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Organization capital and analyst coverage[☆]

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ABSTRACT

We hypothesize that analyst coverage reduces firms' cost of capital and thereby facilitates more investments in organization capital, one of the most important intangible investments. To test our hypothesis, we use the exogenous variation in analyst coverage due to the mergers and closures of brokerages and measures of organization capital based on SG&A expenditures and text-based information manually collected from firms' 10-K filings. Our results show that firms' organization capital investments significantly decline with reduced analyst coverage. The post-event decline in organization capital is concentrated in firms with higher costs of capital, greater financial constraints, and greater dependence on external equity. Our findings are in contrast to other studies that have shown how the adverse effect of analyst coverage enhances managerial myopia and reduces corporate R&D.

1. Introduction

Organization capital has become increasingly important as it enhances the productivity, performance, and valuation of firms (Corrado et al., 2009; Eisfeldt and Papanikolaou, 2013, 2014).[1] Organization capital is the accumulated intangible assets that result from investments in management practices as embodied in unique corporate designs and processes. As organization capital effectively combines physical and human capitals, it enhances a firm's production efficiency and competitive advantage (Prescott and Visscher, 1980; Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013, 2014; Hasan and Cheung, 2018).[2]

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[1] Eisfeldt and Papanikolaou (2014) report that aggregate organization capital relative to physical capital grew two percent from 1975 to 2012, reaching its peak in 1993 when organization capital to physical capital was 19 percent higher than that in 1975. Corrado et al. (2009) show that firm-specific human and organization capital investments constitute the single largest category of business intangibles, accounting for about 30 percent of all intangible assets of U.S. firms. Recent research shows that organization capital has a positive effect on firm performance and stock returns (Lev and Radhakrishnan, 2005; Lev et al., 2009; Li et al., 2018).

[2] A few well-known examples illustrate success in installing organization capital. First, Cisco is known for its internet-based production installation and maintenance system, a unique example of organization capital (know-how) that helped Cisco save $1.5 billion in late 1990s (Economist, 1999). Second, Amazon's

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In this paper, we examine whether and how the research coverage by analysts affects corporate investments in organization capital. While there is much research on corporate innovation in the finance literature, organization capital, which is referred to as “the mother of intangible assets” by Lev and Radhakrishnan (2015), receives much less attention. Studies suggest that among multiple types of intangible assets, organization capital is more significant for the economy as a whole and for individual firms. Some studies (Corrado et al., 2005; Squicciarini and Le Mouel, 2012) use macroeconomic measures for the investments in organization capital and report that the measure of macroeconomic growth can be distorted considerably if the expenditures on organization capital are not adequately capitalized. Our own analysis also indicates that the average investments in organization capital by US public firms are roughly three to five times those in R&D between 1980 and 2016. Organization capital consists of business processes and systems that facilitate the more efficient and productive use of tangible and intangible resources. Therefore, the investments in organization capital are critical in helping firms systematically outperform their competitors and maintain their leadership position for a longer period of time (Lev and Radhakrishnan, 2005).[3]

We propose and empirically test the *cost of capital hypothesis* that analyst coverage can have a decisive and positive effect on corporate investments in organization capital. Our hypothesis builds on two strands of literature. First, firms’ intangible investments can be highly susceptible to less informative prices and market mispricing. The high uncertainty and degree of information asymmetry inherent in the output of organization capital creates challenges for its valuation and makes debt financing less accessible (Brown et al., 2009). Firms have to rely mostly on equity issuances to finance organization capital investments and are subject to varying costs of equity capital (Cornell and Shapiro, 1987; Eisfeldt and Papanikolaou, 2013). The negative effect of an increase in the cost of capital on organization capital investments can be therefore accentuated for firms dependent on equity issuance. Second, our study relates to those studies on the effects of a firm’s analyst coverage on its cost of capital. As one of the most important information intermediaries in capital markets, financial analysts can be critical in correcting market mispricing and mitigating the problem of information asymmetry between firms and market investors (Merton, 1987; Easley and O’Hara, 2004; Bowen et al., 2008; Derrien and Kecskés, 2013; Li and You, 2015; Chen et al., 2015a).[4] The role of financial analysts in reducing a firm’s cost of capital by attracting more institutional investors is also highlighted in the investment banking sector (Easley and O’Hara, 2004). Financial analysts can be instrumental and influential in evaluating the benefits of organization capital by using their expertise in perusing information on a firm’s management, talent, new technologies, and improved business processes (Hunton et al., 2002; Benner and Ranganathan, 2012; Soltes, 2014). Many intangible-intensive firms are reliant on external equity financing (Johnson, 2006; Aghion et al., 2013). This reliance makes them vulnerable to excessive costs of capital if there is a cutback in analyst coverage (Chang et al., 2006; Doukas et al., 2008). Therefore, ceteris paribus, if a firm is covered by fewer analysts, then it will experience a higher cost of capital that adversely affects its organization capital investments. As a result, the *cost of capital hypothesis* predicts a positive relation between analyst coverage and investments in organization capital.

However, the literature also identifies a conflicting and “dark-side” to analyst coverage on corporate intangible investments that presumably has effects applicable to firms’ organization capital. Stein (1988) argues that the external participants in capital markets can pressure myopic managers to sacrifice long-term benefits to boost current profits. Long-term investments, such as research and development (R&D) and marketing activities, can be reduced in exchange for high current earnings that result from such managerial myopia (Bushee, 1998; Mizik, 2010). Analysts can play the role of pressuring managers to reduce corporate innovation (He and Tian, 2013) and incentivize managers to acquire external technologies or licensing patents in place of in-house R&D and innovation to inflate current earnings (Guo et al., 2019). Therefore, in contrast to the cost of capital hypothesis, we evaluate the *managerial myopia hypothesis* that predicts that as more (fewer) analysts follow firms, managers are more (less) likely to experience market pressure and thus reduce (increase) investments in organization capital.

We investigate these two competing hypotheses by examining how the change in analyst coverage affects firms’ investments in organization capital. To enhance our identification, we use the mergers and closures of brokerages as an exogenous source of variation in analyst coverage. When brokerages merge or close, they eliminate analysts due to redundancy or termination. As a result, (treatment) firms affected by these events inevitably lose analysts. We use a difference-in-differences (DiD) analysis to examine how the organization capital investments of the treatment firms, relative to those of a group of control firms, respond to the exogenous decreases in analyst coverage.

We follow the literature and measure the organization capital of individual firms by accumulating SG&A expenses with the perpetual inventory method (Eisfeldt and Papanikolaou, 2013). SG&A expenses cover most of the expenditures to generate organization capital, such as marketing, recruiting and training employees, and information technology (Lev and Radhakrishnan, 2005). Following Eisfeldt and Papanikolaou (2013), we scale the SG&A (level) measure by a firm’s total assets. We measure the

item-to-item collaborative filtering algorithm that recommends goods reflecting the potential interests of customers and attracts more returning customers is a form of organization capital (Fortune, 2012). Third, Zappos.com was famous for its outstanding customer service in online apparel and shoes business. Amazon later acquired Zappos.com for about $1.2 billion, most of which was paid to acquire the inextricable intangible in Zappos’ business (Forbes, 2015).

3 Our focus of organization capital makes our paper distinct from previous papers examining corporate real investments in several aspects. Intangible assets, unlike tangible assets, are generally not traded in the organized markets with a minimal possibility to acquire information from asset price (Aboody and Lev, 2000). Accounting rules and practices require periodic reports on physical assets (e.g., asset impairment); while the investments on intangibles, such as organization capital and R&D, are expensed with no mark-to-market update on the value of organization capital (Lev and Sougiannis, 1996). In addition, intangible assets can be more firm-specific in nature and investors can derive little information by observing other firms’ intangible investments (Aboody and Lev, 2000; Barth et al., 2001). All these issues contribute to information asymmetry and inherent uncertainty for firms with investments in intangible capital. Financial analysts can be crucial in providing information to investors for firms with intangible investments. Therefore, the role and channel of analyst coverage in affecting organization capital investments can be different from previous studies focusing on investments in tangible assets.

4 Financial analysts provide routine information collection and dissemination to market participants through their research reports, stock recommendations and earnings forecasts (see, e.g., Barth et al., 2001; Barron et al., 2002; Brown et al., 2015; Hirst et al., 1995).

investment in organization capital as the one-year and two-year changes in the estimated organization capital. Alternatively, to mitigate potential measurement errors in the SG&A-based variable, we conduct textual analyses with the key concepts and aspects of organization capital on the firms' disclosures in the 10-K filings to construct a 10-K-based measure.

Using the SG&A-based measure, we show that the organization capital investments of treatment firms are significantly lower than those of control firms in the post-merger or closure window. This negative treatment effect is economically significant, as our results indicate an average 3.3% (about $241 million) decrease in organization capital investments by treatment firms within two years of that window. We also find similar results when we use the 10-K-based measure. These results support the *cost of capital hypothesis*.

To solidify our argument, we also exploit the cross-sectional variation in the cost of capital, financial constraints, and equity dependence of treatment firms. If cost of capital is indeed the channel through which firms reduce investments in organization capital when analyst coverage decreases, then this reduction should be larger in firms with a higher cost of capital, as a higher cost of capital discourages firms from making investments (e.g., Derrien and Kecskés, 2013). Furthermore, reduced analyst coverage can restrict firms' access to the equity market and curb their external financing (Chang et al., 2006; Hadlock and Pierce, 2010). Thus, the treatment effect on financially constrained and equity dependent firms should be stronger. By contrast, the myopia hypothesis suggests a positive treatment effect among firms with low costs of capital, as managers of such firms are more likely to undertake long-term and intangible investments when analyst coverage and market pressure decline. The myopia hypothesis also indicates that the treatment effect should be particularly strong for firms without financial constraints or which are less equity dependent because these firms can easily obtain the funds required to make investments.

Our empirical tests show that the negative treatment effect on organization capital investments is significant only in the subsample of firms with a high cost of capital, especially when the firms are more financially constrained or heavily dependent on equity financing. We do not find a significantly positive treatment effect for firms with a low cost of capital, nor for firms with less financial constraints or lower equity dependence. Thus, our results support the cost of capital hypothesis, while they are at odds with the myopia hypothesis.

We perform robustness checks to address the potential problems of omitted variables and measurement errors. First, we control for the firm fixed effect in the regression and obtain similar results. Second, we conduct a placebo test by randomly selecting non-treatment firms as pseudo treatment firms. The results show that less than 1% of the randomly selected firms generate a treatment effect as significant as the effect in our sample. Thus, our results are not driven by chance.[5]

This paper contributes to three strands of literature. First, we show that managerial incentives on organization capital investments can be remarkably different from those on other intangibles (such as R&D and innovation). The majority of organization capital are firm-specific and cannot be easily replicated, imitated, or transferred across firms. The non-transferability makes organization capital distinctly different from R&D. Because firms can acquire innovative firms or license patents to substitute for in-house development (Guo et al., 2019), managers can reduce the costs of innovation to increase current earnings under pressure of analysts' earnings reports (He and Tian, 2013). Unlike for R&D, there is no substitute for the internal investment in organization capital, which makes the costs of cutting the short-term outlays outweigh the benefit of meeting analysts' expectations. As a result, organization capital investments are less susceptible to managerial myopia than R&D and innovation. To the best of our knowledge, our study is one of the first to show that not *all* intangible investments are susceptible to managerial myopia from the pressure of financial analysts.

Second, our study contributes to the understanding of the sources of value addition by financial analysts. Research on analysts largely focuses on the influence of their research on shareholders' decisions and capital market outcomes (Brown et al., 2015; Hirst et al., 1995). The literature has long been dedicated to evaluating whether analysts can influence the major strategies of the firms they follow (Merton, 1987; Easley and O'Hara, 2004; Bowen et al., 2008; Derrien and Kecskés, 2013; Li and You, 2015; Chen et al., 2015b). Our study extends this literature by highlighting the cost of capital channel on how financial analysts exert their influence on firms' major intangible investments.[6]

Finally, while there is an emerging set of studies on the growing economic importance of organization capital (Ohanian, 2001; Samaniego, 2006), an understanding of how market mechanisms and institutions can affect firms' organization capital investments remains limited.[7] Our paper addresses this gap by identifying the effect of how shocks to the financial intermediary sector can affect

[5] We also exclude the R&D capital from our organization capital measure and re-run all tests. Our results hold. We further investigate the real impact of changes in organization capital. With the cost of capital hypothesis, to the extent that the organization capital investment is critical to the firms' future operating success, we would expect a corresponding decline in both the productivity and operating performance of treatment firms in the post-event window. This result is accentuated in treatment firms that experience larger decreases in organization capital. Conversely, with the myopia hypothesis, treatment firms will increase their investments in organization capital and the post-event firm performance is expected to improve. Such an effect should be stronger for treatment firms with larger increases in organization capital. Our empirical results indicate that treatment firms exhibit lower total factor productivity and return on assets in the post-event window, with a significant performance deterioration among treatment firms with a larger decline in organization capital investments. We do not observe any improvement in the post-event firm performance for treatment firms, even if they experience a large increase in organization capital. These results again support the cost of capital hypothesis, but not the myopia hypothesis. We present these results in the Internet Appendix.

[6] Kim et al. (2021) report that firms' organization capital affects analysts' forecast accuracy. Our paper differs from Kim et al. (2021) in the following three aspects. First, while Kim et al. (2021) focus on how organization capital can affect analyst forecasts, our findings advance the understanding of how analysts can have a real effect on corporate investment decisions and add value. Our study identifies the prominence of the cost of capital in the ability of financial analysts to exert their influence on the intangible investments of firms. Second, we take advantage of the exogenous shock in analyst coverage to fully address the endogeneity concern. Third, we perform the textual analysis on 10-K filings to estimate organization capital. Our use of an alternative measure alleviates potential measurement errors and noise in the SG&A-based OC measure.

[7] Most studies focus on R&D investments and report that R&D investments heavily relies on external equity finance. As a result, financial market development can affect economic growth. When a financial market is well developed, the cost of capital is lowered, and accordingly eases the financial constraints on the R&D investments, fueling economic growth (Brown et al., 2009, 2013; Guo et al., 2019).

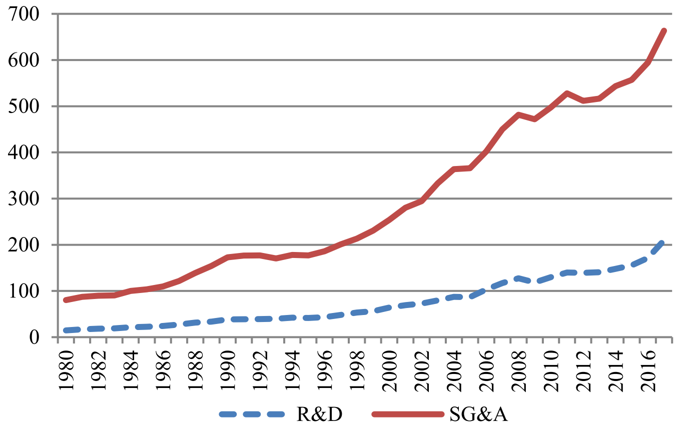


Fig. 1. Average R&D and SG&A Expenses of US firms (in Millions).

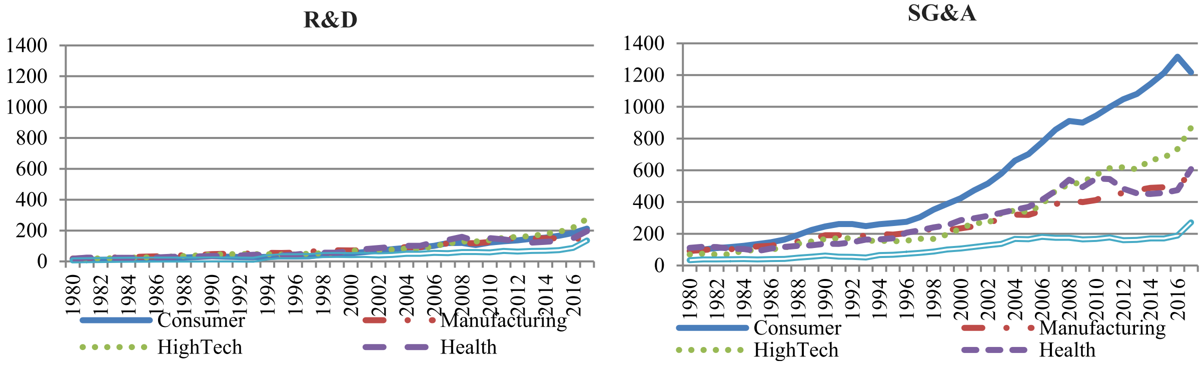


Fig. 2. Average R&D and SG&A Expenses of US Firms Sorted by Industry (in Millions).

corporate investment decisions on major intangibles through the cost of capital. Thus, we add to the argument that financial market development can affect economic growth.

The rest of the paper proceeds as follows. Section 2 discusses the related research and develops the hypotheses. Section 3 presents the data, sample, and research design. Section 4 provides the empirical results. Section 5 concludes.

2. Organization capital, analyst coverage, and hypothesis development

Our focus in this paper is on organization capital. Organization capital constitutes 30% of intangible assets and is the largest category among all intangible assets in the US (Corrado et al., 2009).[8] Given the extensive and growing literature on innovation (such as R&D and patents), organization capital is surprisingly under explored in the academic research. We compare the trends in SG&A expenditures as a proxy for organization capital to those in R&D expenses as a proxy for innovation for US firms between 1980 and 2017. Fig. 1 displays the average annual spending on R&D and SG&A for the firms in Compustat. We find that SG&A increased more rapidly and significantly than R&D, especially during the last two decades. When firms are sorted into the Fama–French five industries, as illustrated in Fig. 2, the rapid growth in organization capital dominates the growth in R&D across all five industries.

How would analyst coverage affect investments in organization capital? The literature offers two competing views. The cost of capital hypothesis posits a positive effect of analyst coverage on organization capital. As one of the most important information intermediaries in capital markets, financial analysts are known to be critical in correcting market mispricing and mitigating the problems of information asymmetry between firms and market investors (Merton, 1987; Easley and O'Hara, 2004; Bowen et al., 2008; Derrien and Kecskés, 2013; Li and You, 2015; Chen et al., 2015a). Analysts actively collect, evaluate, and disseminate detailed information that is related to a firm's future performance (Asquith et al., 2005). Through public disclosures (i.e., analyst reports),

[8] Corrado et al. (2009) examine three categories of intangible assets: computerized information, innovative property, and economic competencies. The category of economic competencies covers brand equity and firm-specific resources, including the costs of employer-provided worker training and management time devoted to enhancing the productivity of the firm. The estimated computerized information, scientific R&D, non-scientific R&D, brand equity, and firm-specific resources are approximately 14%, 25%, 24%, 7%, and 30% of intangible assets, respectively. Firm-specific resources (i.e., organization capital in our definition) are the largest item in intangible assets.

analysts can reduce information asymmetry between managers and investors, and increase investor awareness of the firm (Merton, 1987). Easley and O'Hara (2004) argue that active analysts increase the accuracy of earnings forecasts, improve the quality of financial reporting, and reduces the cost of (raising) capital. Subsequent empirical evidence supports the view that a reduction in analyst coverage can increase information asymmetry and inflate firms' cost of capital (e.g., Bowen et al., 2008; Kelly and Ljungqvist, 2012). The output of organization capital can be highly uncertain and subject to a high degree of information asymmetry (Eisfeldt and Papanikolaou, 2013). This uncertainty creates challenges for the valuation of organization capital. The uncertainty and information asymmetry of intangible assets, such as organization capital, make debt financing less possible (Brown et al., 2009), and firms tend to rely on equity financing to support organization capital investments. As a higher cost of capital would discourage firms from making investments (Brown et al., 2009, 2013; Derrien and Kecskés, 2013), managers can cut investments in organization capital when the cost of capital is sufficiently high. Therefore, a firm's investments in organization capital would be sensitive to varying costs of equity capital (Cornell and Shapiro, 1987; Eisfeldt and Papanikolaou, 2013).[9] In sum, the cost of capital view indicates that reduced analyst coverage can negatively affect organization capital investments by an increase in the cost of capital.

By contrast, the managerial myopia hypothesis posits that financial analysts can put pressure on managers that encourages myopia (Brennan and Subrahmanyam, 1995; Hong et al., 2000; He and Tian, 2013). Consequently, myopic managers may sacrifice long-term interests to boost current earnings. R&D and marketing activities are long-term investments that can be scaled back to boost current earnings (Stein, 1988; Bushee, 1998; Mizik, 2010; He and Tian, 2013). Firms can purchase externally R&D or by substituting licensing patents to substitute for in-house development (Guo et al., 2019). The option of external purchase can incentivize corporate managers to sacrifice long-term growth and reduce R&D and innovation in an attempt to increase current earnings, especially when they are under the pressure of meeting analysts' earnings expectation (He and Tian, 2013). Similarly, myopic managers can underinvest in organization capital in order to meet or beat short-term earnings targets. Therefore, the managerial myopia hypothesis predicts that as more (fewer) analysts follow a firm, managers are more (less) likely to be pressured into engaging in myopic strategies such as cutting long-term investments and investing less (more) in organization capital.

To further enhance our identification, we use the mergers and closures of brokerages as an exogenous source of variation in analyst coverage. When brokerages merge or close, they eliminate analysts due to redundancy or termination. As a result, the firms that are affected by these events will inevitably lose analysts. If the analysts' information production reduces the information asymmetry with external investors and lowers the cost of (equity) capital, an exogenous reduction in analyst coverage should lead to a decrease in organization capital investment. Conversely, if a reduction in analyst coverage simply puts less pressure on managers to behave myopically, then an exogenous reduction in analyst coverage should lead to an increase in that investment. We state our competing hypotheses H1a and H1b as follows:

H1a (cost of capital): ***An exogenous reduction in analyst coverage leads to a*** decrease ***in organization capital investment in the treatment sample, relative to the control sample.***

H1b (managerial myopia): ***An exogenous reduction in analyst coverage leads to an*** increase ***in organization capital investment in the treatment sample, relative to the control sample.***

The cost of capital hypothesis has further implications for the effect of analyst coverage on organization capital investments.[10] As a high cost of capital prevents firms from making investments (e.g., Derrien and Kecskés, 2013), we postulate that reduced analyst coverage should cause a greater decrease in investments in organization capital. In particular, if the cost of capital is high, it is more difficult for firms to finance the funds needed for organizational capital investments under expensive external financing. Moreover, Chang et al. (2006) examine analyst coverage and equity issuance decisions and find that reduced analyst coverage restricts firms' access to the equity market that makes external financing more of a constraint. Thus, reduced analyst coverage matters most for firms facing financial constraints. For such firms, we predict a more pronounced treatment effect. Since constrained firms are more reliant on external financing (Hadlock and Pierce, 2010), they will cut their investments in organization capital more substantially. In sum, if the cost of capital is the channel through which analyst coverage affects investments in organization capital, the effect of financial constraints and equity issuance on the relation between analysts and organization capital will be stronger in firms with a high initial cost of capital.

By contrast, the myopia hypothesis indicates that the increases in organization capital after analyst coverage reductions will be stronger for firms with a low cost of capital. This is because, all else being equal, it is relatively easier for firms with a low cost of capital to raise funds to make investments in organization capital. As unconstrained firms can easily obtain the funds required to make investments, we predict that the increase in organization capital after reduced analyst coverage should be stronger for unconstrained firms. Further, we predict that reduced analyst coverage will restrict firms' access to the equity market that makes external financing more of a constraint for firms. Therefore, the increase in organization capital investments will be larger in firms that are less dependent on external equity financing.

[9] Recent studies examine whether analysts influence the real activities and corporate policies of the firms they follow. The literature highlights three potential channels through which analysts can add value to a firm: reducing the cost of capital (Derrien and Kecskés, 2013), increasing investor recognition (Li and You, 2015), and monitoring managers (Chen et al., 2015b). We do not find any compelling evidence to support the latter two channels. Therefore, we focus on the cost of capital channel in this paper.

[10] While we highlight the "cost of capital" hypothesis in our experiment design, we do not exclude monitoring or investor recognition as potentially channels through which analyst coverage affects organization capital investment. Although we do not suggest that the "cost of capital" is the exclusive channel, we include a discussion of empirical results that are inconsistent with the monitoring and investor recognition arguments.

We thus construct our competing hypotheses H2a and H2b.

H2a (cost of capital): ***The decrease in organization capital investment after the negative exogenous shocks of mergers and closures to analyst coverage is more pronounced for firms with a*** higher ***cost of capital,*** greater financial constraints, and greater dependence on external equity.

H2b (managerial myopia): ***The increase in organization capital investment after the negative exogenous shocks of mergers and closures to analyst coverage is more pronounced for firms with a*** lower ***cost of capital,*** lower financial constraints, and less dependence on external equity.

3. Data and summary statistics

3.1. Sample selection

Our sample consists of US firms for the period from 1990 to 2016. We construct our sample from multiple sources. Accounting information is collected from Compustat, market prices from CRSP, and analyst-related information from the Thomson Reuters Institutional Brokers' Estimate System (I/B/E/S). Patent data come from the European Patent Office (EPO) Worldwide Patent Statistical Database, and institutional ownership data are collected from the Thomson's CDA/Spectrum database (13F). We drop observations with missing accounting information on organization capital or analyst coverage. Our full sample contains 58,121 firm-year observations from 8,526 firms.

3.2. Measuring organization capital

We follow Eisfeldt and Papanikolaou (2013) and estimate organization capital based on selling, general, and administrative (SG&A) expenses. The SG&A expenses cover most of those aimed at creating and enhancing organization capital, such as employee training costs, information technology outlays, branding promotion, payment to consultants, and costs of internet-based supply and distribution channels (Lev and Radhakrishnan, 2005; Lev et al., 2009). The stock of organization capital (OC) is first calculated with the perpetual inventory method:

$$OC_t = (1 - \delta_0)OC_{t-1} + \frac{SG\&A_t}{cpi_t}, \tag{1}$$

where δ_0 is the depreciation rate of 15% (used by the Bureau of Economic Analysis in its estimation of R&D capital in 2006), and *cpi* is the consumer price index. We compute the initial organization capital (OC_0) as in Eq. (2):

$$OC_0 = \frac{SG\&A_1}{g + \delta_0}, \tag{2}$$

where g is the average real growth rate of firm-level SG&A expenses (10% in our sample). A firm's SG&A expenses are assigned a value of zero if they are missing in Compustat. Firms with no records of SG&A expenses are removed from the sample. The stock of organization capital calculated in Eq. (1) is scaled by the firm's total assets (*TA*). As the OC stock (as in Eq. (1)) is accumulated by depreciating SG&A expenses, the current period OC stock at time t incorporates information from previous periods.[11]

The variable of interest is the investment in organization capital (*INVOC*), or the *incremental* input of capital contributed to the OC stock that is a flow measure. We define two variables of changes in OC stock, namely, *INVOC1* and *INVOC2*, as the future one-year and two-year changes in OC stock, respectively, relative to the OC stock in the current period.

$$INVOC1_t = OC_{t+1}/TA_{t+1} - OC_t/TA_t \tag{3}$$

$$INVOC2_t = OC_{t+2}/TA_{t+2} - OC_t/TA_t \tag{4}$$

Then we compute the logarithm of changes in OC stock to minimize the potential problem of heteroscedasticity.[12]

$$LnINVOC1_t = Ln(1 + OC_{t+1}/TA_{t+1} - OC_t/TA_t) \tag{5}$$

$$LnINVOC2_t = Ln(1 + OC_{t+2}/TA_{t+2} - OC_t/TA_t) \tag{6}$$

Although the Eisfeldt and Papanikolaou (2013) measure can include noise from items unrelated to organization capital, we decide to report results using SG&A-based OC measure for the following reasons. First, the measure of Eisfeldt and Papanikolaou (2013) is based on SG&A expenses and information is available for most firms covered in Compustat. We are able to have a much larger sample with dollar amount as measures of organization capital investments to conduct empirical tests. Second, a large body of literature examining the intangible capital uses the SG&A-based measure to gauge organization capital.[13] Using the Eisfeldt and Papanikolaou (2013) measure facilitates the comparison between our paper and previous studies. Third, even SG&A expenses can include some

[11] We use depreciation rates of 8%, 13%, and 20% and growth rates of 15% and 8% in robustness checks, and results are quantitatively similar under various combinations of depreciation rates and growth rates. The detailed description and results are reported in the Internet Appendix.

[12] Less than 1% of sample observations have negative values of one plus INVOC1. For these cases, we assign a missing value to LnINVOC1 in Eqs. (5).

[13] See, for example, Hasan and Cheung (2018), Kai et al. (2018), Sun and Xiaolan (2019), Zhang (2014), Hasan et al. (2020), Hou et al. (2020), Francis et al. (2021), and Gao et al. (2021).

items unrelated to organization capital, our control for the industry effect can eliminate any heterogeneity in recording SG&A spending across industries. We believe that using SG&A expenses, which include major outlays of organization capital investments (Lev, 2001), can estimate organization capital well in many industries (Eisfeldt et al., 2022).

Alternatively, we construct a new organization capital measure by conducting textual analyses on firms' disclosure in the 10-K filings. The procedure of our text analysis is built on the key concepts and aspects of organization capital. In a seminal paper, Prescott and Visscher (1980) define organization capital as the capital formed through continuous learning within the company. They argue that the personnel, team, and firm-specific human capital information constitutes organization capital. For example, firms can choose on-the-job training and suitable work positions for employees through internal information to complete team production tasks and create higher organizational efficiency. Lev et al. (2009) state that "there are many reasons why companies differ in the efficiency of resource usage, but most of these reasons (better information technology, higher quality employees, improved incentive and compensation systems) are related to the organization capital" (page 278). Lev and Radhakrishnan (2005) and Lev et al. (2009) contend that organization capital is an agglomeration of business processes and systems that maintain the firm's competitive advantage. Gao et al. (2021) argue that SG&A expenses, including IT infrastructure, information system, R&D, employee training, are expenses for developing a firm's knowledge and business processes and for improving the utilization of resources. Francis et al. (2021) report that organization capital includes elements specific to firms, such as unique business processes that firms develop, recruiting and training of employees, and incentive programs. Hasan et al. (2021) suggest that organization capital is embedded within the organization, e.g., organizational knowledge and expertise, business processes and practices, recruiting and training programs.

Following the literature, we define organization capital by the following six key concepts: employee training (Prescott and Visscher, 1980), information technology (Lev et al., 2009), incentive compensation (Lev et al., 2009), business processes and systems (Lev and Radhakrishnan, 2005; Lev et al., 2009), infrastructure costs (Gao et al., 2021), and recruiting (Francis et al., 2021; Hasan et al., 2021). As a result, we use these six keywords, training, information technology, incentive compensation, improved processes and systems, infrastructure costs, and recruiting, to search for organization capital investment in the 10-K filings.[14] We also conduct a validation test in which we randomly select 10 firms over the period from 2002 to 2008 and count the frequency of the six keywords in our 10-K filing searches.[15] We find that these six keywords indeed occur more frequently than others for these 10 firms.[16]

To construct this measure of organization capital investment, we use the following procedure:

(a) To minimize the noise introduced by keyword searches, we conduct a screening test. We first read through the relevant paragraphs in the 10-K filings and manually determine if the information we find is indeed related to organization capital. We identify the investment in organization capital with the variables of *Comp*, *Infra*, *IT*, *Improve*, *Recruit*, and *Train*. These variables represent the keywords of incentive compensation, infrastructure costs, information technology, improved process and systems, recruiting, and training, respectively. We conduct this manual evaluation to ensure we have found relevant information about corporate investments in organization capital.
(b) After going over the 10-K filings, we create a dummy variable for each of the six keywords for each sample firm. We define the dummy variable D_i of a keyword to be one (otherwise zero) if a sample firm discloses the keyword in its 10-K filings and if the disclosure is related to organization capital investment with $i = \{Comp, Infra, IT, Improve, Recruit, Train\}$. We do not use the disclosed dollar amount, as the majority of sample firms do not disclose such information when these six keywords are mentioned in the filings (less than 2% of our DiD sample firms disclose the dollar amount). Out of the initial sample, 19.5% of firms do not make any relevant disclosures with the six keywords and are excluded from the final sample.
(c) We record the frequencies of the six keywords in the MD&A section of 10-K filings. The MD&A section covers managerial opinions on financial statements, information and systems, and includes actions being planned or taken for any challenges the firm is facing. Therefore, we use the information in the MD&A section to assess the relative importance of each keyword for organization capital investment. In this 10-K-based OC measure, we assume that the more frequently a keyword is mentioned in the MD&A section, the more important the corresponding OC area is to the firm.
(d) We then combine the keyword dummies and corresponding frequency counts to compute the organization capital measure. We use the frequency count to weigh keyword dummies D_i (as constructed in step b) to compute the *10-K-based OC*:

$$10\text{-}K\text{-}based OC = \sum_i w_i \times D_i, w_i = \frac{frequency_i}{\sum frequency}, \tag{7}$$

[14] Our choice of these keywords is also consistent with those reported in Eisfeldt and Papanikolaou (2013). Eisfeldt and Papanikolaou (2013) review the expenditure items included in the SG&A. They report that the most frequent expenditure items include employee-related costs (such as salaries, wages, incentive compensation, labor costs), administrative expenses (corporate governance, expense of executive and administrative staff, human resource, management salaries), incentive compensation (such as performance-based compensation, bonuses), employee relations (such as recruiting, travel, training), and technology infrastructure (such as information technology, improve processes and systems, infrastructure costs).

[15] The 10 randomly selected firms are Atmi Inc., Abbott Laboratories, Abercrombie & Fitch, Choice Hotels International, MGM Resorts International, Overstock.com Inc., Pss World Medical Inc., Ralcorp Holdings Inc., Teledyne Technologies Inc., and Qlogic Corp.

[16] For each randomly selected firm in each year from 2002–2008, we use the following words, "selling, general and administrative", "capital expenditure", "information technology", "incentive compensation", and "train" to locate any discussions of SG&A in the 10-K filings. In these 350 searches (10 firms × 7 years × 5 words), the numbers of our keywords, information technology, training, improved processes and systems, incentive compensation, infrastructure costs, and recruiting, are 59, 48, 45, 44, 39, and 24, respectively. Other keywords that may be related to organization capital, such as information system, labor costs, salaries, human resource, performance-based compensation, corporate governance, and bonuses, appear 10 or fewer times.

where i ={*Comp*, *Infra*, *IT*, *Improve*, *Recruit*, and *Train*}, $frequency_i$ is the frequency count of keyword i in the MD&A section, and $\sum frequency$ is the total frequency count of all keywords used.[17]

3.3. Control variables

We use the summary file of the $I/B/E/S$ database for data on the analyst coverage. For each fiscal year of a firm, we compute *Coverage* as the average number of analysts who make earnings forecasts in a given year (He and Tian, 2013) and calculate the natural logarithm of their coverages, *LnCoverage*. Sample firms with no annual earnings forecasts found in $I/B/E/S$ in the specified window are dropped from our sample.

We control for several firm and industry characteristics that may influence organization capital and analyst coverage. *LnSale* is the logarithm of sales; *RD* is the expenditure in R&D divided by total assets; *ROA* is the operating income before depreciation divided by total assets; *PPE* is the property, plant, and equipment divided by total assets; *Leverage* is the sum of short-term and long-term debts divided by total assets; *Capex* is the capital expenditure divided by total assets; *TobinQ* is the market value of equity plus the book value of assets, minus the book value of equity, minus the balance-sheet deferred taxes, and then divided by total assets; *Patent* is the logarithm of the number of patents that a firm applies for at the United States Patent and Trademark Office; *HHI* is the Herfindahl–Hirschman index calculated by the sum of squared market shares of firms in a 2-digit SIC industry; *IO* is the institutional ownership calculated as the average of four quarterly institutional ownership ratios (i.e., shares held by institutional investors divided by shares outstanding) reported in form 13F from the Thomson's CDA/Spectrum database. Appendix A lists the definitions of the variables.

The predicted effects of the control variables on investments in organization capital are as follows: We add sales (*LnSale*) to control for firm size. We expect a positive relation between organization capital and sales since larger firms may have more resources to build up their organization capital. We add *PPE* and *Capex* to capture tangibility and corresponding real investments. Given that tangible and intangible assets may be substitutes or complements, there is no definite prediction for the expected signs of these two variables. Bushee (1998) reports that institutional investors can play a monitoring role and prevent the myopic managerial behavior of cutting long-term investments. Hence, firms with greater institutional ownership are predicted to have more organization capital. Since our OC measure is constructed based on the SG&A expenses in the income statement, we expect that *ROA* will be negatively related to organization capital. Tobin's Q (*TobinQ*) is likely to be positively related to organization capital because firms with growth opportunities tend to invest more in intangible assets. We add *RD* and *Patent* to the regression to control for the innovation effects and the *HHI* to control for the industry competition effect.

3.4. Summary statistics

Panel A of Table 1 presents the descriptive statistics. We winsorize all variables at the 1st and 99th percentiles to alleviate the effect of outliers. Firms are followed by an average of 6.7 analysts who provide earnings forecasts of firms. On average, sample firms have one-year (from t to t+1) and two-year (from t to t+2) changes in organization capital of 0.0169 and 0.0312, respectively, relative to total assets. There is a large variation in firms' investments in organization capital, with the differences between the 10th and 90th percentiles of 31% and 49%, respectively, of total assets for the one-year and two-year changes in organization capital. These variations indicate the need to identify the explanatory factors.

4. Empirical results

4.1. Identification strategy

We examine whether analyst coverage has any effect on a firm's investment in organization capital. The results of the ordinary least squares (OLS) on firms' organization capital investment based on the full sample (see Appendix C) indicate a positive and significant coefficient for analyst coverage at the 1% level and support the cost of capital hypothesis. However, the OLS analysis suffers seriously from endogeneity. Analysts selectively choose the firms they research and cover. For example, other studies have shown that analysts tend to cover firms with a better information environment (Lang and Lundholm, 1996; Francis et al., 1997; Bhushan, 1989; Bushman et al., 2005). Analysts may have an incentive to cover firms with ample organization capital because the fair value of intangible assets is hard to estimate. Barth et al. (2001) report that firms with more intangible assets receive greater analyst coverage. Furthermore, a potential bias could result from omitted variables, with unobservable firm characteristics accounting for higher analyst coverage and greater investments in organization capital at the same time. These concerns make it difficult to come to clear conclusions about the causal relationships indicated by the OLS.

To address endogeneity, we use a quasi-natural experiment that allows us to examine the reaction of firms to a plausibly exogenous decrease in analyst coverage caused by closures and mergers of brokerages (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012). These exogenous shocks are *ex ante* uncorrelated with corporate investments. In our experimental design, the *treatment* firms are identified as those experiencing exogenous reductions in analyst coverage.

[17] We also use the industry frequency, the median of total frequency count of keywords for all firms covered in the industry with the same 2-digit SIC code, as a weight to construct the 10-K-based OC measure. All our empirical results remain similar using the industry frequency count.

Table 1
Summary statistics.

Panel A: Full sample						
Variable	Obs.	10th percentile	Mean	Median	Standard deviation	90th percentile
INVOC1	58,121	−0.1458	0.0169	0.0000	0.2260	0.1649
INVOC2	51,146	−0.2279	0.0312	−0.0015	0.3347	0.2657
Coverage	58,121	1.0000	6.6871	4.3333	6.4697	16.0833
LnCoverage	58,121	0.6931	1.7414	1.6740	0.7583	2.8381
LnSale	58,121	3.6072	6.0005	5.9112	2.0063	8.6799
RD	58,121	0.0000	0.0413	0.0000	0.0753	0.1333
ROA	58,121	−0.0258	0.0985	0.1171	0.1500	0.2376
PPE	58,121	0.0250	0.2569	0.1859	0.2294	0.6235
Leverage	58,121	0.0000	0.2063	0.1670	0.1997	0.4798
Capex	58,121	0.0061	0.0578	0.0385	0.0626	0.1305
TobinQ	58,121	0.9388	2.0241	1.4972	1.5329	3.7218
Patent	58,121	0.0000	0.4824	0.0000	1.0530	2.0575
HHI	58,121	0.0255	0.0655	0.0437	0.0622	0.1155
IO	58,121	0.1420	0.5408	0.5507	0.2875	0.9155
Panel B: DiD sample						
Variable	Obs.	10th percentile	Mean	Median	Standard deviation	90th percentile
INVOC1	11,400	−0.1282	−0.0157	−0.0011	0.1470	0.0908
INVOC2	5,700	−0.2267	−0.0318	−0.0034	0.2255	0.1450
10-K-based OC	9,176	0.0000	0.3306	0.3333	0.2752	0.6667
Coverage	11,400	2.9167	10.2134	8.6923	6.7223	19.8397
LnCoverage	11,400	1.3652	2.2295	2.2713	0.6373	3.0369
LnSale	11,400	4.8899	6.9643	6.9451	1.6639	9.1842
RD	11,400	0.0000	0.0333	0.0016	0.0587	0.1113
ROA	11,400	0.0245	0.1383	0.1417	0.1107	0.2566
PPE	11,400	0.0339	0.2870	0.2248	0.2329	0.6562
Leverage	11,400	0.0000	0.2162	0.1982	0.1852	0.4472
Capex	11,400	0.0097	0.0638	0.0451	0.0631	0.1385
TobinQ	11,400	1.0175	2.1473	1.6895	1.4782	3.7007
Patent	11,400	0.0000	0.7392	0.0000	1.2998	2.9444
HHI	11,400	0.0247	0.0658	0.0434	0.0622	0.1164
IO	11,400	0.3310	0.6765	0.7087	0.2358	0.9457

The Panel A of this table presents the summary statistics of the variables in the full sample for the period from 1990–2016. The variables of interest are investments in organization capital (*INVOC*) that are defined as organization capital (OC) at year t+1 minus OC at year t (*INVOC1*), and OC at year t+2 minus OC at year t (*INVOC2*). Panel B shows the summary statistics of the variables in the difference-in-differences sample. All variables are winsorized at the 1% and 99% percentiles.

The first event in our natural experiment consists of brokerage closures. Kelly and Ljungqvist (2012) document that closures of brokerage houses are usually motivated by the business strategy considerations of the brokerages themselves, and are not associated with the heterogeneous characteristics of firms that they cover. The list of closures for the sample period from 2000–2007 is collected from Kelly and Ljungqvist (2012). The treatment firms are subject to a potential increase in information asymmetry when analyst coverage declines because of these closures.

The second event in our natural experiment consists of brokerage mergers. When two brokerages merge, their integration and consolidation inevitably lead to a high turnover in analysts (Hong and Kacperczyk, 2010; Wu and Zang, 2009). Similarly, a loss in analyst coverage resulting from mergers is not directly associated with the characteristics of the firms covered by analysts. We use a procedure similar to that of Hong and Kacperczyk (2010) and Irani and Oesch (2013) to identify mergers in the financial industries from the Securities Data Company (SDC) Mergers and Acquisitions database for the period from 1994 to 2005. The treatment firms are identified from the list of firms with duplicate coverage provided by analysts at *both* the acquiring and target brokerages; or the list of firms with coverage provided by analysts working at the closing brokerages who have issued earnings forecasts in the window of 365 calendar days prior to the mergers or closures.

The *control* sample consists of non-treatment firms with similar pre-treatment characteristics. We match each treatment firm with one control firm on *Coverage*, *PPE*, and *Capex* in the year prior to the brokerage mergers or closures.[18] We also require the control firm to be matched with the treatment firm on lagged *LnINOVC1*, the one-year change in organization capital in year t-2 (i.e., the change from year t-2 to year t-1), so that the control firm can be readily identified prior to the event. We use propensity

[18] We control for capital investments (*PPE* and *Capex*) because a firm that scales back its capital investments may also scale back hiring and other SG&A (e.g., marketing) expenses. For the accounting information, we retrieve the financial statement data from the last fiscal year that ends before the merger to construct the variables in the pre-event window and data from the first complete fiscal year-end after the merger to construct the variables in the post-event window.

Table 2
Change in organization capital: difference-in-differences.

Model	(1) LnINVOC1	(2) LnINVOC2
Treatment	0.0110*	0.0186
	(1.96)	(1.59)
After	0.0287***	0.0579***
	(4.81)	(4.25)
Treatment × After	**−0.0169****	**−0.0331****
	(−2.45)	**(−2.34)**
LnSale	0.0027**	0.0041
	(2.07)	(1.54)
RD	−0.2488***	−0.5962***
	(−3.58)	(−4.05)
ROA	−0.1525***	−0.3211***
	(−4.78)	(−4.91)
PPE	−0.0217	−0.0349
	(−1.61)	(−1.25)
Leverage	0.0669***	0.1099***
	(5.93)	(4.62)
Capex	0.0385	0.0679
	(0.97)	(0.75)
TobinQ	−0.0173***	−0.0149***
	(−6.33)	(−3.83)
Patent	0.0016	0.0016
	(0.98)	(0.48)
HHI	0.1517**	0.0899
	(1.99)	(0.64)
IO	0.0077	0.0297
	(0.80)	(1.43)
Intercept	−0.0107	−0.0375
	(−0.73)	(−1.19)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	11,400	5,700
Adjusted R^2	0.103	0.118

This table shows the difference-in-differences analyses of changes in organization capital. The dependent variables are *LnINVOC1* and *LnINVOC2*. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. We include the year and industry fixed effects in the regressions. The t-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

score matching (PSM) to select the control firms and require a caliper width of 0.005 for the PSM to ensure similarity in the characteristics between the treatment and control firms.[19]

We further require non-missing control variables for the treatment and control firms and measure them with a four-year window that comprises the two pre-event years (years t-3 and t-2) and the two post-event years (years t and t+1). We skip the year t-1 because the one-year change in organization capital in event year −1 (i.e., from year t-1 to year t) covers the event. For our difference-in-differences analysis, we have 1,425 pairs of treatment-control observations in the sample period from 1994 to 2007. We illustrate our identification strategy with a timeline in Appendix B.

We compare the average firm characteristics for both the treatment and control firms in the pre-event year. All variables are measured at year t-1, except for *LnINOVC1* that is measured from year t-2 to year t-1. The difference between the treatment and control firms is insignificant across many of the firm characteristics we examine.[20] Thus, our causal inferences on the effect of analyst coverage on organization capital investments are less likely to be driven by the pre-treatment effects. Panel B of Table 1 presents the summary statistics for the DiD samples. Compared to the full sample (Panel A), the DiD sample is much smaller. Firms in the DiD sample have less organization capital investments (median is slightly negative), higher analyst coverage, and larger firm size (slightly higher LnSale) relative to the non-DiD firms. We lose about 20% of the sample observations when measuring the 10-K-based OC. The variation in the 10-K-based OC is also large, with a 2.4 standard deviation between the 10th and 90th percentiles.

4.2. Difference-in-differences: The treatment effect

To empirically carry out our identification strategy, we adopt a DiD method to examine the investment in organization capital after an exogenous reduction in analyst coverage. The DiD analysis makes it possible to compare the *LnINVOC1* and *LnINVOC2*

[19] Our results remain unchanged whether we select a 0.01, 0.05, or 0.1 caliper for the propensity score.

[20] The summary statistics for treatment and control samples are reported in the Internet Appendix.

Table 3
Change in organization capital: difference-in-differences for subsamples sorted by costs of capital.

Model Ind. Var. \Subsample	High cost of capital		Low cost of capital	
	(1) LnINVOC1	(2) LnINVOC2	(3) LnINVOC1	(4) LnINVOC2
Treatment	0.0125	0.0171	0.0089	0.0212
	(1.36)	(0.91)	(1.14)	(1.22)
After	0.0486***	0.0947***	0.0044	0.0065
	(4.89)	(4.38)	(0.52)	(0.30)
Treatment × After	**−0.0247****	**−0.0392***	−0.0036	−0.0142
	(−2.19)	**(−1.73)**	(−0.38)	(−0.65)
LnSale	0.0029	0.0071*	0.0016	0.0031
	(1.49)	(1.91)	(0.81)	(0.78)
RD	−0.1090	−0.3393	−0.2896***	−0.7047***
	(−0.95)	(−1.60)	(−3.06)	(−3.48)
ROA	−0.0941	−0.1147	−0.1795***	−0.4262***
	(−1.39)	(−1.02)	(−4.16)	(−5.20)
PPE	−0.0357*	−0.0803**	−0.0307*	−0.0326
	(−1.77)	(−2.05)	(−1.66)	(−0.90)
Leverage	0.0600***	0.0962**	0.0485***	0.0918***
	(3.30)	(2.51)	(3.49)	(3.56)
Capex	0.0724	0.1853**	−0.0394	−0.0836
	(1.42)	(2.01)	(−0.85)	(−0.73)
TobinQ	−0.0294***	−0.0320***	−0.0137***	−0.0116**
	(−4.24)	(−3.54)	(−4.88)	(−2.57)
Patent	0.0001	0.0007	0.0019	0.0014
	(0.03)	(0.14)	(0.87)	(0.31)
HHI	0.1323	0.0652	0.1452	0.0218
	(1.34)	(0.33)	(1.29)	(0.09)
IO	0.0106	0.0341	0.0039	0.0016
	(0.66)	(1.04)	(0.29)	(0.06)
Intercept	−0.0141	−0.0783	0.0246	0.0419
	(−0.68)	(−1.58)	(1.09)	(0.97)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	5,176	2,588	5,140	2,570
Adjusted R^2	0.134	0.146	0.100	0.132

This table presents the difference-in-differences analysis of changes in organization capital for subsamples of the cost of capital. The cost of capital is the average of four cost of capital estimates by Claus and Thomas (2001), Gebhardt et al. (2001), Gode and Mohanram (2003), and Easton (2004). We divide the sample into two groups based on the cost of capital at the year-end immediately after the brokerage merger or closure event. A sample firm is classified in the *High cost of capital* group if its cost of capital is higher than the median, and in the *Low cost of capital* group otherwise. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. We include the year and industry fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

between the treatment and non-treatment (control) firms before and after the shock. A direct comparison organization capital of treatment firms before and after the shocks could result in misleading conclusions as a potential trend could affect the investments in organization capital for all firms over time. The DiD analysis mitigates this potential problem. We implement it using the following regression model (using *LnINVOC1* as the example):

$$\begin{aligned} LnINVOC1_{it} =& \beta_0 + \beta_1 Treatment_i + \beta_2 After_t + \beta_3 Treatment_i \times After_t \\ &+ \beta_4 LnSale_{it} + \beta_5 RD_{it} + \beta_6 ROA_{it} + \beta_7 PPE_{it} + \beta_8 Leverage_{it} \\ &+ \beta_9 Capex_{it} + \beta_{10} TobinQ_{it} + \beta_{11} Patent_{it} + \beta_{12} HHI_{it} \\ &+ \beta_{13} IO_{it} + u_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{8}$$

where *Treatment* is equal to one for the treatment firms and zero otherwise (control firms), *After* is equal to one for the broker post-mergers/post-closures time period and zero otherwise, the interaction term *Treatment* × *After* captures the difference-in-differences effect, and u_i and υ_t denote the industry and year fixed effects, respectively. Gormley and Matsa (2014) suggest adding industry fixed effects as a preferred method to control for the unobserved industry-specific effects.

We conduct tests on the cost of capital versus the managerial myopia hypothesis. The cost of capital hypothesis posits that the interaction term should be negative as the reduction in analyst coverage increases the information asymmetry, increases the cost of capital, and makes the firm less likely to invest in organization capital in the post-event period. However, under the managerial myopia hypothesis, when the analyst coverage decreases, managers act less myopically because they receive less market pressure and thus are more likely to increase investments in organization capital. In such a case, the interaction term should be positive. As

Table 4
Difference-in-differences: effect of financial constraints.

Model Ind. Var. \Subsample	High cost of capital		Low cost of capital	
	(1) High SA	(2) Low SA	(3) High SA	(4) Low SA
Treatment	0.0277	0.0054	0.0058	0.0227*
	(1.42)	(0.58)	(0.40)	(1.71)
After	0.0800***	0.0263**	−0.0137	0.0061
	(3.86)	(2.56)	(−0.85)	(0.36)
Treatment × After	**−0.0556****	−0.0032	0.0089	−0.0124
	(−2.37)	(−0.28)	(0.48)	(−0.70)
LnSale	0.0059	0.0075***	0.0043	0.0037
	(1.07)	(2.70)	(1.15)	(1.00)
RD	−0.2665	0.1364	−0.3027**	−0.1204
	(−1.62)	(1.09)	(−2.18)	(−0.78)
ROA	−0.1174	−0.0638	−0.1733**	−0.2529**
	(−1.11)	(−0.87)	(−2.57)	(−2.10)
PPE	−0.0947**	0.0409	−0.0354	−0.0025
	(−2.09)	(1.27)	(−1.12)	(−0.06)
Leverage	0.1180***	0.0909***	0.0428*	0.0948***
	(3.89)	(3.39)	(1.95)	(3.14)
Capex	0.1521	−0.0992	−0.0932	0.0608
	(1.61)	(−1.37)	(−1.37)	(0.36)
TobinQ	−0.0362***	−0.0237***	−0.0137***	−0.0125**
	(−4.02)	(−2.71)	(−3.76)	(−2.12)
Patent	0.0158**	−0.0045*	0.0069	−0.0047
	(2.53)	(−1.90)	(1.37)	(−1.50)
HHI	0.4186	0.1246	0.2630	0.2902
	(1.30)	(0.84)	(1.27)	(1.18)
IO	0.0495	0.0155	0.0209	−0.0100
	(1.60)	(0.64)	(1.00)	(−0.36)
Intercept	−0.0704*	−0.0888**	0.0076	−0.0267
	(−1.74)	(−2.19)	(0.21)	(−0.62)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,864	1,700	1,920	1,528
Adjusted R^2	0.191	0.130	0.099	0.109

This table presents the effect of financial constraints on the difference-in-differences analysis of changes in organization capital for subsamples of the cost of capital. The dependent variable is *LnINVOC1*. We divide the sample into two groups based on the cost of capital at the year-end immediately after the brokerage merger or closure event. A sample firm is classified in the *High cost of capital* group if its cost of capital is higher than the median, and in the *Low cost of capital* group otherwise. We use the SA index to measure financial constraints. A firm is classified into the *High SA* (*Low SA*) group if its SA index is in the top (bottom) tercile of the sample. We measure the SA index at the year-end immediately before the event. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment×After* captures the treatment effect. Detailed definitions of the other variables are presented in Appendix A of the paper. We include the year and industry fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

a result, the sign of the interaction term in DiD regressions can help us disentangle the two hypotheses. We also incorporate in the regressions several control variables as suggested in He and Tian (2013): *LnSale*, *PPE*, *Capex*, *IO*, *Leverage*, *ROA*, *TobinQ*, *RD*, *Patent*, and *HHI*. Standard errors are clustered at the firm level.

Table 2 presents our results of the effect of difference-in-differences. The dependent variable is *LnINVOC1* in Model 1 and *LnINVOC2* in Model 2. For both models, the interaction term is negatively significant at the 5% level. This treatment effect is also economically meaningful. For example, in Model 2, the coefficient of −0.0331 for *Treatment* × *After* indicates that a drop in analyst coverage for our treatment firms results in a 3.3% reduction in their investments in organization capital over the two post-event years. This reduction translates to a 241.4 million decrease in organization capital.[21] The marginal effect of analyst coverage on the investment in organization capital is greater than that of most of the control variables: *ROA*, *PPE*, *Leverage*, *Capex*, *Patent*, and *HHI*. This result shows a positive relation between analyst coverage and investments in organization capital. When the analyst coverage is exogenously reduced, the investment in organization capital of treatment firms falls. Therefore, our test provides evidence in support of the cost of capital hypothesis but not for the managerial myopia hypothesis.[22]

[21] As the coefficient of *Treatment* × *After* in Model 2 is −3.31%, the treatment effect on the change in organization capital (INVOC2) from t to t+2 is −3.26% (i.e., exp(−3.31%)-1). Since the average total assets of treatment firms in our sample is 7,413.66 million, the treatment effect in dollar amount is about −241.4 million (i.e., 7413.66*(−3.26%)). That is, the treatment firms lower their organization capital by 241.4 million over the two years after the closures and mergers.

[22] The level of analyst coverage may play a role in these results. A firm with high analyst coverage is less affected by the exogenous shock. However, the exogenous shock may have a stronger impact if the firm initially has low analyst coverage. Therefore, we examine whether the impact of reduced coverage

Table 5
Difference-in-differences: effect of external equity dependence.

Model Ind. Var. \Subsample	High cost of capital		Low cost of capital	
	(1) High net issuance	(2) Low net issuance	(3) High net issuance	(4) Low net issuance
Treatment	0.0207	0.0023	−0.0078	0.0027
	(1.30)	(0.17)	(−0.51)	(0.25)
After	0.1056***	0.0081	−0.0046	0.0027
	(5.87)	(0.52)	(−0.26)	(0.20)
Treatment × After	**−0.0585***	0.0031	0.0326	−0.0183
	(−3.05)	(0.20)	(1.62)	(−1.40)
LnSale	0.0022	0.0069	0.0030	0.0010
	(0.62)	(1.61)	(0.98)	(0.36)
RD	−0.2527	−0.0592	−0.3041**	−0.2421
	(−1.47)	(−0.23)	(−2.44)	(−1.49)
ROA	−0.2413**	−0.0428	−0.2466***	−0.1370*
	(−2.34)	(−0.42)	(−3.39)	(−1.96)
PPE	−0.0986**	−0.0182	−0.0196	−0.0266
	(−2.31)	(−0.61)	(−0.51)	(−0.88)
Leverage	0.0714**	0.0264	0.0214	0.0569**
	(2.32)	(0.66)	(0.90)	(2.32)
Capex	0.1940**	0.0312	−0.0262	−0.0751
	(2.45)	(0.35)	(−0.35)	(−0.81)
TobinQ	−0.0373***	−0.0202***	−0.0197***	−0.0092**
	(−3.59)	(−2.65)	(−3.93)	(−2.09)
Patent	0.0096**	−0.0022	0.0063	−0.0061**
	(2.08)	(−0.78)	(1.59)	(−2.50)
HHI	−0.0897	−0.0350	−0.0114	0.0715
	(−0.69)	(−0.22)	(−0.05)	(0.44)
IO	0.0521*	−0.0503*	0.0081	−0.0374**
	(1.79)	(−1.81)	(0.33)	(−2.26)
Intercept	−0.0105	0.0139	0.0491	0.0627**
	(−0.29)	(0.25)	(1.26)	(2.01)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,844	1,632	1,812	1,840
Adjusted R^2	0.262	0.091	0.128	0.115

This table displays the effect of external equity on the difference-in-differences analysis of organization capital investments for subsamples of the cost of capital. The dependent variable is *LnINVOC1*. We divide the sample into two groups based on the cost of capital at the year-end immediately after the brokerage merger or closure event. A sample firm is classified in the *High cost of capital* group if its cost of capital is higher than the median value, and in the *Low cost of capital* group otherwise. We measure the net equity issuance as the issuance of common and preferred stocks before the event year. The net equity issuance is computed as the item SSTK (sale of common and preferred stock) minus the items PRSTKC (purchase of common and preferred stock) and DV (cash dividend) in Compustat. When the cash dividend is missing, we replace it with zero. A firm is classified into the *High Equity Issuance* (*Low Equity Issuance*) group if its net issuance is in the top (bottom) tercile of the sample. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment×After* captures the treatment effect. Detailed definitions of other variables are presented in Appendix A of the paper. We include the year and industry fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

4.3. Difference-in-differences: The role of the cost of capital

We next investigate the channel by which the external research coverage provided by analysts can affect the internal managerial decision on investing in organization capital. The cost of capital hypothesis argues that a high level of analyst coverage will lead to a lower cost of capital and thus firms can raise funds much easier in order to make more investments in organization capital. As a result, there is a positive causal effect of analyst coverage on investments in organization capital. This positive relation would be much stronger for firms with a high cost of capital. When a firm has a high level of cost of capital after analyst coverage drops, it would be more difficult to raise funds required to invest in organization capital. By contrast, the myopia hypothesis highlights the market pressure from analysts impeding managerial incentives to make long-term investments. According to this view, when analyst coverage drops, managerial short-termism mitigates, and firms increase investments in organization capital. This causal effect of analyst coverage on organization capital would be stronger for firms with a low cost of capital as it is much easier for these firms to raise funds to make investments. To test our two hypotheses, we use the DiD analysis with subsamples sorted by the cost of capital.

is more significant for firms with lower analyst coverage. We find that the impact of coverage reduction on investments in organization capital is statistically significant only in the low initial analyst coverage subsample. We report the result in the Internet Appendix.

Table 6
Difference-in-differences: 10-K-based organization capital.

Ind. Var. \Model	(1)	(2)	(3)	(4)	(5)
Treatment	0.1776***	0.2063***	0.1434***	0.1750***	0.1844***
	(10.68)	(10.46)	(8.30)	(9.89)	(9.73)
After	0.0043	0.0028	−0.0062	0.0056	0.0072
	(0.45)	(0.26)	(−0.64)	(0.61)	(0.73)
Treatment × After	**−0.0316*** **	**−0.0520*** **	**−0.0405*** **	**−0.0389*** **	**−0.0374*** **
	(−3.21)	**(−4.20)**	**(−3.94)**	**(−3.97)**	**(−3.92)**
LnSale	−0.0064	−0.0078	−0.0023	−0.0098	−0.0151**
	(−1.07)	(−1.15)	(−0.38)	(−1.50)	(−2.11)
RD	−0.2529	−0.5074***	−0.3088*	−0.1309	−0.1252
	(−1.53)	(−2.62)	(−1.74)	(−0.70)	(−0.66)
ROA	−0.0825	−0.1101	−0.0430	−0.0498	−0.0196
	(−0.91)	(−1.03)	(−0.49)	(−0.56)	(−0.20)
PPE	−0.0277	0.0331	−0.0372	0.0259	−0.0468
	(−0.48)	(0.46)	(−0.65)	(0.43)	(−0.73)
Leverage	−0.0176	0.0296	0.0243	−0.0135	−0.0224
	(−0.44)	(0.68)	(0.61)	(−0.32)	(−0.47)
Capex	0.2063	0.3036	0.1429	0.2549*	0.1205
	(1.45)	(1.63)	(0.93)	(1.79)	(0.75)
TobinQ	0.0027	0.0021	0.0040	0.0027	0.0066
	(0.48)	(0.33)	(0.76)	(0.49)	(1.05)
Patent	0.0097	0.0139	0.0091	0.0064	0.0042
	(1.11)	(1.45)	(1.12)	(0.76)	(0.46)
HHI	−0.3082*	−0.0814	−0.0165	−0.0860	−0.2298
	(−1.73)	(−0.35)	(−0.08)	(−0.46)	(−1.09)
IO	0.0322	0.0836**	0.0436	0.0391	0.0038
	(1.00)	(2.25)	(1.38)	(1.19)	(0.10)
Intercept	0.3151***	0.2922***	0.2225***	0.2506***	0.3589***
	(6.62)	(5.25)	(4.65)	(4.96)	(6.37)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	9,176	9,176	9,176	9,176	9,176
Adjusted R^2	0.254	0.210	0.181	0.187	0.220

This table shows the difference-in-differences analysis of organization capital investments. The dependent variables are *10-K-based OC* obtained from searching for 10-K filings. For Models (1) to (5), 10-K-based OC is generated by different combinations of keywords as follows:
Model (1): $10\text{-}K\text{-}based\ OC = \sum w_i \times D_i$, where we include the keywords of incentive compensation, infrastructure costs, information technology, improved processes and systems, recruiting, and training.
Model (2): $10\text{-}K\text{-}based\ OC = \sum w_i \times D_i$, where we include the keywords of incentive compensation, improved processes and systems, and infrastructure costs.
Model (3): $10\text{-}K\text{-}based\ OC = \sum w_i \times D_i$, where we include the keywords of incentive compensation, improved processes and systems, and recruiting.
Model (4): $10\text{-}K\text{-}based\ OC = \sum w_i \times D_i$, where we include the keywords of infrastructure costs, improved processes and systems, and recruiting
Model (5): $10\text{-}K\text{-}based\ OC = \sum w_i \times D_i$, where we include the keywords of improved processes and systems, training, and recruiting.
Detailed definitions of these 10-K-based OC variables are stated in Section 3. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. Detailed definitions of other variables are presented in Appendix A of the paper. We include the year and industry fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

We assign firms into two groups, High cost of capital and Low cost of capital, depending on whether their cost of capital is higher or lower than the median cost of capital. The cost of capital is measured at the year-end immediately after the brokerage closures or mergers.[23] We use an average of four cost of capital estimates by Claus and Thomas (2001), Gebhardt et al. (2001), Gode and Mohanram (2003), and Easton (2004).[24] Details of these estimates are described in Appendix A.

We perform the DiD regressions for the two cost of capital groups separately and present the results in Table 3. The results show that the difference-in-differences effect is significantly negative in the High cost of capital group and not significant in the Low cost of capital group. The treatment effect, documented in Table 2, where firms decrease their investments in organization capital

[23] In unreported results, we run the DiD regressions using the cost of capital as the dependent variable. The result shows that *Treatment ×After* is significantly positive. This is consistent with other papers (Bowen et al., 2008; Kelly and Ljungqvist, 2012; Derrien and Kecskés, 2013) that show the cost of capital increases after brokerage closures and mergers.

[24] We use the average cost of capital because averaging different estimates reduces the idiosyncratic measurement error across models (e.g., Hail and Leuz, 2009; Chen et al., 2009; Ghoul et al., 2011; Hou et al., 2012). Our results (not reported) are qualitatively similar if we use the individual cost of capital estimate. Thus, our result is not driven by one particular model of for computing the cost of equity capital.

Table 7
10-K-based organization capital: difference-in-differences for subsamples sorted by costs of capital.

Model	(1)	(2)
Ind. Var. \Subsample	High cost of capital	Low cost of capital
Treatment	0.1405***	0.1695***
	(6.74)	(7.07)
After	−0.0152	0.0277*
	(−1.15)	(1.80)
Treatment × After	**−0.0494*****	−0.0193
	(−3.59)	(−1.16)
LnSale	0.0184***	−0.0049
	(2.62)	(−0.54)
RD	0.3137	0.0930
	(1.05)	(0.39)
ROA	0.0183	−0.0218
	(0.21)	(−0.23)
PPE	0.0090	−0.0090
	(0.12)	(−0.12)
Leverage	0.0180	−0.0714
	(0.36)	(−1.17)
Capex	0.3784*	0.0369
	(1.87)	(0.20)
TobinQ	−0.0050	0.0082
	(−0.66)	(1.22)
Patent	0.0009	−0.0018
	(0.10)	(−0.15)
HHI	−0.1945	−0.4156
	(−1.02)	(−1.40)
IO	−0.0102	−0.0616
	(−0.26)	(−1.34)
Intercept	0.1762***	0.3683***
	(3.11)	(4.74)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	4,160	4,136
Adjusted R^2	0.280	0.268

This table presents the difference-in-differences analysis of organization capital investments for subsamples of the cost of capital. The cost of capital is the average of four cost of capital estimates by Claus and Thomas (2001), Gebhardt et al. (2001), Gode and Mohanram (2003), and Easton (2004). The dependent variable is *10-K-based OC,* obtained from searching for 10-K filings, and is defined as the dependent variable in Model (1) of Table 6, where we include the keywords of incentive compensation, infrastructure costs, information technology, improved processes and systems, recruiting, and training. Detailed definitions of the dependent variable are stated in Section 3. We divide the sample into two groups based on the cost of capital at the year-end immediately after the brokerage merger or closure event. A sample firm is classified in the *High cost of capital* group if its cost of capital is higher than the median, and in the *Low cost of capital* group otherwise. *Treatment* is an indicator variable, which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. Detailed definitions of other variables are presented in Appendix A of the paper. We include the year and industry fixed effects in the regressions. The t-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

after an exogenous reduction of analyst coverage, exists only when a firm maintains a higher level of cost of capital. When a firm's cost of capital is low, the relation between analyst coverage and investments in organization capital is not significant. This result supports the cost of capital hypothesis which posits the casual effect of analyst coverage on investments in organization capital occurs through the cost of capital channel. As the treatment effect in the Low cost of capital group is not significant, we do not find evidence supporting the myopia hypothesis.

4.4. Difference-in-differences: The role of financial constraints and external equity financing

To further explore these two hypotheses, we examine the roles of financial constraints and external equity financing on the causal effect of analyst coverage on organization capital. Specifically, as financially constrained firms will be more subject to the increase in the cost of capital resulting from analyst coverage reduction (Chen and Wang, 2012), the cost of capital hypothesis predicts that the impact of reduced analyst coverage on organization capital should be more pronounced when firms are financially constrained. Similarly, as constrained firms are dependent on external financing (Fazzari et al., 1988; Hadlock and Pierce, 2010), under the cost of capital hypothesis, the causal effect of analyst coverage on organization capital should be stronger for firms relying on external equity financing. By contrast, based on the myopia hypothesis, firms are more likely to increase investments in organization capital when analyst coverage drops and managerial myopia reduces. As unconstrained firms can easily obtain required

Table 8
10-K-based organization capital: difference-in-differences for effect of financial constraints.

Model	High cost of capital		Low cost of capital	
Ind. Var. \Subsample	(1) High SA	(2) Low SA	(3) High SA	(4) Low SA
Treatment	0.1187***	0.1722***	0.1342***	0.1778***
	(3.24)	(5.45)	(3.88)	(4.35)
After	−0.0133	0.0022	0.0163	0.0072
	(−0.59)	(0.12)	(0.62)	(0.38)
Treatment × After	**−0.0654*****	**−0.0416***	−0.0187	−0.0268
	(−2.79)	**(−1.80)**	(−0.63)	(−1.25)
LnSale	0.0161	0.0152	0.0264*	−0.0266*
	(1.14)	(1.08)	(1.82)	(−1.71)
RD	0.3720	0.1568	0.1260	0.4029
	(1.07)	(0.30)	(0.40)	(0.62)
ROA	0.0222	0.0234	−0.1380	−0.3803
	(0.22)	(0.11)	(−1.08)	(−1.47)
PPE	−0.0042	0.2460*	0.1791*	−0.0996
	(−0.04)	(1.70)	(1.84)	(−0.74)
Leverage	0.0151	0.0780	−0.1066	−0.1933*
	(0.19)	(0.66)	(−1.17)	(−1.97)
Capex	0.4725**	−0.7301***	−0.1010	−0.2608
	(2.34)	(−2.80)	(−0.43)	(−0.71)
TobinQ	−0.0141	0.0066	−0.0027	0.0178
	(−1.57)	(0.28)	(−0.38)	(1.37)
Patent	0.0054	−0.0046	0.0090	−0.0070
	(0.27)	(−0.34)	(0.53)	(−0.54)
HHI	−0.3378*	−0.5803	0.2416	0.9774*
	(−1.96)	(−0.79)	(0.49)	(1.97)
IO	0.1171**	−0.0385	0.0173	−0.1575*
	(2.17)	(−0.46)	(0.27)	(−1.67)
Intercept	0.1665*	0.1737	0.1263	0.6032***
	(1.86)	(1.29)	(1.13)	(3.47)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,392	1,268	1,484	1,152
Adjusted R^2	0.375	0.316	0.327	0.364

This table presents the effect of financial constraints on the difference-in-differences analysis of organization capital investments for subsamples of the cost of capital. The dependent variable is *10-K-based OC*, obtained from searching for 10-K filings, and is defined as the dependent variable in Model (1) of Table 6, where we include the keywords of incentive compensation, infrastructure costs, information technology, improved processes and systems, recruiting and training. Detailed definitions of the dependent variable are stated in Section 3. We divide the sample into two groups based on the cost of capital at the year-end immediately after the brokerage merger or closure event. A sample firm is classified in the *High cost of capital* group if its cost of capital is higher than the median, and in the *Low cost of capital* group otherwise. We use the SA index to measure financial constraints. A firm is classified as in the *High SA* (*Low SA*) group if its SA index is in the top (bottom) tercile of the sample. We measure the SA index at the year-end immediately before the event. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. Detailed definitions of the other variables are presented in Appendix A of the paper. We include the year and industry fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

funds to make investments, one would expect that the increase in organization capital after analyst coverage reductions should be stronger for unconstrained firms. Further, analyst coverage reductions will restrict firms' access to the equity market, making firms more constrained by external financing. Therefore, the increase in organization capital would be accentuated in firms that are less dependent on external equity financing.

To further explore our two hypotheses, we use the SA index to measure the level of financial constraints.[25] Firms with a higher financial constraint index are more likely to experience tighter financial conditions. We follow Hadlock and Pierce (2010) and use size, squared size, and firm age to construct the SA index as:

$$SA = -0.737 Size + 0.043 Size^2 - 0.040 Age \tag{9}$$

[25] Hadlock and Pierce (2010) identify several advantages of using the SA index to measure financial constraints. First, the construction of SA index requires two factors only, yielding fewer missing values and a larger sample. Second, traditional constraint indices rely on cash and leverage, which are endogenous financial choices in the constraint index construction. Finally, the SA index is intuitively logically appealing and independent of various theoretical assumptions.

Table 9
10-K-based organization capital: difference-in-differences for effect of external equity dependence.

Model Ind. Var. \Subsample	High cost of capital		Low cost of capital	
	(1) High net issuance	(2) Low net issuance	(3) High net issuance	(4) Low net issuance
Treatment	0.1070***	0.0971**	0.0839**	0.2821***
	(3.24)	(2.19)	(2.36)	(8.11)
After	−0.0040	0.0047	0.0314	0.0448*
	(−0.18)	(0.17)	(0.97)	(1.74)
Treatment × After	**−0.0576*** **	−0.0173	−0.0027	−0.0241
	(−2.63)	(−0.52)	(−0.07)	(−0.87)
LnSale	0.0273**	0.0353**	0.0034	−0.0234
	(2.24)	(2.31)	(0.30)	(−1.35)
RD	0.4707	0.6444	0.1103	0.3892
	(1.14)	(1.08)	(0.39)	(0.66)
ROA	−0.0192	0.0043	−0.0534	0.2688
	(−0.14)	(0.03)	(−0.41)	(1.32)
PPE	0.2479*	0.0949	0.1003	−0.0680
	(1.85)	(0.74)	(0.95)	(−0.47)
Leverage	−0.1067	−0.1422	−0.0900	0.0820
	(−1.36)	(−1.48)	(−1.04)	(0.79)
Capex	−0.1103	0.5828*	0.0218	−0.2687
	(−0.45)	(1.76)	(0.09)	(−0.62)
TobinQ	−0.0070	0.0015	0.0009	0.0090
	(−0.80)	(0.12)	(0.11)	(0.90)
Patent	0.0104	0.0008	−0.0029	−0.0065
	(0.66)	(0.06)	(−0.23)	(−0.51)
HHI	−0.1029	−0.8848*	0.0857	0.0827
	(−0.52)	(−1.79)	(0.20)	(0.15)
IO	0.0186	0.0640	−0.0574	0.0244
	(0.33)	(0.75)	(−0.97)	(0.26)
Intercept	0.1171	0.0140	0.3202***	0.2799*
	(1.29)	(0.10)	(3.23)	(1.73)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,396	1,076	1,404	1,280
Adjusted R^2	0.437	0.350	0.255	0.470

This table presents the effect of external equity on the difference-in-differences analysis of organization capital investments for subsamples of the cost of capital. The dependent variable is ***10-K-based OC***, obtained from searching for 10-K filings, and is defined as the dependent variable in Model (1) of Table 6, where we include the keywords of incentive compensation, infrastructure costs, information technology, improved processes and systems, recruiting, and training. Detailed definitions of the dependent variable are stated in Section 3. We divide the sample into two groups based on the cost of capital at the year-end immediately after the brokerage merger or closure event. A sample firm is classified in the *High cost of capital* group if its cost of capital is higher than the median, and in the *Low cost of capital* group otherwise. We measure the net equity issuance as the issuance of common and preferred stocks before the event year. The net equity issuance is computed as the item SSTK (sale of common and preferred stock) minus the items PRSTKC (purchase of common and preferred stock) and DV (cash dividend) in Compustat. When cash dividend is missing, we replace it with zero. A firm is classified into the *High Equity Issuance* (*Low Equity Issuance*) group if its net issuance is in the top (bottom) tercile of the sample. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. Detailed definitions of other variables are presented in Appendix A. We include the year and industry fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

where *Size* equals the log of inflation-adjusted total assets (in 2004 dollars), and *Age* is the number of years that the firm is listed with non-missing stock prices on Compustat.[26] We follow Hadlock and Pierce (2010) and winsorize *Size* and *Age* at the 1% tail on the low end, and winsorize *Size* at the \$4.5 billion and *Age* at 37 years on the high end. Thus, we can classify a firm as in the *High SA* (*Low SA*) group if its *SA* is in the top (bottom) tercile to detect financial constraints.[27]

Table 4 presents the results of the DiD regressions with subsamples double-sorted by costs of capital and financial constraints. We run the DiD regressions for the High cost of capital and Low cost of capital groups, and for High SA and Low SA, respectively. The results show that the interaction term, *Treatment* × *After*, is negative and significant at the 5% level in the High cost of capital-High SA subgroup. This result indicates that the treatment effect under High cost of capital in Table 3 exists mainly for constrained

[26] Hadlock and Pierce (2010) construct the SA index and show that smaller firms are more likely to be constrained and firm age is also useful in predicting financial constraints. We follow Hadlock and Pierce (2010) and winsorize *Size* and *Age* at the 1% tail on the low end, and winsorize *Size* at the \$4.5 billion and *Age* at 37 years on the high end.

[27] Our results are qualitatively similar when we use the median or quartiles to define the financial constraint group. We also try the WW index of Whited and Wu (2006) to gauge financial constraints, and our results are qualitatively similar.

Table 10
Robustness checks: controlling for firm fixed effect.

Panel A: Dependent variable is SG&A-based OC

Model	(1) LnINVOC1	(2) LnINVOC2
Treatment	−0.0005	0.0056
	(−0.06)	(0.29)
After	0.0172***	0.0326**
	(3.00)	(2.52)
Treatment × After	**−0.0132****	**−0.0277****
	(−2.00)	**(−2.10)**
LnSale	0.0811***	0.1448***
	(9.80)	(9.00)
RD	−1.0674***	−2.1175***
	(−8.15)	(−6.18)
ROA	−0.3560***	−0.6387***
	(−6.87)	(−6.81)
PPE	−0.1214***	−0.2085**
	(−2.60)	(−2.34)
Leverage	0.1353***	0.1682***
	(5.36)	(3.43)
Capex	−0.0124	0.0807
	(−0.20)	(0.65)
TobinQ	−0.0257***	−0.0172***
	(−6.37)	(−3.11)
Patent	−0.0021	−0.0015
	(−0.43)	(−0.15)
HHI	0.1999**	0.1841
	(2.20)	(0.88)
IO	−0.0087	0.0264
	(−0.42)	(0.66)
Intercept	−0.3718***	−0.7450***
	(−6.59)	(−7.18)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	11,400	5,700
Adjusted R^2	0.170	0.218

Panel B: Dependent variable is 10-K-based OC

Model	(1)	(2)	(3)	(4)	(5)
Treatment	0.1331***	0.0888**	0.0748*	0.0573*	0.1428***
	(4.01)	(2.08)	(1.83)	(1.66)	(3.34)
After	0.0005	−0.0019	−0.0089	0.0026	0.0020
	(0.06)	(−0.19)	(−1.02)	(0.33)	(0.22)
Treatment × After	**−0.0304*****	**−0.0502*****	**−0.0396*****	**−0.0374*****	**−0.0370*****
	(−3.13)	**(−4.10)**	**(−3.88)**	**(−3.88)**	(−3.89)
LnSale	−0.0008	−0.0021	−0.0090	0.0016	−0.0037
	(−0.06)	(−0.15)	(−0.72)	(0.13)	(−0.29)
RD	−0.0321	−0.0700	0.0090	0.0102	−0.0485
	(−0.28)	(−0.45)	(0.07)	(0.08)	(−0.33)

(*continued on next page*)

firms. These results support the cost of capital hypothesis. However, they do not the myopia hypothesis because when the cost of capital is high after the reduction in analyst coverage, constrained firms face more difficulty in obtaining funds that thus lowers their investments in organization capital. But, for firms without financial constraints, we do not find any that significantly increase their investments in organization capital. Therefore, this result does not support the myopia hypothesis.

To measure the external equity financing, we retrieve the net equity issuance before the event from Compustat. The net equity issuance is the sale of common and preferred stock, minus the purchase of common and preferred stock and cash dividends, and all divided by the book value of total assets. We classify a firm as in the *High Equity Issuance* (*Low Equity Issuance*) group if its net equity issuance is in the top (bottom) tercile to detect the external equity financing dependence. Similar to Table 4, we run the DiD regressions for the High cost of capital and the Low cost of capital groups, and for High net issuance and Low issuance, respectively.

Table 5 presents results of the DiD regressions with subsamples double-sorted by costs of capital and external equity financing. Similar to Table 4, the results show that the interaction term, *Treatment* × *After*, is significantly negative only in the High cost of capital-High net issuance subgroup. This finding indicates that firms that rely heavily on equity financing have trouble raising funds due to the higher cost of capital after the reduction in analyst coverage and choose to reduce investments in organization capital. Consistent with the cost of capital hypothesis, the effect of reduced analyst coverage on organization capital is more pronounced among firms with higher equity issuance. As we do not find that firms increase their investments in organization capital when they are not reliant on external equity financing, we do not obtain compelling evidence to support the myopia hypothesis.

Table 10 (*continued*).

Panel B: Dependent variable is 10-K-based OC					
Model	(1)	(2)	(3)	(4)	(5)
ROA	−0.0142	−0.0100	0.0327	−0.0104	0.0146
	(−0.30)	(−0.16)	(0.66)	(−0.16)	(0.22)
PPE	−0.0057	−0.0184	−0.0017	−0.0041	−0.0403
	(−0.09)	(−0.22)	(−0.02)	(−0.07)	(−0.64)
Leverage	0.0258	0.0067	0.0116	0.0101	0.0495
	(0.76)	(0.15)	(0.33)	(0.30)	(1.41)
Capex	0.0385	0.2049*	0.0578	0.1711**	−0.0395
	(0.44)	(1.84)	(0.62)	(2.06)	(−0.44)
TobinQ	−0.0021	−0.0023	0.0002	−0.0019	−0.0007
	(−0.70)	(−0.61)	(0.05)	(−0.62)	(−0.20)
Patent	0.0041	−0.0021	0.0059	−0.0023	0.0124**
	(0.67)	(−0.20)	(0.86)	(−0.28)	(2.05)
HHI	−0.1954	−0.0210	0.0652	−0.0285	0.0194
	(−1.15)	(−0.10)	(0.40)	(−0.16)	(0.11)
IO	−0.0070	0.0255	0.0412	−0.0049	−0.0071
	(−0.21)	(0.69)	(1.30)	(−0.17)	(−0.23)
Intercept	0.3070***	0.3536***	0.2795***	0.2591***	0.2843***
	(3.52)	(3.22)	(3.00)	(3.09)	(3.21)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	9,176	9,176	9,176	9,176	9,176
Adjusted R^2	0.751	0.722	0.728	0.757	0.776

This table shows the robustness checks of the difference-in-differences analysis by controlling for the firm fixed effect. Panel A presents the results based on the SG&A-based OC, where the dependent variables are *LnINVOC1* and *LnINVOC2*. Panel B presents the results based on 10-K-based OC, where the dependent variables are the same as those in Models (1) to (5) of Table 6, respectively. *Treatment* is an indicator variable which is equal to one for the treatment sample (firms covered by brokerage mergers/closures), and zero otherwise (control firms). *After* is equal to one for the brokerage post-mergers/post-closures time period, and zero otherwise. The interaction term of *Treatment* × *After* captures the treatment effect. We include the firm and year fixed effects in the regressions. The *t*-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two tailed), respectively.

4.5. Difference-in-differences: Using 10-k-based measure of organization capital

In this section, we adopt an alternative measure of organization capital investment by conducting textual analyses on the firms' disclosures in the 10-K filings to perform the robustness checks. In Table 6, we use different combinations of organization capital keywords to form the 10-K-based OC and rerun the DiD regressions. The results show a significantly negative treatment effect. The investments in organization capital lower after the reduction in analyst coverage in all models. These results indicate that the relation between organization capital investments and reduced analyst coverage is robust when using different OC measures.[28]

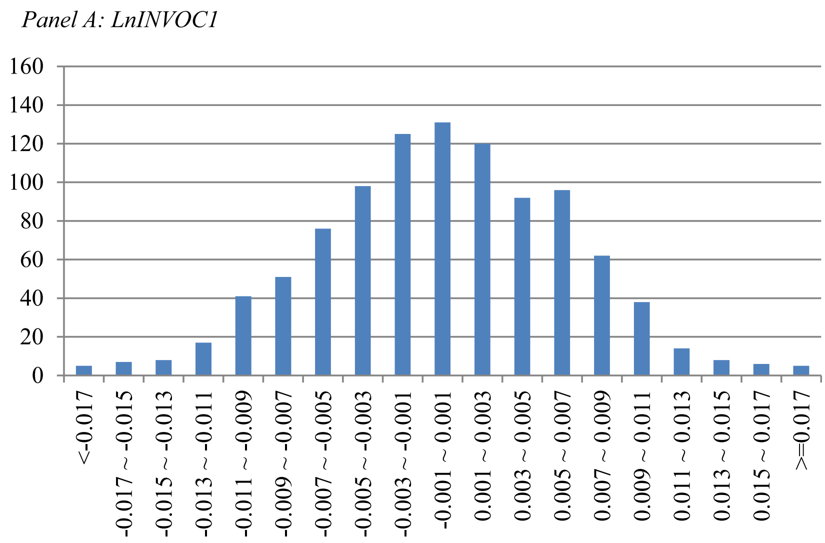
We then use the 10-K-based OC with all six organization capital keywords (i.e., the definition of Model (1) of Table 6) and rerun the tests for the groups sorted by costs of capital (Table 7), and further classified by financial constraints (Table 8) and equity dependence (Table 9). We find that the positive relation between analyst coverage and organization capital is significant only in firms with a high cost of capital. We also find the analyst effect on organization capital to be more pronounced for firms with financial constraints and high equity dependence. All these results support the cost of capital hypothesis and confirm our earlier findings using the SG&A-based measures.

4.6. Robustness check

We perform further robustness checks on our DiD results. First, we examine whether the unobserved factors not captured by firm characteristics drive our results. To address these possible omitted variables, we include a firm fixed effect to the DiD regressions and present the results in Table 10. Panel A gives the results for *SG&A-based OC* results with the firm fixed effect when the dependent variables are *LnINVOC1* and *LnINVOC2*. Panel B gives the results for *10-K-based OC* with the firm fixed effect when the dependent variables are based on Models (1) to (5) of Table 6. The interaction term of *Treatment* × *After* continues to be significantly negative. Most of the control variables are consistent with those in Table 2. These results indicate that reductions in investments in organization capital due to lower analyst coverage are not likely driven by time-invariant omitted variables. In untabulated results, we rerun the tests in Tables 3, 4 and 5 by controlling for the firm fixed effect. The results are qualitatively similar to those in the previous tables. Therefore, our empirical findings are not likely to be explained by the time-invariant firm-specific factors.[29]

[28] We have also tried a simple 10-K-based measure of organization capital by adding the six dummies that correspond to the keywords (incentive compensation, infrastructure costs, information technology, improved processes and systems, recruiting, and training) without considering the frequency of each keyword. The results are reported in Internet Appendix and very similar to what we report in Tables 6–9.

[29] As SG&A consists of all commercial expenses of operations incurred in the regular business process, R&D expenses are part of SG&A. We further perform the test based on a non-R&D measure of organization capital. The results of this test are qualitatively similar to what we report in Table 2, suggesting that our findings are not driven by R&D. The detailed description and results are reported in the Internet Appendix.



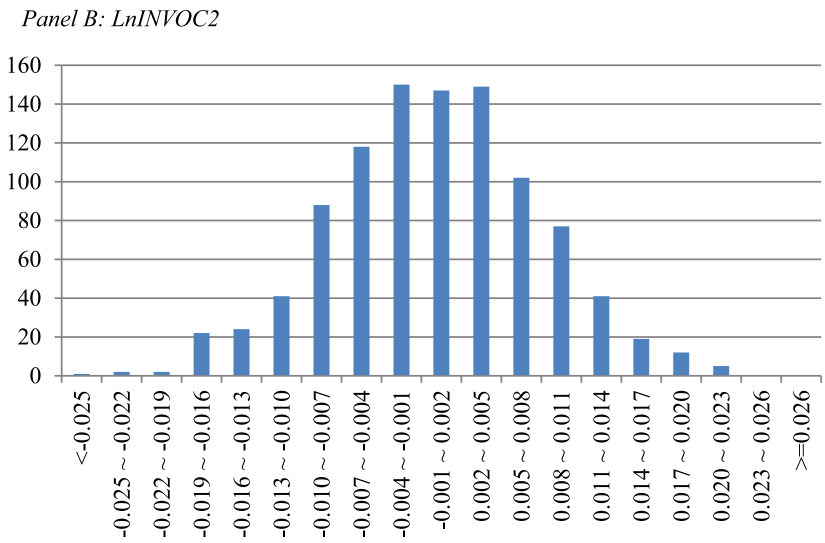


Fig. 3. Distribution of Coefficients for the Interaction Variable in Models (1) and (2) of Table 2: A Placebo Test.
This figure presents a placebo test for the distribution of coefficients on the interaction term in difference-in-differences the in models (1) and (2) of Table 2. We replace the treatment firm with another firm randomly selected from the non-treatment sample with the pseudo brokerage closure and merger events. Then, we use propensity-score matching to select the control sample. *Treatment* is equal to one for a pseudo brokerage closure and merger events, and zero otherwise. *After* is equal to one for the years after the pseudo event year, and zero otherwise. We rerun the difference-in-differences regression in models (1) and (2) of Table 2. We record the coefficient for the interaction term, *Treatment* × *After*. We repeat this procedure 1,000 times and hence obtain 1,000 estimated coefficients on the interaction term. This figure presents the distribution of these coefficients.

Second, we investigate whether our results are merely driven by chance: an issue in part related to the data snooping bias. We address this issue by conducting a placebo test. We randomly select non-treatment firms, pretend that their analyst coverage decreases due to a merger or a closure, and conduct another DiD analysis. Specifically, we first replace each treatment firm with another firm randomly selected from the non-treatment pool and treat it as a pseudo treatment firm. We estimate the coefficient for *Treatment* × *After* by rerunning Models 1 and 2 in Table 2 that are based on Eq. (8) in which the dependent variables are *LnINVOC1* and *LnINVOC2*, respectively, for the sample of pseudo treatment firms and their matching firms. We retain the coefficient estimates of *Treatment* × *After* and then repeat the above procedure 1,000 times. Because these pseudo treatment firms are randomly assigned, we should not observe any treatment effect in this exercise, that is, on average, the coefficient for *Treatment* × *After* should not be significant.

Table A.1
Variable definition.

Variables	Definition and description
OC	We first calculate the stock of organization capital using the perpetual inventory method: $OC_t = (1-\delta_0)OC_{t-1} + \frac{SG\&A_t}{cpi_t}$, where *SG&A* is selling, general, and administrative expenses; δ_0 is the depreciation rate of 15% that was used by the Bureau of Economic Analysis in its estimation of R&D capital in 2006; and cpi_t is the consumer price index. We compute the initial organization capital (OC_0) as: $OC_0 = \frac{SG\&A_1}{g+\delta_0}$, where g is the average real growth rate of firm-level SG&A expenses that is assumed to equal 10% in our sample. *OC* is then scaled by total assets and measured at year *t*.
INVOC1	*OC* in year t+1 minus *OC* in year *t*.
INVOC2	*OC* in year t+2 minus *OC* in year *t*.
LnINVOC1	Logarithm of one plus *INVOC1*.
LnINVOC2	Logarithm of one plus *INVOC2*.
10-K-based OC	We use the frequency count to weigh keyword dummies D_i to compute the 10-K-based OC: $10\text{-}K\text{-}basedOC = \sum_i w_i \times D_i,\ w_i = \frac{frequency_i}{\sum frequency}$, where D_i is equal to one if the keyword *i* is identified and manually checked in the 10-K filings and zero otherwise, *i*={*Comp*, *Infra*, *IT*, *Improve*, *Recruit*, *Train*}, $frequency_i$ is the frequency count of keyword i in the MD&A section, and $\sum frequency$ is the total frequency count of all keywords included in the 10-K-based OC.
Coverage	*Coverage* is the average number of analysts making earnings forecasts in year *t*.
LnCoverage	*LnCoverage* is the logarithm of *Coverage* in year *t*.
LnSale	*LnSale* is the logarithm of sales measured at the end of year *t*.
RD	*RD* is the research and development expenditures divided by the book value of total assets measured at the end of year *t*. It is set to zero if missing.
ROA	*ROA* (Return-on-assets ratio) is defined as operating income before depreciation divided by the book value of total assets that is measured at the end of year *t*.
PPE	*PPE* is the ratio of property, plant, and equipment divided by the book value of total assets measured at the end of year *t*.
Leverage	*Leverage* is defined as the book value of short-term and long-term debts divided by the book value of total assets measured at the end of year *t*.
Capex	*Capex* is the capital expenditure scaled by the book value of total assets measured at the end of year *t*.
TobinQ	*TobinQ* is the market-to-book ratio during the year *t*, calculated as the market value of equity plus the book value of assets, minus the book value of equity, minus balance-sheet deferred taxes (set to zero if missing), and then divided by the book value of assets.
HHI	*HHI* is the Herfindahl–Hirschman index and is defined as the sum of squared market shares of firms in a 2-digit SIC industry. Market share is measured on the basis of sales.
Patent	*Patent* is the logarithm of the number of patents that a firm applies for with the United States Patent and Trademark Office in year *t*.
IO	*IO* is the institutional ownership in year t that is calculated as the average of four quarterly institutional ownership ratios (i.e., shares held by institutional investors divided by shares outstanding) reported through form 13F.

(*continued on next page*)

Fig. 3 displays the distribution of *Treatment* × *After* coefficients from the placebo tests. The coefficients from 1,000 random placebos cluster around −0.001 and −0.002 for the rerun Models 1 and 2, respectively. Therefore, given that the coefficients for *Treatment* × *After* in Models 1 and 2 of Table 2 are −0.0169 and −0.0331, respectively, then less than 10 cases out of 1,000 trials can yield a treatment effect similar to that shown in Table 2. This result means that our finding of a positive effect of analyst coverage on investments in organization capital is highly significant and unlikely to be driven by chance.

Finally, we examine post-event firm performance to disentangle the two competing hypotheses. We examine the real effect of changes in organization capital due to reduced analyst coverage to identify the economic value of organization capital. Prior literature shows that organization capital is positively associated with firm performance. Therefore, the cost of capital hypothesis argues that firms with lower organization capital after analyst coverage reduction are more likely to experience reduced productive efficiency. Conversely, the myopia hypothesis suggests that firms are likely to increase investments in organization capital after analyst coverage drops, and thus improve subsequent firm performance. We detect the real effect by examining the post-event total factor productivity and operating performance. In the Internet Appendix, we show that decreases in analyst coverage result

Table A.1 (*continued*).

Variables	Definition and description
Cost of Capital	The definition of the cost of capital is based on a composite measure that is the average of the following four individual cost of capital estimates: Claus and Thomas (2001), Gebhardt et al. (2001), Gode and Mohanram (2003), and Easton (2004). Detailed descriptions of individual cost of capital estimates are as follows: (1) Claus and Thomas (2001) $P_0 = B_0 + \sum_{i=1}^{T} \frac{E_0[(ROE_i - r_0) \times B_{i-1}]}{(1+r_0)^i} + \frac{E_0[(ROE_T - r_0) \times B_4](1+g)}{(r_0 - g) \times (1+r_0)^T}$ where P_0 is the market equity; r is the implied cost of capital; B is the book equity; g is set to the current risk-free rate minus 3%; $T = 5$. (2) Gebhardt et al. (2001) $P_0 = B_0 + \sum_{i=1}^{T-1} \frac{E_0[(ROE_i - r_0)B_{i-1}]}{(1+r_0)^i} + \frac{E_0[(ROE_T - r_0)B_{T-1}]}{r_0 \times (1+r_0)^{T-1}}$ where P_0 is the market equity; r is the implied cost of capital; B is the book equity; $T = 12$. (3) Gode and Mohanram (2003) $r_0 = A + \sqrt{A^2 + \frac{EPS_1}{P_0} \times \left(\frac{\frac{EPS_2 - EPS_1}{EPS_1} + \frac{EPS_5 - EPS_4}{EPS_4}}{2}\right) - (\gamma - 1)}$ $A \equiv \frac{1}{2}\left((\gamma - 1) + \frac{dps_1}{P_0}\right)$ where P_0 is the market equity; r is the implied cost of capital; $\gamma = r_f - 3\%$; forecasted dividend per share: $dps_i = k \times EPS_i$, where k is estimated using the current dividend payout ratio and equals [*dividends paid/earnings*] (4) Easton (2004) $r_0 = \sqrt{\frac{EPS_2 - EPS_1}{P_0}}$ where P_0 is the market equity; r is the implied cost of capital; EPS_i: forecasted earnings
SA	*SA index* is constructed by Hadlock and Pierce (2010), and is measured as $SA = -0.737\ Size + 0.043\ Size^2 - 0.040\ Age$ where *Size* equals the log of inflation-adjusted total assets (in 2004 dollars), and *Age* is the number of years the firm is listed with non-missing stock prices on Compustat. In calculating the index, we winsorize *Size* and *Age* at the 1% tail on the low end, and winsorize *Size* at the \$4.5 billion and *Age* at 37 years on the high end.
Equity Issuance	*Equity Issuance* is the net equity issuance divided by the book value of total assets. The net equity issuance is computed as item SSTK (sale of common and preferred stock) minus item PRSTKC (purchase of common and preferred stock) and DV (cash dividend) in Compustat. When the cash dividend is missing, we replace it with zero.

in declines in a firm's productivity and operating performance, especially when firms lower their organization capital after the reduction in analyst coverage. These results support the cost of capital hypothesis but dispute the myopia hypothesis.

5. Conclusion

Organization capital plays an important role in improving corporate performance and serves as a key component of the intangible assets of a firm. In this paper, we report a positive and significant causal effect of analyst coverage on a firm's organization capital investment.

We test two competing effects of analyst coverage on organization capital. First, we hypothesize that greater analyst coverage could narrow a firm's information gap with the external market, reduce its cost of capital, and make it easier to access external markets to finance organization capital investment. Investment in organization capital is costly and relies heavily on external financing. Moreover, the intangibility of organization capital creates information asymmetry that makes organization capital investment highly susceptible to changes in the cost of equity capital. By contrast, the managerial myopia hypothesis argues that managers sacrifice long-term interests to boost current profits, especially under the undue pressure from financial analysts. Therefore, the hypothesis offers that more analyst coverage can discourage investments in organization capital.

We use quasi-natural experiments of the mergers and closures of brokerages as our identification strategy and then perform a difference-in-differences to establish the causal effect. The results from the difference-in-differences support the cost of capital hypothesis. They show that both the one-year and two-year changes in the organization capital of treatment firms are significantly lower than those of control firms after the treatment firms experienced exogenous reductions in analyst coverage caused by brokerage mergers or closures. We confirm our finding by using 10-K-based measures of organization capital and performing a battery of robustness checks. This treatment effect is concentrated in firms with high costs of capital, and for financially constrained and external equity dependent firms.

Table C.1
Baseline regressions of organization capital on analyst coverage.

Model Dependent variable	(1) LnINVOC1	(2) LnINVOC2
LnCoverage	0.0216***	0.0343***
	(12.85)	(11.77)
LnSale	−0.0002	−0.0036***
	(−0.26)	(−2.84)
RD	−0.0232	−0.2001***
	(−0.73)	(−3.53)
ROA	−0.3440***	−0.4768***
	(−23.82)	(−20.55)
PPE	−0.0382***	−0.0870***
	(−5.60)	(−7.34)
Leverage	0.0431***	0.0642***
	(7.04)	(6.04)
Capex	0.0675***	0.1588***
	(3.36)	(4.73)
TobinQ	−0.0230***	−0.0256***
	(−19.54)	(−14.87)
Patent	−0.0056***	−0.0094***
	(−5.80)	(−5.55)
HHI	0.0440	0.0565
	(1.45)	(1.02)
IO	−0.0203***	−0.0323***
	(−4.80)	(−4.29)
Intercept	0.0497***	0.0791***
	(9.44)	(8.47)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	58,121	51,146
Adjusted R^2	0.110	0.095

This table presents the regressions of organization capital (OC) on analyst coverage. Dependent variables are the changes in OC, namely, OC in year t+1 minus OC in year t (*LnINVOC1*) and OC in year t+2 minus OC in year t (*LnINVOC2*). *LnCoverage* is the logarithm of the average number of analysts issuing earnings forecasts in year t. Other variables are described in Appendix A. All regressions have the year and industry fixed effects. The t-statistics in parentheses are computed based on standard errors clustered at the firm level. The ***, ** and * denote significance at the 1%, 5% and 10% levels (two-tailed), respectively.

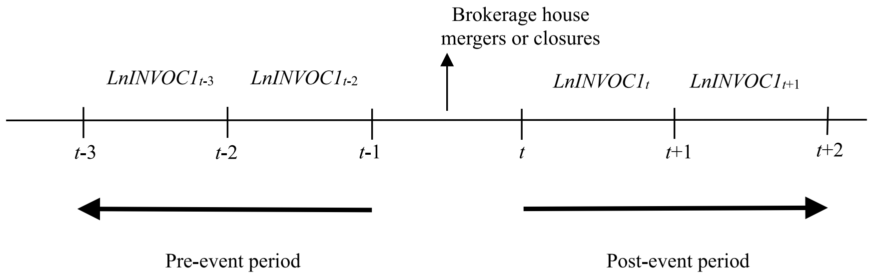
CRediT authorship contribution statement

Konan Chan: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Re-Jin J. Guo:** Conceptualization, Data curation, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Yanzhi A. Wang:** Conceptualization, Data curation, Funding acquisition, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Hsiao-Lin Yang:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

Appendix A. Variable definition

See Table A.1.

Appendix B. Timeline of identification strategy- using LnINVOC1 as the example



Appendix C. Baseline regressions of organization capital on analyst coverage

See Table C.1.

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2022.08.003.

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