel B of Table 8 presents the results using book leverage ratio as the dependent variable for Eq. (2). Our results are consistent with our baseline results in section 4.

Third, Hoberg and Phillips (2016) argue that frequently used industry classifications such as SIC or NAICs may not be able to accurately reflect the evolution of the product market structure and account for the similarities in products both across and within the industry. To mitigate the concern that our peer firms are inappropriately defined by the traditional industry classification codes, we conduct further robustness tests by adopting the Text-based Network Industry Classifications (TNIC) of Hoberg and Phillips (2016) as an alternative to define peer firms. As an alternative way of defining industry peers, TNIC has two major advantages. First, TNIC classifications are updated on an annual basis, therefore could capturing the most up-to-date product linkage between firms. Second, TNIC is constructed based on textual analysis of firms' product descriptions from their 10-K files, therefore ensures that the peer firms selected are all relevant product-market competitors. Panel C of Table 8 presents the results of baseline tests using the TNIC classification as the definition of the peer group. The coefficients of interaction terms (*EAS*× *Peer leverage* and *Dret*× *Peer leverage*) in the panel are qualitatively similar to the coefficients reported in the baseline regression (Table 3).

Another potential concern is that the peer effects identified in our model may result from common systematic shocks that influence all industries simultaneously. If this is the case, then our identified comovement of capital structure may not be industry-specific. The comovement of leverage would be observed among firms, even if they are not real peers, if the peer effects are in fact a reflection of systematic common shock. To address this concern, we follow Bustamante and Frésard (2020)'s paper and conduct a set of placebo tests. In each year, for each firm with n peer firms in the same 3-digit SIC industry, we randomly select n firms from the entire sample universe to form the sets of pseudo-peer firms and use the average leverage of these pseudo-peers to rerun our baseline regression (column (4) and (6) of Table 3). After repeating this process 1000 times, we plot the distribution of the coefficients of interest (β_1 in Eq. 2) in Fig. 1. The average value of these coefficients from placebo tests is significantly smaller than our baseline results (0.004 vs 2.035 and 0.007 vs 0.295). The insignificant coefficients from the tests indicate that our results are unlikely to be driven by the omit factors that influence the entire market.

In panel D of Table 8, we include high dimensional fixed effects (*industry*× *year*) to further control for unobserved time-variant heterogeneity across industries. We also include firm fixed effects to control for time-invariant confounding factors. Our results remain significant after adding stricter fixed effects.

Finally, we conduct further robustness checks by controlling for some additional factors that may simultaneously influence IIQ and leverage peer effects. First, smaller firms are more likely to follow big firms (Leary & Roberts, 2014). Since the smaller firms are also more likely to be characterized by poor information quality, it is possible that our result might be driven by the size effect. Second, information asymmetry could increase the cost of capital (Armstrong, Core, Taylor, & Verrecchia, 2011) which increases the likelihood of financial distress, while financial distress in one firm may change managers' risk aversion in peer firms, providing incentives for them to adjust leverage in response (Kalda, 2020). If this adjustment coincides with leverage adjustment in the focal firms, we could also observe amplified peer effects in firms' financial policy. Finally, existing studies find that corporate governance is another factor that can impact a firm's mimicking behavior (Fairhurst & Nam, 2020). One may argue that since IIQ is related to corporate governance, our findings are simply another way to look at the effect of corporate governance on leverage peer effects.

To mitigate those concerns, we conduct further analysis by adding interaction terms between firms' relative size (firm size scaled by peer's average size), the Altman (1968) *Z*-score, takeover index, and CEO entrenchment to our baseline model.[17] Our estimation results in panel E of Table 8, show that the coefficient of both *EAS* × *Peer leverage* and *Dret* × *Peer leverage* remain positive and statistically significant in all specifications. These results show that our findings are not driven by size effect, financial distress-related leverage adjustment, or corporate governance quality.

5. Conclusion

This paper investigates how a firm's internal information quality influences its financial policy peer effects. We find that firms that operate in a low IIQ environment tend to follow the financial policy of their industry peer firms more closely. We also adopt a difference-in-difference test to address the potential endogeneity concern. By exploiting the exogenous shock to the IIQ resulting from the enactment of SOX 404 as our setting, we find that improvement in IIQ leads to weaker financial policy peer effects.

We also investigate the implication of financial policy peer effects on firm performance. We find that when IIQ is low, mimicking the financial policy of peer firms will have a negative impact on firm performance, showing that peer effects are value-destroying. Our further analysis provides evidence that poor IIQ exacerbates agency costs, which enables managers of the firm to follow the strategy of their industry peers even though this is not beneficial to the shareholders. Overall, our paper contributes to the literature on corporate policy peer effects, the effects of internal information quality, and corporate governance.

Acknowledgements

We thank Jan-Hendrik Meier (Discussant), Wil Martens (Discussant), Chen Chen, Zhenghong Ding, Yi Hu, Xingyu Huang, Cesario Mateus, Jing Ruan, Lisa Schopohl, Ivan Sangiorgi, Ran Tao, Andrew Urquhart and all participates from BAFA Annual Conference 2018, PFN 2020 Conference, 2021 FMA Virtual European Doctoral Student Consortium, BAFA Annual Conference 2022, and EAA Annual Congress 2022 for useful comments. We also thank Stephen McKeon for sharing the data.

[17] In unreported tests, we also control for industry level cash flow volatility. Fairhurst and Nam (2020) argue that industry level cash flow volatility will increase the difficulty that managers set an optimal capital structure. In addition, Zhang (2006) indicates that cash flow volatility will lead to higher information uncertainty of the firm. Our results stay quantitively similar after controlling for industry level cash flow volatility.

Appendix A. Variable Definitions

Table A1
Variable Definitions.

Variable Name	References	Variable Definition
Total Book Assets		Total Book Assets: **at**
Total Debt		Short-Term Debt (**dltt**) + Long-Term Debt(**dlc**)
Book Leverage		Total Debt/Total Book Assets
Market Value of Assets (MVA)	Leary and Roberts (2014)	Stock Price (**prcc_f**) × Common Share (**cshpri**) + Long-TermDebt (**dlc**) + Short-Term Debt (**dltt**) + Preferred Stock left(**pstkl**)-Liquidating Value (**txditc**)
Market Leverage		Total Debt/MVA
Size		Log (Sales) = Log(**sale**)
Tang		Asset tangibility. Net PPE (**ppent**)/ Total Book Assets (**at**)
Prof		Profitability. EBITDA (**oibdp**) / Total Book Assets (**at**)
MTB		Market-to-book ratio. MVA/Total Book Assets (**at**)
EAS		Number of days between the fiscal year end and earnings announcement date, scaled by 365.
Restatement	Gallemore and Labro (2015)	Dummy variable: equal to one if the firm reported restatements caused by unintentional errors in the fiscal year, and zero otherwise.
Weakness		Dummy variable: equal to one if the firm reported a SOX Section 404 material weakness in the fiscal year, and zero otherwise
Dret	Chen et al. (2018)	Difference between the profitability of insider trading for divisional managers and top managers during the last three years. Trading profit is measured by the average cumulative size-adjusted abnormal return following opportunistic trade over the six-month period for firm *i* in year *t*, over the prior three fiscal years. Routine trades are excluded (trades will be defined as routine trade if a manager trade in the similar month for at least three years). CEO, CFO and COO are defined as top managers. Divisional managers are managers with role code = AV, EVP, O, OP, OT, S, SVP, VP, GP, LP, M, MD, OE, TR, GM, C, CP in Thomson Financial database.
ROE		Return on equity: net income (**ni**)/ (Price× Number of shares outstanding)
ROA		Return on Asset: net income (**ni**)/ Total assets (**at**)
Entrenched	Baginski et al. (2018)	Entrenched CEO. A dummy variable equal to one if a CEO is defined as entrenched and zero otherwise. A CEO is defined as entrenched if he/ she is also the chair of the board.
Takeover	Cain et al. (2017)	Takeover index from Cain et al. (2017). A higher index indicates a higher level of corporate governance for the firm.
Size_rel		Relative size. Firm size compared with peer firms' average size.
Z-score	Leary and Roberts (2014)	Altman's Z-score (Altman, 1968). Z-score = (3.3 × pretax income (**pi**) + sales (**sale**) + 1.4 × retained earnings (**re**) + 1.2 × (current asset (**act**) − current liabilities (**lct**)))/ total asset (**at**).

We draw firms' monthly stock return data from the Center for Research in Security Prices (CRSP) database, and accounting data from the Compustat database available on the Wharton Research Data Services server. Earnings announcement data comes from Compustat and I/B/E/S database. Insider trading data comes from Thomson Financial. Firm's restatement and material weakness data come from Audit Analytics. CEO duality data is drawn from the ExecuComp database. Firms' takeover index data comes from Dr. Stephen McKeon's personal webpage. Following Leary and Roberts (2014)'s paper, we start our sample from 1965 and extend it to 2017. All financial firms (SIC code 6000–6999), utility (SIC code 4900–4999) and government entities (SIC code greater than or equal to 9000) are excluded from the sample.

Appendix B

Table B1
Stock Return Factor Regression Results.

	Mean	Median	SD
α_{it}	0.007	0.006	0.020
β_{it}^{M}	0.407	0.444	0.992
β_{it}^{IND}	0.640	0.537	0.689
Obs. Per Regression	54	60	11
Adjusted R^2	0.233	0.213	0.176
Average Monthly Return	0.014	0.000	0.176
Expected Monthly Return	0.016	0.014	0.087
Idiosyncratic Monthly Return	−0.002	−0.010	0.167

The sample includes monthly return for all non-financial, non-utility firms in the monthly CRSP database from 1965 to 2017. The sample excludes firms which are not available in the annual Compustat database. The table displays the average value of factor loadings and adjusted R^2 values from regression:

$$R_{ijt} = \alpha_{ijt} + \beta_{ijt}^{M}(RM_t - RF_t) + \beta_{ijt}^{IND}\left(\overline{R}_{-ijt} - RF_t\right) + \eta_{ijt}$$

Where R_{ijt} is the return to firm *i* in industry *j* during month *t*. $(RM_t - RF_t)$ is the market excess return. $\left(\overline{R}_{-ijt} - RF_t\right)$ is the industry excess return for all the firms average return excluding firm *i*'s return. The industries are defined by 3-digit SIC codes. The regression is estimated for each firm on a rolling annual basis using historical monthly returns data from the CRSP database. Each regression requires at least 24 months of historical data and uses up to 60 months of data in the estimation. Expected returns are computed using the estimated factor loadings and realized factor returns one year. Idiosyncratic returns are computed as the difference between realized and expected returns.

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