The (Mis)Allocation of Corporate News*

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Abstract

This paper studies how the distribution of media's reporting of firm news affects the macroeconomy. We document three connected facts on media's reporting of firm news: corporate news coverage is highly concentrated among the largest firms; equity financing and investments rise after media coverage; and yet these responses are largest among small, rarely-covered firms. We develop a heterogeneous-firm model with a media sector that matches these facts, and use it to quantify the aggregate effects of the distribution of media coverage. In the model, asymmetric information between firms and investors leads to financial frictions that constrain firms' investments. Media may alleviate these information frictions, but its effects are limited by its focus on large and financially unconstrained firms. Reallocating just 10% of news coverage eliminates half of the output loss from information frictions, which suggests a substantial aggregate effects of the distribution of media coverage.

JEL: E22, G32, D82, L82

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1. Introduction

Information asymmetry between firms and potential investors distorts resource allocation and restricts firm growth (Myers and Majluf, 1984). At the same time, growing evidence suggests that the news media serves as a key information source for investors (e.g., Dougal et al., 2012; Peress, 2014). However, media coverage on firms—like other types of news (e.g., Gentzkow and Shapiro, 2008; Nimark and Pitschner, 2019)—is not randomly distributed. Rather, editors and journalists selectively report on the firms they consider most newsworthy. To the extent that information asymmetry constrains firms' ability to obtain financing and grow, the way that the news media closes this information gap has macroeconomic implications. In this paper, we study what "newsworthiness" means for firms. At the micro level, which firms are considered newsworthy, and how does media coverage relate to a firm's financing and investment? At the macro level, how does the distribution of media coverage affect aggregate outcomes?

We answer these questions using new firm-level data on media coverage, and a macro-finance model with heterogeneous firms that incorporates a media sector. Empirically, we document that news coverage is highly concentrated among the largest firms; after receiving coverage, firms' equity financing and investments increase; but firms who receive the most coverage are those that respond the least to it. This negative correlation between media's coverage and firms' responsiveness points to a potential misallocation in media coverage, motivating our model that quantifies the aggregate importance of the *distribution* of corporate news. In the model, information asymmetry between firms and investors leads to financial frictions that constrain firms' investments. Media can alleviate these information frictions, but its role is limited, because its coverage focuses on the largest firms, who are typically not reliant on external financing. In a counterfactual, reallocating just 10% of news coverage eliminates half of the output loss from information frictions, highlighting the importance of the distribution of media coverage in shaping aggregate outcomes.

Empirical evidence We begin our empirical analysis by constructing a new dataset on firm-level media coverage in the U.S., consisting of firm news in three major U.S. newspapers (*The Wall Street Journal*, *The New York Times*, and *USA Today*) and social media coverage on Twitter (now X). These coverage data are combined with firms' balance-sheet data from Compustat, forming a dataset of the timing and frequency of firm news covering the universe of publicly traded firms in the U.S. over a 30-year period. Using this dataset, we document three connected facts on the distribution of news coverage.

The first fact we document is that corporate news coverage is highly concentrated. The variation in news coverage can be mostly accounted for by firm-specific factors. Among the set of observable firm characteristics, news coverage displays a particularly strong nonlinear relationship with firm size. The largest 10% of firms account for more than 85% of all news coverage. This concentration is unique to firm size; media coverage is substantially less concentrated by other firm characteristics.

The second fact concerns the relationship between media coverage and firms' financing and investment. The causation here is likely to go two ways: highly active firms tend to attract media coverage, and media coverage might affect firms' outcomes. We first measure the total association between the two, combining these effects. In the quarters following the media coverage, firms have a greater likelihood of raising equity financing and invest at a higher rate. At its peak, a one-standard deviation increase in media coverage is associated with a 0.25 percentage point greater probability that the firm issues new equity, and a 0.5 percentage point increase in the probability of "investment surges" (with an investment rate greater than 20%). The association between coverage and firm outcomes is not present after receiving social media coverage, indicating that these relationships are not simply because the coverage makes a firm more salient to investors. News sentiment does not appear to affect firm outcomes beyond the association with news frequency, suggesting that it is unlikely that the coverage acts as a coordination device for investors.

To isolate the effect of media coverage on firm outcomes, we then purge the coverage measure of articles discussing firm financing or investment identified using detailed texts of news articles. This removes the articles most likely to be associated with the endogenous selection of media coverage. We find that a firm's investment and equity financing are still positively associated with this purged measure of news coverage.

We provide further evidence that this positive correlation might be causal, using strikes in the media sector to introduce variation in news coverage unrelated to individual firms' outcomes. For this analysis, we complement the U.S. data with evidence from France, where strikes are more common. We collect news coverage data from four major newspapers in France and link them with firms' financial data from Compustat Global. Among the firms that have issued equity, those that did so in quarters with a media strike invest 14% less in the subsequent year compared to firms that issued equity outside of strikes, suggesting that the lack of information during media strikes has made the equity issuance more costly. Furthermore, firms that received high coverage before the strike were more severely affected by the strikes than firms without previous coverage, consistent with these firms being reliant on the media to communicate information to investors.

Finally, the last empirical fact we examine is the joint distribution between media coverage and firm responsiveness. Recent studies suggest that the macroeconomic impact of micro-level heterogeneity depends heavily on the distribution (e.g., Auclert, 2019; Alves et al., 2020). Ranking firms by size, we document that the association between news coverage and firm responses is strongest for small firms and almost negligible for large firms. Therefore, firms that receive the most coverage are those that respond the least to it.

Taken together, our empirical results suggest that media reporting helps alleviate information asymmetries between firms and investors.[1] Under this interpretation, media's reporting reveals firm information that investors are previously unaware of. This channel is most relevant for retail investors, who make up more than a quarter of the trading volume in the U.S. and have large effects on asset prices.[2] Compared to retail investors, newspapers plausibly have better information about firms' conditions. Indeed, we document a set of additional findings consistent with this information channel. In particular, the association of media coverage with firm financing is specific to *equity* financing, but is not present for cash or debt, which are much less sensitive to information (Gorton and Ordonez, 2014).

Quantitative analysis Our findings on the negative correlation between media coverage and firm responsiveness suggest that the firms that receive the most coverage are the least responsive to it, thereby potentially reducing the aggregate effects of media reporting. This

[1] Similarly, Tetlock (2010) documents several empirical features of equity prices around news-coverage events that support the view that a media report removes information asymmetries.

[2] JP Morgan research suggests retail investors accounted for between 20-30% of US market volume in the first months of 2025 (Elder, 2025). For the effects of retail investors on asset prices, see, for example, Kumar and Lee (2006); Greenwood et al. (2023). Even though we focus on retail investors, there are examples of the media drawing attention to information that institutional investors had been ignoring (e.g. Huberman and Regev, 2001).

highlights the importance of considering the distribution of media coverage when evaluating its aggregate consequences. We also use the model to isolate the causal effects of media, which may be challenging empirically.

To conduct this quantification, we introduce a media sector to a macro-finance model with heterogeneous firms. Firm managers seek to maximize their firm's value to existing shareholders and can raise external equity from retail investors to finance investments. However, retail investors face asymmetric information about the quality of firms' heterogeneous assets. Without media reporting, concerns over adverse selection limit equity issuance, as in the large literature pioneered by Myers and Majluf (1984). Media outlets observe full information about firms but are constrained to only reporting on a subset of firms. Once a firm appears in news reports, investors gain full information about the firm, which alleviates the asymmetric information in the equity market. However, this effect is limited to the firms that news outlets choose to cover.

The key elements of the model are therefore that (*i*) firms are heterogeneous; (*ii*) some of the firm heterogeneity is not observed by investors; and (*iii*) media outlets endogenously choose which firms to cover, and thus which firms' state variables to reveal to investors. The heterogeneity is necessary to study the distribution of media coverage among firms. The information asymmetry creates a role for the media sector. Incorporating a micro-found media sector into this macro model then allows us to study the aggregate importance of the externalities from media's reporting decisions.

In taking the model to the data, we pay particular attention to matching media outlets' news reporting. Optimal editorial decisions indicate that a firm's probability of being reported increases with its "newsworthiness"—a measure positively related to a firm's size and idiosyncratic productivity. We calibrate the parameters of this reporting probability function to target empirical moments on news coverage and equity issuance.

Consistent with the data, the media outlets in our calibrated model disproportionately report on large firms. The model also matches the dynamics and magnitudes of the local projections empirically estimated between media coverage and firm financing and investment. These are untargeted moments in the calibration and therefore provide a strong validation of the model's ability to capture the relationships between firms and the media.

Our key result is that the media's focus on large firms strongly limits the media's effect on aggregate outcomes. Investments of large firms are unaffected by media coverage, since these firms are typically financially unconstrained and do not need external funding to finance their optimal investments. In contrast, small and financially constrained firms do respond to news reporting, because information asymmetries otherwise cause them to under-issue and under-invest. By concentrating coverage on the firms least influenced by coverage, the media plays a limited role in alleviating the negative effects of asymmetric information on aggregate investment. This misalignment between media's reporting and firm benefits arise because media outlets do not internalize the effect of their reporting on a firm's value.

To quantify the aggregate consequences of the distribution of media reporting, we conduct a counterfactual experiment that reallocates a portion of news coverage, while keeping the total media space constant. Specifically, we open a competitive market in which a fraction of the media coverage is available for purchase by firms. Firms that stand to gain the most from coverage have the highest willingness to pay. Targeting the media reporting to those firms significantly boosts their financing and investment, leading to a substantial reduction in the aggregate output loss because of information frictions. A reallocation of just 5% of media resources towards firms with higher demand for coverage doubles the media's effect in reducing output loss, while a 10% reallocation mitigates half of the overall output loss from information asymmetry. Our results highlight that the distribution of media reporting is critical for its aggregate effects.

Related literature Our paper is related to four strands of literature. First, we contribute to the literature on the macroeconomic consequences of the news media.[3] Most of this literature focuses on the role of the media in reporting macroeconomic news, demonstrating that both the selection of the macroeconomic news and the way it is reported can affect aggregate dynamics (e.g., Nimark, 2014; Bybee et al., 2020; Larsen et al., 2021; Macaulay and Song, 2022). Beyond macroeconomic news, Chahrour et al. (2021) study the reporting of sectoral news and find that it plays a substantial role in driving the business cycle. We contribute to this literature by studying the aggregate consequences of firm-level news, which we show varies substantially even within sectors. Closer to us, Hu (2024) provides empirical evidence

[3]A related but distinct strand of literature studies news shocks, where news typically refers to signals obtained by agents about future productivity, with the signals arriving from an unspecified source (see Beaudry and Portier, 2014, for a review).

that the media's production of firm news responds to macroeconomic conditions and that this variation in news production amplifies aggregate fluctuations. We instead focus on the cross-sectional heterogeneity in the media coverage among firms, and our quantitative analysis shows that the distribution of the media coverage influences long-term macroeconomic outcomes.

Second, we document that both empirically and theoretically, there is a selectivity in media's reporting of firms, which shapes the distribution of information supplied by the media. Therefore, we also relate to the broader literature studying the editorial decisions of news media. Gentzkow and Shapiro (2008), Nimark and Pitschner (2019), among others, document and model the selectivity in media reporting across political and other forms of news. Chiang (2020), Martineau and Mondria (2022), Perego and Yuksel (2022), Denti and Nimark (2022), among others, provide theoretical foundations for incentives in the news industry. We extend this literature by documenting that the selectivity is also present in the reporting of firm-level news, and characterizing the makings of newsworthy firms.[4]

Third, our findings highlight the macroeconomic importance of micro-level heterogeneity. In our model, firms have heterogeneous investment responsiveness to media coverage. As a result, redistributing media reporting to more responsive firms can significantly raise aggregate investment. This mechanism is analogous to the crucial mechanism in the literature studying household heterogeneity (e.g., Auclert, 2019; Alves et al., 2020; Auclert et al., 2024), which highlights the aggregate relevance of redistributing financial resources across households with heterogeneous marginal propensities to consume. This mechanism also relates to the literature studying the importance of information frictions for firms' choices and resource allocations (Gorton and Ordonez, 2014; Asriyan, 2021; Coibion et al., 2020, 2023).

Finally, our paper relates to the broader literature on the effects of financial frictions on firm dynamics and investment (e.g., Cooley and Quadrini, 2001, Sterk et al., 2021, and see Brunnermeier et al., 2012 for a survey). Eisfeldt (2004), Kurlat (2013), Bigio (2015), and Caramp (2024) study the macroeconomic and financial implications of financial frictions that arise from asymmetric information. To study the aggregate effects of corporate news allocation, we build the firm and investor blocks of our model on Guo et al. (2024), who study the implications of information asymmetry in a model with firm heterogeneity. We

[4] Related, a large body of empirical work in finance documents that media reporting affects equity markets (e.g., Cutler et al., 1988; Chan, 2003; Engelberg and Parsons, 2011; Dougal et al., 2012).

extend the model to incorporate a media sector, which generates endogenous variation in the degree of asymmetric information and consequently financial frictions across firms. We find that the allocation of media-reporting resources plays a substantial role in shaping the firm distribution and dynamics.

Road map The rest of the paper proceeds as follows: in Section 2, we describe our data, document stylized facts on the structure of corporate news and study its effects on firm outcomes; in Section 3, we present a model of corporate news reporting; in Section 4, we use the model to quantify the effects of selective news reporting; Section 5 concludes.

2. Empirical Evidence

This section documents three inter-related facts on corporate news coverage: news coverage is concentrated among the largest firms, is associated with real effects on firm outcomes, and is allocated to the least responsive firms.

2.1. Illustrative framework: a decomposition

To begin with, we present a simple model, in which media coverage interacts with firms' financing cost. This simple model highlights that there are three moments needed to measure the aggregate consequences of media coverage: the average level of the coverage, the average firm response to the coverage, and the covariance between the news coverage and the firms' responses.

The model is static and there is a unit mass of firms. Firm i has investment technology $f(I_i) = \frac{1}{\theta} I_i^{\theta}$. To finance its investment, the firm raises external equity from a frictional market. The news coverage of the firm, $m_i \in \{0, 1\}$, is considered exogenous to the firm and interacts with financial frictions. The marginal cost of investment is given by $\log c_i = a + a_i m_i$, where $a \in \mathbb{R}$ denotes the component of the financing costs that does not interact with the media coverage (assumed constant across firms), and $a_i \in \mathbb{R}$ denotes the component that does interact with the financing costs. This set-up allows us to study the potential role of news reporting on aggregate investment, our object of interest.

Firms choose I_i to maximize $f(I_i)$ net of the investment costs. The first-order condition of firm i's optimal investment leads to $\log I_i^* = \psi(a + a_i m_i)$, where $\psi = -\frac{1}{1-\theta}$. Aggregating individual firms' investments implies that aggregate investment is given by $I = \int_{i\in[0,1]} I_i^* di = \mathbb{E}(I_i^*) = \exp(\psi a)\,\mathbb{E}(\exp(\psi a_i m_i))$. To study the effects of the news coverage, from the media sector, on aggregate investment, we denote the log of aggregate investment without a media sector as $\log I^0 \equiv \psi a$. The effects of the media sector on aggregate investment can then be characterized as

$$\begin{aligned}\log I - \log I^0 &= \log \mathbb{E}(\exp(\psi a_i m_i)) \\ &\approx \mathbb{E}(\psi a_i m_i) \\ &= \mathbb{E}(m_i)\,\mathbb{E}(\psi a_i) + \mathbb{C}\mathrm{ov}(m_i, \psi a_i) \\ &= \mathbb{E}(m_i)\,\mathbb{E}\left(\frac{\partial \log I_i}{\partial m_i}\right) + \mathbb{C}\mathrm{ov}\left(m_i, \frac{\partial \log I_i}{\partial m_i}\right), \qquad (1)\end{aligned}$$

where the second line uses a first-order Taylor approximation, the third line uses properties of an expectations operator, and the last line substitutes for ψa_i with $\frac{\partial \log I_i}{\partial m_i}$, which follows directly from differentiating firm i's optimal investment with respect to m_i.

The decomposition in (1) shows that the aggregate effects of the media depend not only on the average level of the coverage, $\mathbb{E}\, m_i$, and the average investment responses to the coverage, $\mathbb{E}\,\frac{\partial \log I_i}{\partial m_i}$, but also on the distribution of the media coverage, consistent with the broader literature on the macroeconomic implications of micro-level heterogeneity (e.g., Auclert, 2019; Alves et al., 2020). Specifically, the covariance term indicates that when the media coverage is negatively correlated with firms' responsiveness, this dampens the aggregate investment response, whereas when the media coverage is positively correlated with firms' responsiveness, it amplifies it. Motivated by this decomposition, we now measure each component in (1) in turn.

2.2. Data

We collect data from Dow Jones Factiva on the frequency of firm news coverage by three of the largest U.S. newspapers by circulation: *The Wall Street Journal*, *The New York Times*, and *USA Today*.[5] The news-coverage frequency is matched to firms' quarterly balance sheet

[5] Factiva is a widely used database for measuring the frequency of news coverage (see, for example, Chahrour et al., 2021; Bui et al., 2022). Our search parameters closely follow those used by Chahrour et al. (2021), which provides media-coverage frequencies, for the top 100 firms, by news coverage in each newspaper and each quarter.

data from Compustat, using a fuzzy matching algorithm (Levenshtein, 1966) based on firm names.[6] The resulting dataset contains firm-level media coverage for the universe of publicly traded firms in the U.S., consisting of 385,698 articles on 18,809 firms from 1990 to 2021. On average, news about publicly traded firms in the U.S. constitutes 9% of total news articles in these newspapers over the sample period.

We complement the main data on news frequency with three additional datasets. The first contains the full texts of the news articles obtained from Dow Jones Data, News, and Analytics. This contains the detailed content of the subset of the news articles that the Dow Jones is licensed to redistribute (representing c 54% of the full coverage sample).

The second is the firms' social media coverage on Twitter (now X), which allows us to compare the role of the curated news coverage with the social media coverage. We identify over 3,000 publicly traded firms with official accounts on this social media platform. We then collect the frequency with which each firm is mentioned (e.g., `@Microsoft`) each quarter from 2014, when Twitter became a popular platform, to 2021.

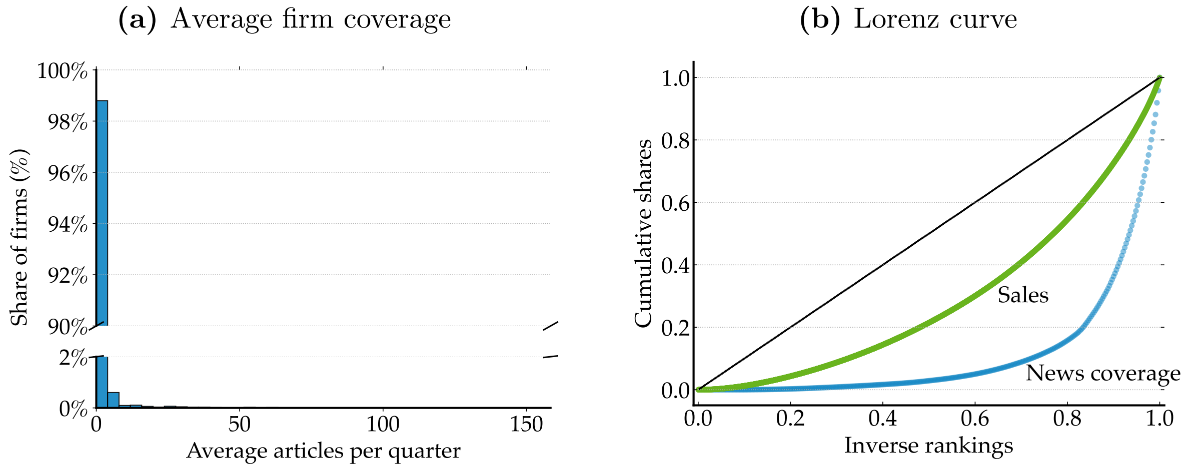
Finally, we use news-coverage data from France, where periods of media strikes introduce variation in the media coverage. We use Factiva to collect the frequency of firms' news coverage from 2005 to 2021 in four major French newspapers: *Les Echos*, *Le Monde*, *La Tribune*, and *Le Figaro*, and link the coverage data with firm variables from Compustat Global as in the U.S. analysis.

2.3. Distribution of media coverage

Panel (a) in Figure 1 shows the distribution of the firm's average per-quarter article counts over the sample period. The distribution is highly skewed, with news coverage concentrated among a small number of firms. To effectively display the right tail of firms with high media coverage, the histogram compresses the vertical axis between the 2nd and 90th percentiles. While most firms receive no media coverage, those in the top 1% appear in an average of

[6] Factiva provides named entity tags identifying the entities mentioned in each news article. These entities include not only firms but also organizations such as the United Nations and Harvard University. Using a fuzzy matching algorithm based on the Levenshtein distance, we match the firm names in Factiva with those of publicly traded U.S. firms in Compustat. Factiva-named entities often include slight variants of the same firm (e.g., "AT&T Inc" and "AT&T Inc."). Our algorithm recognizes that both names refer to the same firm. To ensure match quality, we perform manual checks on each of the matches.

Figure 1: Distribution of corporate news coverage



Notes: Panel (a) reports the histogram of the average number of articles that firms receive per quarter over the sample period. To effectively display the right tail of firms with high media coverage, we condense the share of firms between $(2\%, 90\%)$ in the vertical axis in the histogram. Panel (b) reports the Lorenz curve of media coverage compared with that of real sales. Firms are ranked by the share of their media coverage (or real sales), measured as a firm's log article counts (or real sales) divided by the sum across all firms over the sample period. The blue line plots the cumulative share of log article counts against firms inversely ranked by media coverage share, and the green line plots the same for log real sales. We invert the ranking in this panel to follow the standard Lorenz curves convention, so that firms with the least media coverage or sales appear on the left. The black line represents the 45-degree line of perfect equality.

21 articles per quarter in major newspapers.[7] Appendix Figure A.1a restricts the sample to firms with non-zero coverage, and Appendix Figure A.1b reports the distribution of firm news coverage within industries, which suggest that the skewed pattern of media coverage is not driven by firms without any coverage or industry-specific media attention.

Panel (b) in Figure 1 presents the Lorenz curve of firm-level media coverage shares. The blue line shows the cumulative share of log article counts across firms, ranked in ascending order by their media coverage share. We invert the ranking in this panel to follow the standard Lorenz curves convention, so that firms with the least media coverage appear on the left. The figure illustrates the high concentration in firm news coverage. For comparison, the green line plots the Lorenz curve for firms' log real sales, which is itself highly concentrated (e.g., Autor et al., 2020), yet notably less so than media coverage.

In light of the concentration in the news coverage, we next study the factors associated

[7]Table A.1 in the Appendix lists the top 10 firms by total media coverage. The top firms are household names such as Blackrock, AT&T, and General Motors, whose brand recognition may attract attention from readers who do not necessarily have a specific interest in business news.

Table 1: Variance decomposition of firms' media coverage

	Mean	SD	R²		Mean	SD	R²
Articles per quarter	0.528	6.623	0.000	Probability of media coverage	1.514%	0.122	0.000
Time		6.622	0.000			0.122	0.002
Industry		6.489	0.040			0.119	0.045
Firm		4.057	0.625			0.085	0.515
Industry × Time + Firm		3.902	0.656			0.081	0.563

Notes: This table reports the variance decomposition of media coverage. The left-hand panel reports the standard deviation of ε_{it} and the R^2 from estimating equation (2): $h_{it} = \alpha_{st} + \alpha_i + \varepsilon_{it}$, where h_{it} is the article counts containing firm i in major newspapers in quarter t, α_{st} is the sector-by-time fixed effect, and α_i is the firm fixed effect. The right-hand panel reports the standard deviation of ε_{it} and the R^2 from a variant of equation (2), where the dependent variable is an indicator variable for media coverage, $\mathbb{1}(h_{it} < 0)$.

with media coverage. We first estimate a panel regression

$$h_{it} = \alpha_{st} + \alpha_i + \varepsilon_{it}, \tag{2}$$

where h_{it} represents the article counts for firm i in quarter t, α_{st} is a sector-by-time fixed effect, and α_i is a firm fixed effect. We include the fixed effects iteratively and report the standard deviations of the residuals, ε_{it}, and the resulting R^2 of the regressions.

Table 1 reports the results. The left-hand panel shows that more than 60% of the variation in the media coverage can be accounted for by firm-specific characteristics. The firm's industry explains 4% of the variation, while the time dimension plays a minor role. The right-hand panel shows the results from the same exercise, replacing the dependent variable with an indicator variable $\mathbb{1}(h_{it} > 0)$, which takes the value of 1 if a firm appears in major newspapers in a given quarter. Similarly, firm-specific characteristics explain a sizable variation of the probability of coverage. It should be noted that Table 1 shows that some 34% of the variation in the media coverage and 44% of the variation in the probability of coverage are unexplained by the aforementioned factors. This unexplained portion, which contains the variation over time at the firm level, is the variation we use to study the relationship between the media coverage and the firm outcomes in the next section.

Figure 2: Firm size and media coverage

(a) Assets (b) Market values (c) Employees (d) Sales

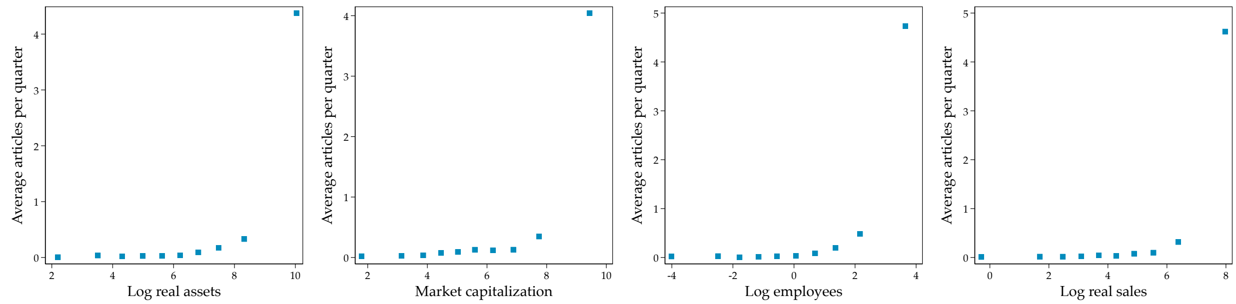
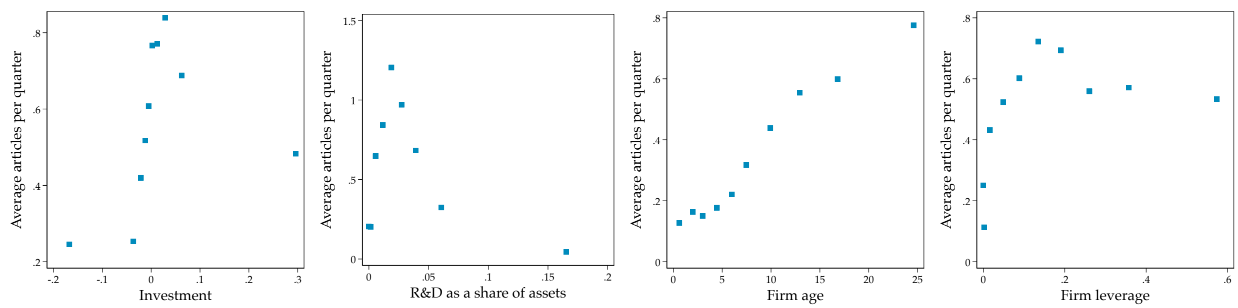


Figure 3: Other firm characteristics and media coverage

(a) Investment (b) R&D (c) Age (d) Leverage



Notes: Figures 2 and 3 report binned scatterplots of average news articles per quarter. Each bin represents a decile of firms, sorted from the smallest to largest. Figure 2 reports the relationship between news coverage and firm size, measured by log real assets in panel (a), market capitalization (prices per share times shares outstanding) in panel (b), log employee numbers in panel (c), and log real sales in panel (d). Figure 3 reports the relationship between news coverage and other firm characteristics, including investment rate in panel (a), and research and development expenses as a share of assets in panel (b), firm age (years since the IPO) in panel (c), market leverage in panel (d).

Before using that within-firm variation, we first explore how various firm characteristics are associated with media coverage. Specifically, we study the variation in the media coverage across firm size, age, and financial conditions.[8] Variables are constructed following standard practices in the literature and are detailed in Appendix A.1. Figures 2 and 3 report binned scatter plots of news coverage against these firm characteristics. Each bin represents a decile of firm-quarter observations. Appendix Figure A.2 further accounts for the role of industries by demeaning each firm characteristic by its industry average. Since patterns are similar across all firms and within industries, we focus our discussion below on untransformed series.

[8]These firm characteristics are considered important for business cycle fluctuations and the transmission of macroeconomic policy (e.g. Gertler and Gilchrist, 1993; Cloyne et al., 2023; Ottonello and Winberry, 2020).

Figure 2 shows the relationship between media coverage and firm size, measured four different ways: log real assets (panel a), market value (b), log number of employees (c), and log real sales (d). Across all measures of size, the relationship is highly nonlinear: media coverage is concentrated among the largest 10% of firms, while the remaining firms receive almost no coverage. Appendix Figure A.2 confirms that this concentration is also present within industries, measured by firm size relative to the average size in the firm's 4-digit NAICS industry.

One potential explanation for the concentration is that large firms have more activities, supplying the media more stories to report on. Panels (a) and (b) in Figure 3 relate media coverage to firms' activity levels, measured by investment (log differences in capital) and R&D (research and development spending relative to assets). The binned scatter plots reveal hump-shaped relationships between media coverage and both investment rates and R&D . Appendix Figure A.2f further shows that, after conditioning on the industry, media coverage decreases with R&D spending. These patterns suggest that media's attention to the largest firms is not a merely a reflection of these firms' activity levels, but rather driven by a focus on their sizes.

Figure 3 also reports the relationship between media coverage and other firm characteristics, which suggest that the strong concentration of media coverage in the top decile is unique to firm size. Panel (c) reports the relationship between news coverage and firm age, measured in years since their IPOs. While the oldest firms receive the most coverage, mid-aged firms also appear in the news, unlike the relationship with firm size. Panel (d) studies the role of firms' financial positions, reflected in their market leverage. The media coverage is hump-shaped with respect to leverage. However, Appendix Figure A.2h shows that for firms within a given industry, the relationship between their leverage and their news coverage is much weaker.

2.4. Firm responses to media coverage

Next, we study the relationship between news coverage and firms outcomes. Both media coverage and firm outcomes are endogenously determined: firms with high investment and financing activities tend to attract media coverage, and media coverage may affect firms' investment and financing. In this subsection, we first estimate the correlation between media coverage and firm outcomes. Then, we focus on the effects of media coverage on firms using a purged coverage measure. Lastly, we provide evidence on the causal mechanism using media strikes.

The main measure of coverage for this analysis is the *within-firm* variation in media coverage, $(\nu_{it} - \mathbb{E}_i \, \nu_{it})$, where ν_{it} denotes the number of mentions of firm i in major U.S. newspapers quarter t, and $\mathbb{E}_i \, \nu_{it}$ denotes the average number of mentions of the firm over the sample. We focus on within-firm variation because it accounts for the time-invariant differences in media coverage across firms documented in Section 2.3, and because it is consistent with the model mechanism in Section 3, which studies ex-post heterogeneity. We complement it with a second measure, $\mathbb{1}(\nu_{it} > 0)$, which is an indicator variable that takes the value of 1 if firm i has any news coverage in quarter t and 0 otherwise. We report robustness with this measure because of its simplicity, which provides a particularly transparent interpretation of the estimate.

2.4.1. Media coverage and firm investment

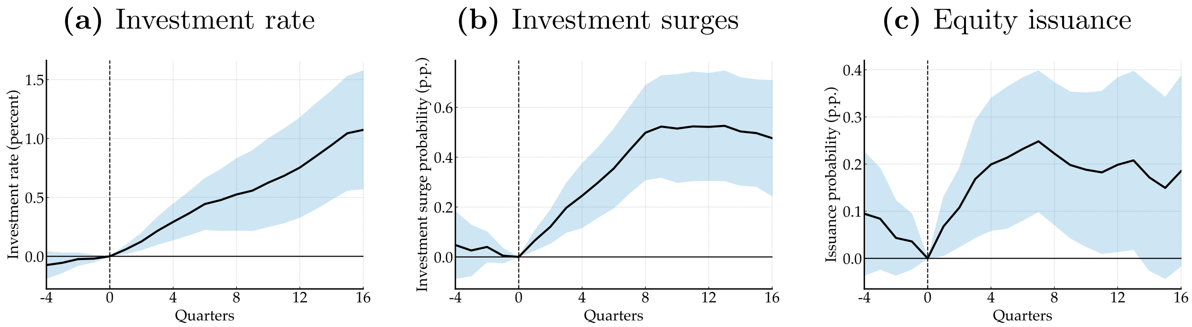
We first estimate the correlation between media coverage and firm outcomes using local projections (Jordà, 2005). For firm i in quarter t, we estimate for each horizon $-4 \leq h \leq 16$

$$\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it} - \mathbb{E}_i \, \nu_{it}) + \Gamma' Z_{it} + u_{ith}, \tag{3}$$

where $\Delta_h y_{it}$ is the firm variable of interest; ν_{it} denotes the number of mentions of firm i in major U.S. newspapers quarter t, and $\mathbb{E}_i \, \nu_{it}$ denotes the average number of mentions of the firm over the sample; $\{\alpha_{st}, \alpha_i\}$ are sector-by-quarter and firm fixed effects; Z_{it} is a vector of firm controls including sales growth, size, and current assets as a share of total assets; and u_{ith} is a random error.

The firm variables of interest include (i) the investment rate, $\Delta_h \log k_{it}$, defined as the log change in the book value of the firm's tangible capital stock; (ii) the cumulative probability of investment surges, $\max_{t \leq \tau \leq t+h} \mathbb{1}(\Delta \log k_{i\tau} > 20\%)$, defined as an indicator equal 1 if a firm has quarterly investment rate higher than 20% between quarters t and $t+h$, and 0 otherwise; and (iii) the cumulative probability of equity issuance, E_{it}, an indicator equal 1 if a firm issues new equity between quarters t and $t+h$ and 0 otherwise. We study investment

Figure 4: News coverage, firm investment, and financing



Notes: This figure reports the results from estimating the local projections in equation (3) for quarters $-4 \leq h \leq 16$: $\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it} - \mathbb{E}_i\, \nu_{it}) + \Gamma' Z_{it} + u_{ith}$, where $\{\alpha_{st}, \alpha_i\}$ denote the sector-by-quarter and firm fixed effects; ν_{it} denotes the number of mentions of firm i in major U.S. newspapers quarter t; $\mathbb{E}_i\, \nu_{it}$ denotes the average number of mentions of the firm over the sample; and Z_{it} is a vector of firm controls including their size, age, and real sales growth. The dependent variable y_{it} includes (a) the investment rate ($\Delta_h \log k_{it}$), defined as the log change in the book value of the firm's tangible capital stock; (b) the cumulative probability of investment surges ($\max_{t\leq\tau\leq t+h} \mathbb{1}(\Delta \log k_{i\tau} > 20\%)$), defined as an indicator variable that takes the value of 1 if a firm has quarterly investment rate higher than 20% between quarters t and $t+h$, and 0 otherwise; and (c) the cumulative probability of equity issuance (E_{it}), defined as an indicator variable that takes the value of 1 if a firm issues new equity between quarters t and $t+h$ and 0 otherwise. We have standardized ($\nu_{it} - \mathbb{E}_i\, \nu_{it}$) over the entire sample. Standard errors are double clustered by firm and quarter. 90% confidence intervals are reported.

surges in addition to investment rates because investment tends to be infrequent and lumpy (e.g., Doms and Dunne, 1998). We double cluster the standard errors by firm and quarter. To help interpret the estimates, we standardize firms' demeaned coverage, $\nu_{it} - \mathbb{E}_i\, \nu_{it}$, over the entire sample, so that the unit can be interpreted as one standard-deviation within-firm change in media coverage.

Figure 4 reports our baseline findings. Panel (a) shows that more coverage is associated with a subsequent increase in investment. A one standard deviation higher media coverage is associated with 0.05% higher investment in the quarter after the coverage. The positive association rises gradually over the estimation horizon, reaching a peak of approximately 1%. Panel (b) takes into account the lumpy nature of investment. It shows that media coverage is also associated with a higher subsequent likelihood of investment surges (defined as an investment rate greater than 20%). The peak association occurs around 8 quarters after the coverage, with a one standard deviation higher coverage associated with a 0.5 percentage point higher probability of investment surges. Panel (c) shows that media coverage is associated with a higher probability of raising financing from the equity market. In the quarter after the news coverage, a one standard deviation higher media coverage is associated with a 0.07 percentage point greater probability of a firm issuing equity. The association rises gradually to a peak of around 0.2 percentage points after 6 quarters.

Table 2 presents a summary of the robustness tests and additional analysis. We report the estimated coefficients and standard errors for the on-impact and peak effects from estimating variants of (3), along with hyperlinks to the full estimated dynamics in the appendix.

Panel (a) of Table 2 presents results using a more transparent measure of media coverage. Rather than using within-firm variation, we use a binary indicator, $\mathbb{1}(\nu_{it} > 0)$, which takes the value of 1 if a firm has any coverage in a quarter and 0 otherwise. Firms' investment rate and investment surges remain positively correlated media coverage under this alternative measure.

Panel (b) of Table 2 accounts for the possibility that publicly traded firms may be related to the newspapers in our sample, by sharing the same owners or operating in the same industry. To address this, we exclude firms that share common owners with the three newspapers, or firms in the media sector (NAICS 5418), and re-estimate the local projection in (3). The estimates are little changed from the baseline, which suggests that the positive relationship between media coverage and firms' investment and equity issuance is not driven by the potential connections between non-media and media firms.

Panel (c) of Table 2 presents two sets of evidence that media coverage reveals information on firms. First, Appendix Figure A.6 shows that the association with news coverage is specific to equity financing: the correlations of media coverage with debt financing and cash financing are much smaller in magnitude and statistically insignificant. This is consistent with equity being an informationally sensitive form of financing, whereas debt and cash financing are much less sensitive to information (Gorton and Pennacchi, 1990; Gorton and Ordonez, 2014; Hoberg and Maksimovic, 2015).

Second, we compare the curated news from newspapers with the social media platform Twitter (now X), which has become a major alternative to traditional news media over the last decade. While newspaper articles are produced by trained journalists and curated by editors, tweets are produced by individual users and are largely unmoderated. Panel (c) of Table 2 (and the full dynamics in Appendix Figure A.7) shows that unlike newspaper coverage, Twitter coverage is associated with a slightly lower rate of investment and equity issuance probability, which suggests that the positive association with firms' outcomes is

Table 2: Media coverage and firm investment: Summary

		Impact	Peak	Average	Obs.	Dynamics
(a) Alternative measures of coverage or investment						
Dependent var.:	*Independent var.:*					
Investment rate	Media coverage	0.058***	1.073***	0.564	385,715	Fig. 4a
		(0.022)	(0.305)			
Investment surges	Media coverage	0.065***	0.526***	0.393	384,653	Fig. 4b
		(0.024)	(0.134)			
Investment rate	Coverage indicator	0.669***	6.124**	3.637	385,715	Fig. A.3a
		(0.225)	(2.407)			
Investment surges	Coverage indicator	0.796***	1.734	1.033	384,653	Fig. A.3b
		(0.294)	(1.048)			
(b) Robustness						
Ex. common ownership		0.060***	1.089***	0.573	383,815	Fig. A.4
		(0.022)	(0.305)			
Ex. media firms		0.059***	1.074***	0.564	383,979	Fig. A.5
		(0.022)	(0.305)			
(c) Information content in media coverage						
By financing types	Equity financing	0.068*	0.248***	0.184	377,708	Fig. A.6
		(0.038)	(0.091)			
	Debt financing	-0.003	-0.003	0.002	287,263	
		(0.003)	(0.003)			
	Cash holdings	0.001	0.010**	0.005	388,255	
		(0.003)	(0.005)			
Twitter coverage		-0.024	-0.454	-0.269	42,942	Fig. A.7
		(0.043)	(0.347)			
(d) Purged measure of media coverage						
Ex. articles on investment and financing		0.071***	1.544***	0.809	385,715	Fig. A.9
		(0.026)	(0.451)			
(e) By sentiment						
Effects by sentiment	Coverage	0.060**	1.109***	0.588	385,715	Fig. A.10
		(0.023)	(0.322)			
	Coverage × Sentiment	-0.000	0.008	0.007		
		(0.004)	(0.039)			

Notes: This table estimates variants of (3): $\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it} - \mathbb{E}_i\, \nu_{it}) + \Gamma' Z_{it} + u_{ith}$. "Impact" denotes estimates at $h = 1$.; "peak" denotes the largest estimates in absolute value for $1 \leq h \leq 16$; and "average" denotes the average of coefficients over $1 \leq h \leq 16$. The first two rows of panel (a) repeats the baseline estimates in Figure 4. The last two rows of panel (a) uses $\mathbb{1}(\nu_{it} > 0)$ as the independent variable, which is an indicator variable that equals 1 if firm i has any coverage in quarter t. Panel (b) excludes firms that share common ownership with the three newspapers in the U.S. sample and those in the media sector (NAICS 5418). The first three rows of Panel (c) use as the dependent variable the cumulative probabilities of equity issuance, debt issuance, and increasing cash holdings, respectively. The last row of Panel (d) uses as the independent variable Twitter coverage, $(\tau_{it} - \mathbb{E}_i\, \tau_{it})$. Panel (d) estimates (3) where the independent variable is $\nu_{it}^{\text{purged}} - \mathbb{E}_i\, \nu_{it}^{\text{purged}}$, a purged measure of media coverage defined in Section 2.4.2 that excludes articles on investment or financing. Panel (e) reports $\beta_{\nu h}$ and $\beta_{\nu sh}$ estimated from $\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_{\nu h}(\nu_{it} - \mathbb{E}_i\, \nu_{it}) + \beta_{sh}\mathrm{sent}_{it} + \beta_{\nu \mathrm{sh}}(\nu_{\mathrm{it}} - \mathbb{E}_{\mathrm{i}}\, \nu_{\mathrm{it}}) \times \mathrm{sent}_{\mathrm{it}} + \Gamma' \mathrm{Z}_{\mathrm{it}} + \mathrm{u}_{\mathrm{ith}}$, where $\mathrm{sent}_{\mathrm{it}}$ denotes the news sentiment of firm i in quarter t defined in Section 2.4.2. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

specific to curated news.

These findings motivate our modelling choices in Section 3, where we assume that media affects firms by providing information to investors. The findings that Twitter coverage does not have similar effects to newspaper reporting provide evidence against alternative theories, such as media acting as a co-ordination device for investors who already hold information, or media affecting investors through behavioral channels such as increasing salience.

2.4.2. Purged measure of media coverage

Having documented the positive association between media coverage and firm outcomes, we now focus on isolating the effects that media coverage has on firms. In this subsection, we address a selection bias where firms with imminent investment or financing tend to attract media attention. Leveraging detailed text of newspaper articles, we identify and remove news articles covering these events from our measure.

We proceed in two steps. First, we use the latent Dirichlet allocation (LDA) model to extract 20 distinct "topics" that represent the articles.[9] The resulting topics are reported in Appendix Figure A.8. The news coverage about firms falls into three broad categories: the news related to overall financial conditions (e.g., "stock markets"), the news related to firms' industries (e.g., "technology" and "automobiles"), and firm-specific news (e.g., "investment," "financing," "litigation," and "employees"). Then, we exclude any news articles that have any positive loadings on topics related to firm investment and financing: topic 5 ("investment"), topic 16 ("financing"), and topic 8 ("financing from international markets") in Appendix Figure A.8. We then re-estimate the baseline local projection

$$\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it}^{\text{purged}} - \mathbb{E}_i\, \nu_{it}^{\text{purged}}) + \Gamma' Z_{it} + u_{ith} \tag{4}$$

using this purged measure of media coverage, $\nu_{it}^{\text{purged}} - \mathbb{E}_i\, \nu_{it}^{\text{purged}}$, which excludes the coverage of firm investment and financing.

Panel (d) of Table 2 reports the estimates (with the full dynamics reported in Appendix Figure A.9). We find that firms' coverage unrelated to investment or financing remains associated with a higher probability of equity issuance and a higher rate of investment, with

[9] Appendix A.3 details the text pre-processing and LDA estimation.

somewhat stronger effects than those estimated using the total news frequency. This suggests that direct reverse causality is unlikely to be driving our results.

Using detailed texts of news articles, we also analyze the effect of *news sentiment*. Sentiment is measured using three approaches: a keyword-based measure (Loughran and McDonald, 2011), a FinBERT-based measure (Araci, 2019), and a GPT-based measure (Ye et al., 2023), as detailed in Appendix A.4. Since each methodology has its strengths and weaknesses, we measure news sentiment, $\mathrm{sent_{it}}$, with the first principal component of the three measures. We then interact the frequency and the sentiment of media coverage and estimate

$$\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_{\nu h}(\nu_{it} - \mathbb{E}_i\, \nu_{it}) + \beta_{sh}\mathrm{sent_{it}} + \beta_{\nu \mathrm{sh}}(\nu_{\mathrm{it}} - \mathbb{E}_{\mathrm{i}}\, \nu_{\mathrm{it}}) \times \mathrm{sent_{it}} + \Gamma' \mathrm{Z_{it}} + \mathrm{u_{ith}}, \tag{5}$$

where $\mathrm{sent_{it}}$ denotes the average sentiment of firm i's media coverage in quarter t.

Panel (e) of Table 2 reports the estimates. The average effect of news coverage frequency remains positive and statistically significant. In contrast, the marginal effect of news sentiment is close to zero and statistically insignificant. These findings suggest that, in the context of firm-specific news, all coverage is good coverage.

2.4.3. Evidence from media strikes

To complete the analysis on the effects of media coverage, we provide evidence on the causal mechanism behind the relationship between coverage and investment. In this subsection, we use episodes of media strikes to introduce variation in the news coverage that is unrelated to firm choices. During strikes, journalists stop reporting, reducing the amount and quality of information provided by the media sector, for reasons that are unrelated to individual non-media firms (Peress, 2014).

Media strikes in the U.S. have been rare in recent history. However, in France we identify 6 episodes of large-scale media strikes, using the criteria developed by Peress (2014), detailed in Appendix Table A.2.[10] We focus on sector-wide strikes and exclude strikes against

[10] We search Factiva for keywords containing (*i*) "strike" and "journalist," or (*ii*) "strike" and "broadcaster," as well as their French translations. Using Factiva's tagging, we restrict the region to France, the industry to Media/Entertainment, and the subject to Labor Dispute. We focus on national strikes and exclude strikes against individual newspapers. The 6 strike episodes are reported in Appendix Table A.2.

individual newspapers, to ensure that these strikes occur not because of individual newspaper or non-media firm factors but rather as a response to the government's policy changes (such as Nicolas Sarkozy's broadcasting-advertising reform and Emmanuel Macron's pension reform).

To facilitate comparison with the U.S. evidence, we first report the distribution and the effects of media coverage in France. Panel (a) of Appendix Figure A.11 shows that the distribution of corporate news coverage in France displays a similar concentration as the U.S. coverage. Panels (b) and (c) estimate the relationship between media coverage and firms' investment and equity issuance, respectively, using the local projection specified in (3).[11] The results are consistent with the U.S. evidence: greater media coverage in France is associated with a higher probability of equity issuance and investment.

Our main analysis tests whether the reduction in media coverage during media strikes affects firms' outcomes. We restrict our focus to firms that issued equity during the sample period. To the extent that equity issuance are pre-scheduled and not strategically timed to coincide with or avoid media strikes, differences in post-issuance investment depending on firms' exposure to media strikes are informative about the effect of media coverage. Indeed, Appendix Table A.3 reports descriptive statistics on firm news, showing that both the number of firm news and their share of total news coverage are lower during media strikes than adjacent quarters without strikes. Further, Appendix Table A.4 shows that the probability of equity issuance do not vary with media strikes, which verifies that there is no evidence of strategic timing in firms' equity issuance related to media strikes.

Having verified our key assumptions, we estimate

$$\log k_{it+4} - \log k_{it} = \alpha_s + \beta S_t + \delta\theta_{it} + \gamma\theta_{it} S_t + \Gamma' Z_{it} + u_{it}, \tag{6}$$

where $\log k_{it+4} - \log k_{it}$ denotes firm i's cumulative investment a year after its equity issuance, α_s denotes the sector fixed effect; S_t is an indicator for media strikes in quarter t; θ_{it} denotes

They are concentrated in 5 quarters: 2005Q4, 2008Q1, 2008Q4, 2013Q1, and 2018Q2.

[11]For horizons $-4 \leq h \leq 12$, we estimate $\Delta_h y_{it+h} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it} - \mathbb{E}_i \nu_{it}) + \Gamma' Z_{it} + u_{ith}$. As with the U.S. analysis, the dependent variables consist of cumulative changes in investment and equity issuance probabilities, and the explanatory variable, ν_{it}, measures firm coverage in the four major French newspapers and is demeaned at the firm level and standardized. α_i and α_{st} refer to the firm and sector-by-quarter fixed effects. We classify sectors using the 2-digit rather than the 4-digit NAICS levels because the French equity market is far smaller than the U.S. market (there are 959 unique publicly traded firms in our French sample compared to 13,207 firms in our U.S. sample). The vector Z_{it} controls for firms' sales growth, size (log real assets), and current assets as a share of total assets.

Table 3: Equity issuance during media strikes and exposure to media coverage

	(1)	(2)	(3)	(4)	(5)
	Investment after issuance (1yr)				
Strike	-0.140*	-0.173	-0.162*	-0.162*	-0.025
	(0.078)	(0.106)	(0.096)	(0.096)	(0.049)
Past coverage		0.004	0.006	0.005	0.005
		(0.004)	(0.005)	(0.005)	(0.005)
Strike × Past coverage		-0.042*	-0.039*	-0.039*	-0.061***
		(0.021)	(0.020)	(0.020)	(0.012)
Observations	1072	1024	882	881	842
R^2	0.029	0.039	0.056	0.056	0.052
Industry FE	yes	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes	yes
Firm + macro controls	no	no	yes	yes	yes
Ex. common ownership	no	no	no	yes	yes
Ex. 2008	no	no	no	no	yes

Notes: This table reports the coefficient γ from estimating equation (6): $\log k_{it+4} - \log k_{it} = \alpha_j + \beta S_t + \delta\theta_{it} + \gamma\theta_{it}S_t + \Gamma' Z_{it} + u_{it}$, where t is the quarter in which a firm issues equity, $\log k_{it+4} - \log k_{it}$ is the cumulative investment 4 quarters after the equity issuance, α_j is a sector fixed effect, S_t is an indicator for media strikes, θ_{it} is the average media coverage of firm i 4 quarters before the strike at time t, and Z_{it} is a vector of controls containing sales growth, size, current assets as a share of total assets, real GDP growth, inflation, and aggregate investment. Column 5 excludes 2008. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

firm i's average news coverage in the year before the strike; and Z_{it} is a vector of firm and macroeconomic controls, including firm sales growth, size, current assets as a share of total assets, fiscal year end, real GDP growth, inflation, and aggregate investment.[12]

The parameter of interest is γ. Among firms that issued equity during media strikes, γ measures the differential impact of a strike on a firm's investment, depending on the firm's past coverage coverage. If the news media disseminates firm news to investors, firms that tend to receive more coverage are expected to suffer bigger impacts during strikes compared to their peers with little coverage to begin with. The specification in (6) allows for the possibility that strikes tend to happen in economic downturns, since the source of the variation in this regression is the cross-sectional variation in firms' exposure to the same strike.

Table 3 reports the results. Column 1 estimates the average effect of media strikes and finds that firms that issue equity during media strikes invest less in the subsequent

[12]We retrieve GDP (CLVMNACSCAB1GQFR), inflation (CPHPTT01FRM659N), and aggregate investment (PRMNVG01FRQ661S) from FRED.

year, compared to firms that issue equity during quarters without media strikes. Since the decision to strike can be related to broad economic conditions, Columns 2 through 5 further exploit the cross-sectional variation in firms' past news coverage to study the effects of the exposure to strikes. Column 2 reports the baseline estimates of (6) without any controls. Column 3 controls for firm performance and macroeconomic fluctuations. Column 4 excludes firms that share a common owner with a major newspaper, to account for a possible direct effect of the labor disputes behind the media strikes on the investments of the firms in our sample.[13] Strikes in newspapers can arise from disputes with their owners, which potentially affect the investment decisions of their non-media subsidiaries for reasons other than media coverage, and we account for this possibility by removing these subsidiaries. Finally, Column 5 excludes episodes from 2008, to ensure that our results are not driven by outliers from the Global Financial Crisis.

We focus our discussion on Column 4 in Table 3, which provides the most conservative estimates based on the full sample. Firms that issue equity during media strikes invest 16% less in the year following the issuance compared to those issuing during non-strikes. This effect is more pronounced for firms with historically higher media coverage. Among firms that issue equity during strikes, those with a historical coverage that is one standard deviation higher invests 4% less post-issuance. The economic magnitude is one quarter of the average effects from the strikes. Remaining columns in Table 3 show that the qualitative effects we document are not sensitive to controls or driven by outliers from the financial crisis. The results suggest that firms that rely more on media coverage to disseminate firm news reduces investment more sharply because of the strikes, which is consistent with the interpretation that media reports can alleviate the information friction firms face and facilitate their financing and investment.

[13]Specifically, *Les Echos* and *Le Figaro* are owned by LVMH and the Dassault Group, respectively. These groups are also the parent companies of some of the non-media firms in our sample. Subsidiaries of the Dassault Group (parent of *Le Figaro*) include Dassault Aviation and Dassault Systems; and the subsidiaries of LVMH (parent of *Les Echos*) include Bulgari and Moet. *La Tribune* was owned by LVMH from 1993 to 2007 and is currently owned by individual investors. *Le Monde* belongs to Groupe Le Monde, which does not have other subsidiaries in our sample.

2.5. Firm responsiveness and media coverage

The decomposition in Section 2.1 highlights that the aggregate effects of corporate news depend on how this news coverage is distributed across firms. Specifically, aggregate investment depends on whether the coverage is correlated with firm-level responsiveness to this news. Motivated by this, we now study the joint distribution between news coverage and the firm responsiveness. We focus on the size dimension, the strongest observed driver of these firms' news coverage.

Sorting firms into 10 size deciles, ranked from smallest to largest as $q = 1, \cdots, 10$, we estimate

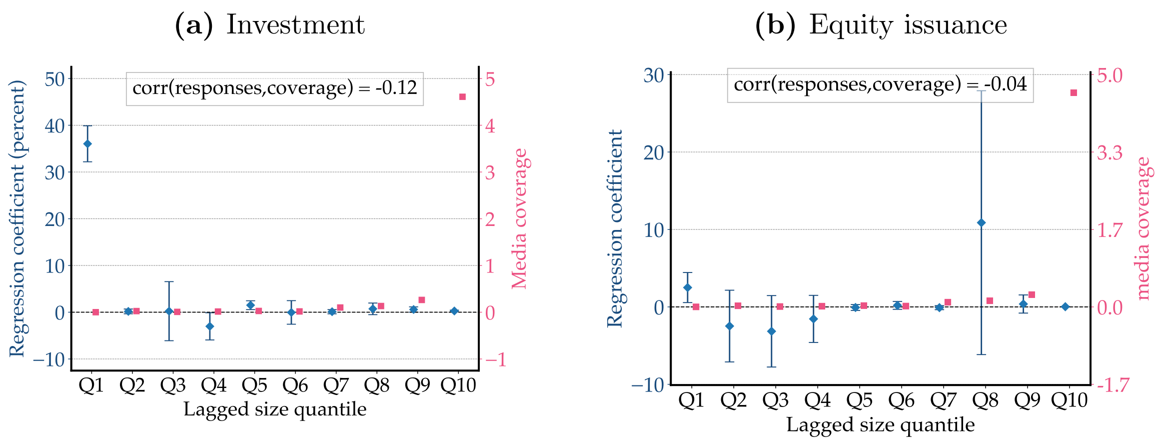
$$\Delta y_{it} = \alpha_{st} + \alpha_i + \beta_q \cdot \mathbb{1}(Q_{it-1} = q)(\nu_{it} - \mathbb{E}_i\, \nu_{it}) + \Gamma' Z_{it} + u_{it}, \tag{7}$$

where y_{it} is the firm variable of interest; $\mathbb{1}(Q_{it-1} = q)$ is an indicator variable that takes the value of 1 if a firm's size quantile in the previous quarter Q_{it-1} belongs to quantile q; $\nu_{it} - \mathbb{E}_i\, \nu_{it}$ is the news coverage of firm i that major U.S. newspapers mention in quarter t, demeaned at the firm level and standardized; $\{\alpha_{st}, \alpha_i\}$ are sector-by-quarter and firm fixed effects; Z_{it} represents a vector of standard firm controls that include sales growth, size, and current assets as a share of total assets; and u_{ith} is a random error. The firm variables of interest include (i) the cumulative investment rate, defined as the log change in the book value of the firms' tangible capital stock one year from coverage, and (ii) the firms' equity issuance one year from coverage, defined as the log equity issuance scaled by the firms' tangible capital stock. We double cluster the standard errors by firm and quarter.

The estimates for β_q are reported in Figure 5 in blue, along with 90% confidence intervals. Firms are ordered from smallest to largest, with "Q1" denoting the smallest 10% of firms and "Q10" denoting the largest 10% of firms. We overlay the estimated coefficients with the average level of media coverage from Figure 2a, reported in red on the right-hand axis.

Panel (a) shows that the smallest 10% of firms are the most responsive to media coverage. A one standard deviation higher media coverage is associated with a 36% higher investment in the year after the coverage. However, these small firms receive close to zero coverage from news outlets. In contrast, the largest 10% of firms receives substantial news coverage, but they do not respond to the media coverage through investment.

Figure 5: Media coverage and firm responsiveness by size quartile



Notes: This figure reports the results from estimating equation (7): $\Delta y_{it} = \alpha_{st} + \alpha_i + \beta_q \cdot \mathbb{1}(Q_{it} = q) \times \nu_{it} + \Gamma' Z_{it} + u_{it}$, where $\{\alpha_{st}, \alpha_i\}$ denote the sector-by-quarter and firm fixed effects; $\mathbb{1}_{Q_{it}=q}$ is an indicator variable that takes the value of 1 if a firm's size quantile within quarter Q_{it} belongs to quantile q; ν_{it} is firm i's news coverage mentioned in major U.S. newspapers in quarter t, demeaned at the firm level and standardized; and Z_{it} is a vector of firm controls including size, age, and real sales growth. The dependent variable Δy_{it} includes the cumulative investment rate in panel (a), defined as the log change in the book value of the firm's tangible capital stock one year from coverage, and the equity issuance one year from coverage in panel (b), defined as the log equity issuance scaled by the firm's tangible capital stock. Standard errors are double clustered by firm and quarter. "Q1" in the figure denotes the smallest 10% of firms, and "Q10" denotes the largest 10% of firms. 90% confidence intervals are reported.

Panel (b) finds a similar pattern for equity issuance. Among firms with equity issuance one year from the news coverage, the smallest firms issue the most equity after having received higher news coverage, while for larger firms, equity issuance do not vary significantly with coverage.

The joint distributions in Figure 5 reveals that the correlation between a firm's news coverage and its responses to this coverage is negative, measured at -0.12 for investment and -0.04 for equity issuance. The firms that receive the most coverage are those that respond the least to it, which, as equation (1) shows, will reduce the aggregate effect of news coverage on firm investment. In fact, these correlations likely understate this effect, since they measure the linear relationship between variables, and we quantify the full effect of the nonlinear relationship between coverage and firm responsiveness in Section 4.

The evidence in this section suggests that news coverage has positive effects on firms' financing and investments. However, the large firms that news outlets focus on are the least responsive to this coverage. In the next section, we incorporate these features in a macro-finance model with a media sector to quantify how the distribution of curated media reporting shapes corporate finance and firms' life cycles.

3. A Model of Corporate News Reporting

The model features heterogeneous firms who finance their activities from internal funds and by issuing equity to external investors. One key dimension of firm heterogeneity is not observed by investors, and it is this information asymmetry that creates a role for the media sector, which can reveal the unobserved state to financial markets. This setup allows us to study the consequences of the distribution of media across firms documented above.

3.1. Environment

Time is discrete and there is no aggregate uncertainty. The economy consists of four groups of agents: firms, investors, forecasters, and media outlets.

3.1.1. Firms

There is a continuum of firms, indexed by $j \in [0,1]$, that are heterogeneous in their capital quantity k, productivity z, and "capital quality" a. Capital quantity and productivity are public information for any agents in the economy, while capital quality is private information for individual firms.

At the beginning of each period, firm j inherits capital k_{jt} from the previous period. This firm also observes its idiosyncratic productivity, z_{jt}, which evolves according to

$$\log z_{jt} = \rho_z \cdot \log z_{jt-1} + \epsilon^z_{jt}, \quad \text{where } \epsilon^z_{jt} \overset{i.i.d}{\sim} \mathcal{N}(0, \sigma_z^2). \tag{8}$$

At this point, each firm receives an i.i.d. exit shock $\epsilon^{\text{exit}}_{jt} \sim \texttt{Bernoulli}(\xi)$. Firms that exit liquidate their assets and are replaced by an equal mass of firms drawn from the distribution $\mathcal{F}^{\text{entrant}}(k, z)$. Firms that remain in operation produce by using capital with the technology

$$y_{jt} = Z \cdot z_{jt} \cdot k_{jt}, \tag{9}$$

where Z denotes aggregate productivity.

After the production stage, a firm receives an i.i.d. capital quality shock, a_{jt}, to its assets in place and chooses its investment, x_{jt}. The i.i.d. assumption and the fact that capital quality shocks occur after production prevent investors from inferring a_{jt} by using observable information from previous periods. A firm's capital evolves according to

$$k_{jt+1} = (1-\delta) \cdot a_{jt} \cdot k_{jt} + x_{jt}^{\theta}, \quad \text{where } a_{jt} \overset{i.i.d}{\sim} \mathcal{G}(a). \tag{10}$$

Capital quality a_{jt} therefore affects the ability of a firm to transfer its current assets-in-place to future capital stock (as in e.g., Bigio, 2015; Gertler et al., 2019).[14]

A firm has access to external funds through an equity market. It allocates the proceeds from production and equity issuance between investment and dividend payouts. A firm's budget constraint is specified by

$$x_{jt} + div_{jt} = y_{jt} + e_{jt} - \phi^{e} \mathbb{1}_{e_{jt}>0}, \tag{11}$$

where the sources of funds consist of revenue, y_{jt}, and the funding raised from issuing new equity, e_{jt}, net of a fixed cost of issuing equity, ϕ^e; and the uses of funds consist of investment, x_{jt}, and dividend payments, div_{jt}.

Firm managers maximize the net present value of the dividend payments to the existing shareholders. Under this objective, a firm's problem is given by

$$\mathrm{V}_t(k,z,a,m) = \max_{e\geq 0} \frac{\mathrm{P}_t(k,z,a,m,e)}{\mathrm{P}_t(k,z,a,m,e)+e} \cdot \mathrm{W}_t(k,z,a,e) \tag{12}$$

Firms take media reporting m as given, where m is an indicator variable which takes the value of 1 if the firm is covered by the news media, and 0 otherwise. $\mathrm{W}_t(k,z,a,e)$, defined shortly below, denotes the firm's post-issuance value. $\mathrm{P}_t(k,z,a,m,e)$ denotes the firm's stock price, which is jointly determined by the firm's characteristics, (k,z,a), media-coverage status, m, and equity issuance choice, e. Normalizing the quantity of the existing shares to 1, a

[14] We assume that the private information a_{jt} is about the firm's existing capital, k_{jt}, rather than new investment opportunities, x_{jt}, so that firms with lower capital quality have stronger incentive to issue equity and issuing equity is viewed as a negative signal from investors' perspective. If the private information is over new investment opportunities, then firms with better investment opportunities will be those that have stronger incentive to issue equity. In this case, as noted by Myers and Majluf (1984), equity issuance event is associated with stock price increases on average, which is inconsistent with empirical evidence (e.g., Choe et al., 1993).

firm needs to issue an additional $\frac{e}{\mathrm{P}_t(k,z,a,m,e)}$ shares to external investors to raise funding e. Therefore, $\frac{\mathrm{P}_t(k,z,a,m,e)}{\mathrm{P}_t(k,z,a,m,e)+e}$ is the share of the firm value accruing to its initial shareholders after any subsequent equity issuance.

$\mathrm{W}_t(\cdot)$ characterizes a firm's value after an equity issuance by incorporating the firm's optimal investment and dividend payment decisions, specified as

$$\mathrm{W}_t(k,z,a,e) = \max_{div \geq 0, x \geq 0} div + \beta \mathbb{E}_t \left[\xi \hat{\mathrm{V}}_{t+1}(k') + (1-\xi) \mathrm{V}_{t+1}(k', z', a', \mathbf{m}_{t+1}(k', z', a', \kappa')|z \right] \tag{13}$$

$$\text{s.t.} \qquad x = Z \cdot z \cdot k + e - \mathbb{1}_{e>0} \phi^e - div \tag{14}$$

$$k' = (1-\delta) \cdot ak + x^\theta, \tag{15}$$

where $\hat{\mathrm{V}}_t(k) \equiv k$ denotes the firm's liquidation value, and $\mathbf{m}_t(\cdot)$ denotes the aggregate media-reporting function, which we characterize in Section 3.1.3. In the remainder of the paper, we denote the firm's policy functions of equity issuance, dividend payments, and investments using bold letters as $\mathbf{e}_t(k,z,a)$, $\mathbf{div}_t(k,z,a)$, and $\mathbf{x}_t(k,z,a)$.

3.1.2. Investors

There is a continuum of risk-neutral retail investors who purchase firm equity to maximize their expected returns. Investors observe each firm's capital, k, and productivity, z, along with their equity issuance decisions, e. They cannot, however, observe a firm's capital quality, a, and must make inferences about it based on media reports and firm behavior.

When a firm is reported by media outlets, its asset quality is fully revealed. When a firm is not reported by the media, investors must instead form a posterior belief about that firm's asset quality, based on its equity issuance choice.[15]

Let $\mathcal{B}_t(a|k,z,e)$ denote the density function of investors' beliefs about a firm's asset quality when this firm is unreported. For equity issuance on the equilibrium path, investors'

[15]Strictly speaking, investors also update their posteriors after observing that the firm has not been reported, analogously to the mechanism in Nimark (2014). In practice, this is irrelevant in our case because we will show that the media equilibrium features reporting which is independent of a. This implies that an editor's decision to not report on firm j provides investors with no information about a_{jt}. For notational simplicity, we therefore omit this aspect of posterior updating from the equations in the text.

beliefs satisfy Bayes' rule

$$\mathcal{B}_t(a|k,z,e) = \frac{\mathcal{G}(a)\mathbb{1}(\mathbf{e}_t(k,z,a,0)=e)}{\int \mathcal{G}(\tilde{a})\mathbb{1}(\mathbf{e}_t(k,z,\tilde{a},0)=e)d\tilde{a}}. \tag{16}$$

For equity issuance that are off the equilibrium path, investors' beliefs satisfy the Divinity Criterion specified in Banks and Sobel (1987).[16]

Given investors' beliefs about a firm's asset qualities, its equity issuance prices must satisfy the break-even condition for investors, so that the expected return from purchasing the newly issued equity equals the risk-free interest rate. That is, for any equity issuance $e > 0$,

$$e = \begin{cases} \frac{e}{\mathrm{P}_t(k,z,a,1,e)+e} \cdot \mathrm{W}_t(k,z,a,e) & \text{if } m=1 \\ \frac{e}{\mathrm{P}_t(k,z,a,0,e)+e} \cdot \int \mathrm{W}_t(k,z,a,e)\cdot \mathcal{B}_t(\tilde{a}|k,z,e)d\tilde{a} & \text{if } m=0, \end{cases} \tag{17}$$

which implies that the equity issuance price is

$$\mathrm{P}_t(k,z,a,m,e) = \begin{cases} \mathrm{W}_t(k,z,a,e) - e & \text{if } m=1 \\ \int \mathrm{W}_t(k,z,a,e)\cdot \mathcal{B}_t(\tilde{a}|k,z,e)d\tilde{a} - e & \text{if } m=0. \end{cases} \tag{18}$$

For firms issuing equity, their issuance price determines their stock market value. For firms not issuing equity, their stock market value is determined by the expected value of the firms. Therefore, firms' stock market valuations are determined by

$$\mathrm{MV}_t(k,z,a,m) = \begin{cases} \mathrm{P}_t(k,z,a,m,\mathbf{e}_t(k,z,a,m)) & \text{if } \mathbf{e}_t(k,z,a,m) > 0 \\ \frac{\int \mathrm{V}_t(k,z,\tilde{a},m)\mathbb{1}_{\mathbf{e}_t(k,z,\tilde{a},m)=0}\mathcal{G}(\tilde{a})d\tilde{a}}{\int \mathbb{1}_{\mathbf{e}_t(k,z,\tilde{a},m)=0}\mathcal{G}(\tilde{a})d\tilde{a}} & \text{if } \mathbf{e}_t(k,z,a,m) = 0. \end{cases} \tag{19}$$

3.1.3. Media

There is a continuum of media outlets, indexed by $i \in [0,1]$, that have full information on all firm fundamentals, including their asset qualities a_{jt}. Each outlet is owned by a

[16] According to the Divinity Criterion, for any off-equilibrium equity issuance, investors assign positive probability only to those firms that are most likely to gain by deviating from their equilibrium issuance to this particular off-equilibrium amount. Appendix B.3 defines the Divinity Criterion in the context of our model (Definition 1) and proves that the belief that supports our equilibrium satisfies the Divinity Criterion.

corresponding forecaster, who reads the news in their outlet and not in other outlets. A media outlet selects the set of firms to report on to maximize its forecaster's expected utility, specified below.[17]

Let $m^o_{ijt} \in \{0,1\}$ denote the reporting decision of media outlet i of firm j. If $m^o_{ijt} = 1$, outlet i reports the exact a_{jt} to its associated forecaster in period t. If $m^o_{ijt} = 0$, outlet i does not report on firm j and transmits no information about a_{jt}. Throughout the paper, we differentiate between m^o_{ijt}—which denotes the reporting choices of an individual news outlet i—and m_{jt}, which denotes the aggregate news-reporting outcome for firm j, and is defined in equation (24) below.

When selecting firms to report on, outlets face constraints, such as physical newspaper space or limited reader attention capacity. As a result, they can only report on a fraction $r \in (0,1)$ of firms in each period:

$$\int_0^1 m^o_{ijt} dj = r. \tag{20}$$

Outlet i's decision problem is to choose firms to report on in order to maximize the expected utility of their forecaster, net of a firm and period-specific reporting cost $\kappa_{jt} \sim \mathcal{H}(\kappa)$, which is independent of firm j's fundamentals.[18] Their problem is given by

$$\max_{m^o_{ijt}} \mathbb{E} \int_0^1 \mathrm{U}_{it}(\mathcal{I}^{\text{news}}_{it}) dj - \int_0^1 \kappa_{jt} m^o_{ijt} dj \tag{21}$$

$$\text{s.t.} \qquad \mathcal{I}^{\text{news}}_{it} = \{a_{jt} : m^o_{ijt} = 1\} \tag{22}$$

$$r = \int_0^1 m^o_{ijt} dj \tag{23}$$

where $\mathrm{U}_{it}(\mathcal{I}^{\text{news}}_{it})$ denotes forecaster i's utility, which we specify in the next subsection, and $\mathcal{I}^{\text{news}}_{it}$ is the information set communicated to the forecaster by their outlet.

Investors are assumed to observe all of the information reported in all of the outlets.[19]

[17]See Armona et al. (2024) for an example of another model with this feature and a discussion of how such "direct maximization" incentives may arise.

[18]These should be thought of as cognitive or effort costs, similar to the information processing costs in the rational inattention literature (surveyed by Maćkowiak et al., 2023). These costs arise from the media outlets and so are different from the attention capacity of readers used to motivate the space constraint (20). Equivalently, κ_{jt} could also capture the variation in the reporting preferences that are due to factors outside our model. These costs allow us to derive a continuous reporting probability function but are not essential.

[19]This assumption can be microfounded as follows: Since there is no noise in the market prices in this model (unlike e.g., Grossman and Stiglitz, 1980), the market prices perfectly aggregate the information. If

Therefore, the investors' information set includes the *total* information reported in the media. We denote this total media information set as $\mathcal{I}_t^{\text{news}} = \{a_{jt} : m_{jt} = 1\}$, where the aggregate news-reporting indicator m_{jt} is defined as

$$m_{jt} = \begin{cases} 0 & \text{if } m^o_{ijt} = 0 \text{ for all } i \\ 1 & \text{otherwise.} \end{cases} \tag{24}$$

That is, if at least one outlet reports on firm j, then investors observe a_{jt}. In the remainder of the paper, we summarize the dependency of the aggregate media-reporting outcomes on firm characteristics through an aggregate media policy function, $\mathbf{m}_t(k_{jt}, z_{jt}, a_{jt}, \kappa_{jt}) = m_{jt}$.

3.1.4. Forecasters

The forecaster's objective, which media outlets aim to maximize, concerns the average forecast errors made about firm market values when using the information provided by that outlet. This is motivated by the intuitive idea that media outlets wish to gain a reputation for providing timely and relevant information to their readers.[20]

Specifically, forecaster i observes the information communicated by outlet i, $\mathcal{I}_{it}^{\text{news}}$, along with the observables k_{jt} and z_{jt}. They make forecasts of firms' market values before equity markets open each period, and so cannot observe equity issuance e_{jt}. We assume that forecasters are able to observe the reporting decisions of other outlets, $m^o_{i'jt}$, but not the contents of those reports, $\mathcal{I}_{i',t}^{\text{news}}$. The former assumption implies that forecasters also observe the aggregate news-reporting outcome m_{jt}. The latter assumption implies that forecasters do not observe a_{jt} unless their own outlet reports on it.

As in the literature on forecaster incentives (reviewed by Marinovic et al., 2013), forecasters derive utility from making market value forecasts that are more accurate than their peers. As shown by (19), the market value is a function of firm fundamentals (k_{jt}, z_{jt}, a_{jt})

even one investor reads the news published by outlet i, they use that information to trade and the market prices adjust to communicate that information to all other investors.

[20]The Financial Times, for example, famously used the slogan "No FT, no comment" from 1982-2006, implying that the paper was required reading for people to be informed on relevant (market) news. More recently, in 2022 they launched the slogan "Make sense of it all," with a similar interpretation.

and the aggregate news-reporting indicator m_{jt}. We therefore specify forecaster i's utility as

$$\mathrm{U}_{it}(\mathcal{I}_{it}^{\text{news}}) \equiv -\int_0^1 \left[\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}) - \overline{\mathrm{FE}}_{-it}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{-it}^{\text{news}})\right] dj. \tag{25}$$

The first component of equation (25) represents the realized forecast errors that forecaster i makes about firm j, defined as

$$\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}) \equiv \left[\mathrm{Pred}_t\left(k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}\right) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt})\right]^2, \tag{26}$$

where $\mathrm{Pred}_t(k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}})$ denotes the forecaster i's prediction. The second component of equation (25) represents the realized average forecast error from forecasters other than i, defined as

$$\overline{\mathrm{FE}}_{-it}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{-it}^{\text{news}}) \equiv \int_{i'\neq i} \left[\mathrm{Pred}_t\left(k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{i',t}^{\text{news}}\right) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt})\right]^2 di'. \tag{27}$$

This formulation implies that a forecaster gains utility from having low average ex-post forecast errors, relative to the forecast errors made by other forecasters using news from other outlets. A forecaster sets the prediction $\mathrm{Pred}_t\left(k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}\right)$ to maximize the expected utility, where the expectation is formed conditional on the forecaster's restricted information set. Since the forecaster's choice has no effect on the realized market values, or the forecasts of others, this is equivalent to minimizing $\overline{\mathrm{FE}}_i(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}})$, which is achieved by each forecaster setting predictions equal to the rational expectation of each firm's value, given that forecaster's information set:

$$\mathrm{Pred}_t(k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}) = \mathbb{E}\left[\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}) | k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}\right]. \tag{28}$$

3.2. Model assumptions and robustness

Before proceeding to the definition of equilibrium, we discuss our key assumptions regarding news reporting and examine the robustness of our model to altering our assumptions.

First, we assume that the objective of the media is to provide its readers with better information, consistent with the notion of newsworthiness by Armona et al. (2024) and the contest model by Ottaviani and Sørensen (2006). In Appendix D, we consider an alternative microfoundation, in which media outlets maximize the sale of their newspapers to investors. In this investor-led model of the media, we introduce *noise traders*, as in Grossman and Stiglitz (1980), which prevent asset prices from perfectly aggregating information. This implies there is a non-degenerate demand for news from investors.[21] We show that this distinct model of the media leads to the same equilibrium news-reporting function as the one we derive below. Since solving this investor-led model of the media requires abstracting from much of the firm side of the model presented here, we keep to the forecaster model for our quantitative analysis.

Second, outlet i's objective function depends on the reporting of other outlets, through $\overline{FE}_{-it}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{-it}^{\text{news}})$, and the realized market values. We assume that when choosing to report m_{ijt}^o, outlet i takes the reporting decisions of other outlets, $m_{-i,j,t}^o$, as given. This is a common assumption in media models, as strategic motives quickly make the model intractable. In our case, it is a simple consequence of the fact that we have a continuum of outlets, so each individual outlet is atomistic and has no impact on the mass of other outlets. The same setup features in, for example, Eliaz and Spiegler (2024), while others use monopoly media supply (Martineau and Mondria, 2022) or the restrictions on media demand (Gentzkow and Shapiro, 2010) to achieve the same removal of strategic reporting incentives. For an example, to see where strategic interactions do occur, refer to Perego and Yuksel (2022).

Third, the media outlet's objective depends on the expectation of U_{it}, taken before the forecaster observes information and makes their prediction. The objective in (21) is, therefore, conditional on the information available to the forecaster when their reporting decisions are made. One way to interpret this baseline formulation, then, is that equations (21)-(23) reflect the reporting problem of an outlet that directly gains utility from generating low relative forecast errors as in equation (25). In principle there is no need for a separate "forecaster" agent. However, we maintain the separation here because small changes in the outlet problem would render the distinction relevant.

We consider several of these alternative assumptions on the media outlets' objective functions in Appendix B.2, including the case when the outlets maximize their *realized*

[21]Without noise traders, prices aggregate investor information, so each individual investor can free-ride on the information acquisition of other investors and, therefore, does not demand news from the media.

utility. Under this assumption, the media outlets observe all firm state variables before choosing which firm to report on and therefore have more information available than their forecasters. Appendix B.2 shows that while such a change has an effect on the exact form of the outlets' equilibrium reporting decisions, the key qualitative characteristics of the reporting functions are robust to these alternative assumptions.

3.3. Equilibrium

The equilibrium consists of the paths for the firms' distributions $\mathcal{F}_t(k, z)$, aggregate media reporting $\mathbf{m}_t(k, z, a, \kappa)$, firms' value functions $\mathrm{V}_t(k, z, a, m)$, policy functions for equity issuance $\mathbf{e}_t(k, z, a, m)$, dividend payouts $\mathbf{div}_t(k, z, a, m)$, investments $\mathbf{x}_t(k, z, a, m)$, investor beliefs $\mathcal{B}_t(a|k, z, e)$, equity issuance prices $\mathrm{P}_t(k, z, a, m, e)$, and the firms' stock market values $\mathrm{MV}_t(k, z, a, m)$ that satisfy the following:

1. given the firm distribution $\mathcal{F}_t(k, z)$ and firms' stock market valuations $\mathrm{MV}_t(k, z, a, m)$, the media outlets determine their reporting choices $\{m^o_{ijt}\}$, which in turn determine the aggregate media reporting $\mathbf{m}_t(k, z, a, \kappa)$;

2. given the equity issuance price function $\mathrm{P}_t(k, z, a, m, e)$, the firms make their optimal choices of equity issuance $\mathbf{e}_t(k, z, a, m)$, dividend payouts $\mathbf{div}_t(k, z, a, m)$, and investments $\mathbf{x}_t(k, z, a, m)$;

3. given the media-reporting function $\mathbf{m}_t(k, z, a, \kappa)$ and the firms' equity issuance policies $\mathbf{e}_t(k, z, a, m)$, investors form their posterior beliefs $\mathcal{B}_t(a|k, z, e)$ on the asset quality of the unreported firms, which satisfies Bayes' rule for equity issuance e on the equilibrium path and the Divinity Criterion for equity issuance e off the equilibrium path;

4. given the posterior belief $\mathcal{B}_t(a|k, z, e)$ and firms' financing and investment policies, the equity prices satisfy the break-even conditions in the equity markets as specified by (18);

5. given the firms' value functions $\mathrm{V}_t(k, z, a, m)$ and equity issuance price function $\mathrm{P}_t(k, z, a, m, e)$, the firms' stock market valuations $\mathrm{MV}_t(k, z, a, m)$ are specified by (19); and

6. the firms' distributions evolve according to

$$\begin{aligned}\mathcal{F}_{t+1}(k',z') =& \xi \cdot \mathcal{F}^{\text{entrant}}(k',z') \\ &+ (1-\xi) \cdot \int \Gamma^z(z'|z) \cdot \mathbb{1}_{\mathbf{k}'_t(k,z,a,\mathbf{m}_t(k,z,a,\kappa))=k'} \mathcal{F}_t(k,z,a)\mathcal{G}(a)dkdzda,\end{aligned} \tag{29}$$

where $\Gamma^z(z'|z)$ denotes the transition probability of firms' idiosyncratic productivity and $\mathbf{k}'_t(k,z,a,m) \equiv (1-\delta)ak + \mathbf{x}_t(k,a,z,m)$.

3.3.1. Equilibrium equity issuance

When a firm is unreported by the media, investors infer its capital quality based on its equity issuance. Appendix B.3 characterizes the equity market equilibrium, in which firms' equity issuance are constrained by the "lemon threat" (Guo et al., 2024): As in Myers and Majluf (1984), a big equity issuance is associated with low asset quality, since such low-quality firms are more willing to exchange ownership of existing capital for funding future investment opportunities. However, because of the information asymmetry, a low-quality firm has the incentive to mimic a high-quality firm's (smaller) equity issuance to attract better pricing by investors. This lemon threat leads a higher-quality firm to under-issue its equity in equilibrium, in order to credibly signal its asset quality to investors and to deter mimicked from its lower-quality peers.

When a firm is reported by media outlets, investors observe the firm's true capital quality, enabling the firm to issue equity without facing the lemon threat. As a result, news reports can relieve a firm from making costly signaling efforts, thereby encouraging greater equity issuance and increasing investment, particularly among high-quality firms.

3.3.2. Equilibrium news-reporting function

We now characterize the reporting decisions of media outlets in equilibrium. Since media outlets and forecasters are ex-ante identical, we focus our analysis on symmetric equilibria in pure strategies.[22] Proposition 1 characterizes the media's equilibrium reporting decisions.

[22]Since forecasters are identical, the motives for media specialization studied in Nimark and Pitschner (2019) and Perego and Yuksel (2022) (among others) are absent. In principal, there can be mixed-strategy equilibria. We focus on pure-strategy equilibria to provide economic insights while minimizing theoretical complexity. Under pure strategy equilibria, m^o_{ijt} is entirely determined by firm j's state variables and there is no randomness in the outlet's reporting decisions. Armona et al. (2024) similarly focus on pure-strategy

***Proposition* 1.** *There is a unique news-reporting policy that can be sustained in a symmetric equilibrium, which is given by*

$$m_{jt} = \mathbb{1}(\mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) - \kappa_{jt} \geq \mathrm{N}_t^*), \tag{30}$$

where the newsworthiness function $\mathrm{N}_t(k_{jt}, z_{jt})$ *is defined as*

$$\mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) = \mathbb{V}[\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)|k_{jt}, z_{jt}], , \tag{31}$$

and the threshold N_t^* *is determined by the space constraint* (20)*:*

$$\int_0^1 \mathbb{1}(\mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) - \kappa_{jt} \geq \mathrm{N}_t^*)dj = r. \tag{32}$$

Proof. Appendix B.1.1 □

Appendix B.1.1 details the proof. To find a news-reporting policy, we begin by considering an arbitrary candidate reporting policy. We then show that there is a unique candidate reporting policy from which no outlet would find it optimal to deviate, since any deviation would lead to an increase in relative forecast errors.

Proposition 1 specifies the media's reporting behavior and equation (31) defines the equilibrium newsworthiness function that drives it. A media outlet ranks firms by their newsworthiness and reports on the top newsworthy firms until its space constraint is reached. A firm is newsworthy if there is a large degree of uncertainty (i.e., high variance) about its market value after observing its capital stock and productivity.

Equation (30) implies that the probability that firm j is reported in the news, denoted by $\mathrm{R}_t(k_{jt}, z_{jt}, a_{jt})$, is given by

$$\mathrm{R}_t(k_{jt}, z_{jt}, a_{jt}) = \Pr(\kappa_{jt} \leq \mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) - \mathrm{N}_t^*) = \int_0^{\mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) - \mathrm{N}_t^*} \mathcal{H}(\kappa) d\kappa. \tag{33}$$

By choosing an appropriate distribution of the reporting costs $\mathcal{H}(\kappa)$, we can match the equilibrium reporting policy to the empirical facts documented in Section 2. In the remainder of the paper, because (31) implies that a firm's newsworthiness is only determined by its pub-

reporting equilibria, with applications to macroeconomic and non-economic news.

licly observable characteristics (k_{jt}, z_{jt}), we simplify the notation of the firm's newsworthiness and reporting probability functions to $\mathrm{N}_t(k, z)$ and $\mathrm{R}_t(k, z)$.

4. Quantitative Analysis

In this section, we study the quantitative importance of the distribution of news reporting. We first present our calibration of the model parameters, paying particular attention to how we use our data to discipline the media-reporting behavior in the model. We then verify the fit of our model by comparing model-implied firm responses with the empirical findings in Section 2. Finally, using the calibrated model, we examine how media reporting affects firms' investments and financing, and how the distribution of media reports shapes the macroeconomic effects of the media. Since there is no aggregate uncertainty in our model, our discussion will focus on the steady state of the economy.

4.1. Calibration

We calibrate the model quarterly to match publicly traded firms between 1990 and 2021. We first set the discount rate to $\beta = 0.99$, which corresponds to a 4% annual real interest rate, and the exogenous exit probability to $\xi = \frac{7.7\%}{4}$, which is consistent with an average exit rate of 7.7% in the Compustat sample. Then, we calibrate the parameters listed in Table 4a to target the empirical moments in Table 4b. The construction of empirical moments is detailed in Appendix C.1.

The calibrated parameters are divided into five groups. The first three (cash flow, investment technology, and life-cycle dynamics) include standard parameters on firm dynamics, which we calibrate following existing approaches. The last two groups govern financial and information frictions in the economy. Given their importance for gauging the role of the media, we discuss their calibration in greater detail below.

4.1.1. Firm dynamics

Cash flow level and dynamics The aggregate productivity, Z, corresponds to the steady-state level of the average operating cash flow rate. Since the aggregate productivity determines firms' average level of internal financing, we calibrate it to match the average operating

Table 4: Model calibration

(a) Calibrated parameters

Parameter		Value
Cash flow		
Z	Level of aggregate productivity	2.25%
ρ_z	Idiosyncratic productivity, persistence	0.95
σ_z	—, innovation standard deviation	0.11
Investment technology		
δ	Depreciation rate	3.3%
θ	Return-to-scale of investment technology	0.81
Life-cycle dynamics		
$\mu^{\text{entrant}}_{\log z}$	Entrants, average (log) productivity	-0.175
$\mu^{\text{entrant}}_{\log k}$	—, average (log) size	-1.761
Information and financial friction		
σ_a	Dispersion of capital quality shock	0.18
ϕ^e	Fixed cost to issuing equity	0.06%
Selective media reporting		
λ_ξ	Curvature of reporting probability	3.35
$(\lambda_\alpha, \lambda_p)$	Location of reporting probability function	(0.8, 0.3)

(b) Targeted moments

Moment	Data	Model
Cash flow (annual, %)		
Operating cash flow rate, mean	10.23	10.98
Idiosyncratic TFP, persistence	0.78	0.70
–, std	0.38	0.39
Investment rate (annual, %)		
Mean	6.00	6.10
Std	5.53	5.58
Life-cycle dynamics		
Growth rate, young minus mature firms	-0.106	-0.105
Idiosyncratic TFP, –	0.075	0.075
Equity financing (%)		
Fraction of firms issuing equity, annual mean	17.90	18.09
Issuance fee ratio, mean	2.17	2.19
Selling concession ratio when issuing, mean	2.97	2.91
Media reporting		
Avg. reporting probability, top vs. bottom 20%	175	176

Notes: This table reports calibrated parameters and targeted moments. All moments are measured based on firms in the Compustat sample from 1990 and 2021, and the definition and measurement of target moments are detailed in Appendix C.1. In Panel (a), ϕ^e is normalized by the average annual profit of the firm population. In Panel (b), the operating cash flow rate and investment rate refer to firms' operating cash flow and investment normalized by their capital stock. The issuance fee ratio is defined as the fixed cost paid by the issuing firms, normalized by their issuance quantity. The selling concession when issuing equity is measured as the log-difference between a firm's stock price before and after revealing its equity issuance decision. Both moments related to equity issuance costs are from Lee and Masulis (2009). The average reporting probability between the top and bottom 20% is defined as the ratio between the average reporting probabilities of the firms in the top and bottom 20% of the market capitalization percentile.

cash flow rate in the data. The idiosyncratic productivity shock, z, is the source of the cash flow risk firms face, which shapes the firms' ex-post heterogeneity and the precautionary motives in their investment decisions. We calibrate the idiosyncratic productivity's persistence and volatility to match the empirical estimates from İmrohoroğlu and Tüzel (2014).

Investment technology and capital accumulation We calibrate the depreciation rate, δ, to match the average investment rate at which firms replenish their depreciated capital and grow. The return-to-scale of investment technology, θ, governs the sensitivity of firms' investments to their capital profitability. We set $\theta = 0.81$ to target the cross-sectional standard deviation of firms' investment rates.

Life-cycle dynamics The ex-post heterogeneity among firms is shaped by the dynamics of the firms' idiosyncratic productivity and the distribution of the entrants. Two parameters of the entrant distribution, $\{\mu^{\text{entrant}}_{\log z}, \mu^{\text{entrant}}_{\log k}\}$, govern the variation across firms in different age groups.[23] Therefore, we calibrate the entrant distribution parameters to match the differences in the growth rate and the measured idiosyncratic TFP between young firms (age ≤ 5) and matured firms (age > 25).

4.1.2. Financial and information frictions

Firms face two frictions for raising equity financing: a fixed cost of equity issuance and an implicit cost arising from asymmetric information. The fixed cost captures all of the explicit expenses related to the administrative and marketing activities necessary for issuing equity. We calibrate the fixed cost to match the average management and underwriting fee ratio reported by Lee and Masulis (2009). The friction caused by asymmetric information is captured by the dispersion of the capital quality shocks. We calibrate the dispersion to match the average selling concession of seasonal equity offerings as reported by Lee and Masulis (2009).[24] Based on our calibrated costs for equity issuance and capital quality dispersion, we further calibrate the media-reporting function to match the average probability of firms issuing equity and the cross-sectional distribution of the media coverage, as documented in Section 2.

Parameterization of the media-reporting policy Equation (33) implies that the probability of a firm being reported is an increasing function of its newsworthiness, $\mathrm{N}_t(k, z)$. Under this relationship, selecting a $\mathrm{R}_t(k, z)$ function is equivalent to selecting a cost distribution, $\mathcal{H}(\kappa)$. Therefore, we work directly with the reporting probability, parameterizing it using the generalized hazard function

$$\mathrm{R}_t(k, z) = \frac{\lambda_p}{\lambda_p + (1 - \lambda_p)(\frac{\lambda_\alpha}{\mathcal{Q}_t(k,z)})^{\lambda_\xi}}, \tag{34}$$

[23] We parameterize the entrant distribution $\mathcal{F}^{\text{entrant}}(z, k)$ as a mixture of two independent normal distributions of the firms' log productivities and log sizes: $\log z \sim \mathcal{N}(\mu^{\text{entrant}}_{\log z}, 0.01)$ and $\log k \sim \mathcal{N}(\mu^{\text{entrant}}_{\log k}, 0.01)$. The standard deviation is set to be 0.01, which is a sufficiently small value to smooth the distribution without affecting the results.

[24] The selling concession represents the stock price reduction that issuing firms must offer investment banks to secure their guarantee for flotation. We measure the average price concession using the average stock price drop after the announcement of an equity issuance decision. The average selling concession rate (2.97%), reported in Lee and Masulis (2009), is within the range of the empirical estimates for the stock price drop associated with the stock issuance (2%∼3%), as documented in the literature. Appendix C.1 provides further details.

where $\lambda_\xi > 1$, $\lambda_\alpha \in (0,1)$, $\lambda_p \in (0,1)$, and $\mathcal{Q}_t(k,z)$ denotes the percentile location of the newsworthiness of a firm with the idiosyncratic observable state (k,z).

With this parameterization, the probability of being reported increases monotonically with firms' newsworthiness and lies between 0 and 1. As a result, there exists some distribution $\mathcal{H}(\kappa)$ that generates this reporting probability function in equation (33). Calibrating $\mathrm{R}_t(k,z)$ directly in this way provides a clearer match between the model and the data, compared to a calibration strategy based explicitly on $\mathcal{H}(\kappa)$.[25] Similarly, specifying equation (34) in terms of the percentile rank $\mathcal{Q}_t(k,z)$—itself a positive monotonic transformation of newsworthiness $\mathrm{N}_t(k,z)$—is consistent with our use of binned scatter plots and regression specifications in Section 2.

Each parameter of equation (34) captures a distinct aspect of how the reporting probability depends on a firm's newsworthiness ranking. As shown in Figure 6a, $\{\lambda_\alpha,\ \lambda_p\}$ are the location parameters: a firm with a newsworthiness percentile of λ_α has a reporting probability of λ_p. Once the newsworthiness percentile exceeds λ_α, the probability of being reported increases rapidly. The rate of this increase is governed by the parameter λ_ξ: a higher λ_ξ implies a steeper increase in the reporting probability.

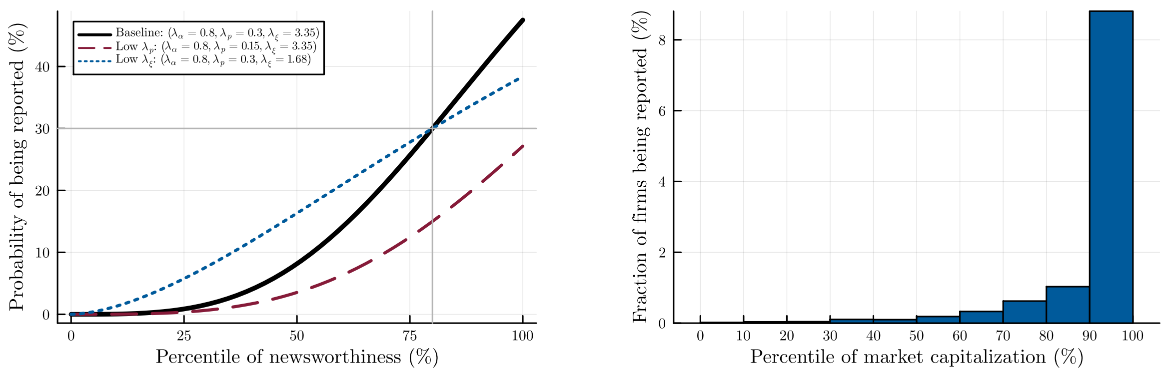
Calibration of the media-reporting policy The ideal empirical moments for disciplining media-reporting parameters would be the relationship between the probability of media coverage and a firm's newsworthiness. However, these moments are not directly observed for three reasons. First, a firm's newsworthiness depends on the variance of the stock market value taken before the equity markets open, conditional on that firm being reported in the media (equation (31)), which is neither directly observed nor priced in options contracts. Second, we do not observe a firm's probability of being reported, only the realization of the reporting found in the data (i.e., whether a firm is reported or not reported). Finally, the three newspapers in our sample represent only a subset of the total news reporting. To address these measurement challenges, we take an alternative calibration approach, inferring the media-reporting function indirectly by targeting two groups of moments.

First, we calibrate λ_α and λ_ξ to match how the share of firms with newspaper coverage

[25] This approach of working directly with hazard functions, rather than the underlying cost distributions, is common in the literature on "lumpy adjustments" of prices, investment, and other firm choices (Caballero and Engel, 1999; Alvarez et al., 2022).

Figure 6: Calibration of the media-reporting policy

(a) Parameterization **(b)** Data moment



Notes: This figure provides details for the calibration of the media-reporting policy. Panel (a) reports how the media-reporting policy varies with the parameters of the generalized hazard function, (λ_α, λ_p, λ_ξ). Panel (b) reports how the average reporting probability varies by the market capitalization in the data. The data moments in Panel (b) are based on the Compustat sample between 1990 and 2021. Firms are sorted into deciles of market capitalization within quarters. For each decile of firms, we report the cross-time average of the share of firms being reported by the media.

varies across market-capitalization percentiles. Figure 6b reports the empirical distribution from the data introduced in Section 2. Firms below the 80th percentile receive minimal coverage, while coverage rises sharply at the 80% threshold. To capture this pattern, we set λ_α to 0.8 and calibrate λ_ξ to 3.35 to match the news-coverage ratio between firms in the top and bottom 20th percentiles of the stock market valuations. Appendix Section B.1.2 shows that this ratio is invariant to the overall level of coverage, as it targets the cross section of data..

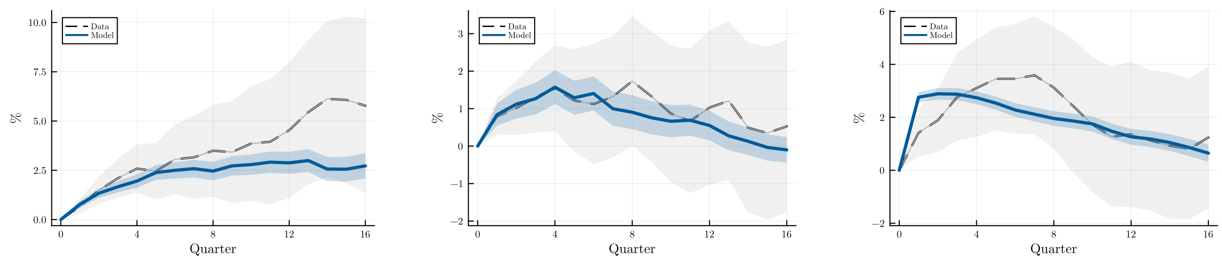
Second, we calibrate λ_p to match the average share of firms with equity issuance each period. With a given fixed cost of equity issuance and dispersion in the capital quality, a greater λ_p implies a higher probability of media coverage, which reduces information frictions, and thus makes firms more likely to issue equity. Therefore, we use the average fraction of firms issuing equity as our target moment to calibrate λ_p. Under this calibration, the average probability of a firm being reported is 13.7% in each quarter.

4.2. Model validation

As in our main empirical analysis, our model features two-way causation between firms and the media: media outlets endogenously select which firms to report based on firm characteristics, and media coverage affects subsequent firm behavior. Before analyzing each

Figure 7: Average effects of media reporting

(a) Investment rate **(b)** Investment surge **(c)** Equity issuance



Notes: This figure reports, in blue, variants of the baseline local projections in equation (3) using the model generated data, for quarters $1 \leq h \leq 16$: $\Delta_h y_{it} = \alpha_i + \beta_h \mathbb{1}(m_{it} > 0) + \Gamma' Z_{it-1} + u_{ith}$, where α_i is a firm fixed effects; $\mathbb{1}(m_{it} > 0)$ is an indicator variable which takes the value of 1 if firm i has any coverage in quarter t, and 0 otherwise; and Z_{it-1} is a vector of firm controls including size, age, and real sales growth. The dependent variable $\Delta_h y_{it}$ includes (a) the log change in capital stock $\log(k_{it+h}) - \log(k_{it})$; (b) the cumulative probability of investment surge between t and $t+h$, defined as $\mathbb{1}\left(\max_{1 \leq \tau \leq h} \log(k_{i,t+\tau}) - \log(k_{i,t+\tau-1}) > 20\%\right)$; and (c) the cumulative probability of equity issuance, defined as $\mathbb{1}\left(\max_{1 \leq \tau \leq h} e_{it+\tau} > 0\right)$. The standard errors are clustered at the firm level and 90% confidence intervals are reported. To facilitate the comparison with our empirical evidence, we repeat our results in Figure A.3 in gray in each plot.

channel separately, we validate our model by estimating the same local projections in Section 2.4 on simulated data from the model.

We simulate a panel of 3000 firms over 32 years, which matches the sample size and period of our empirical analysis, and estimate a variant of the local projections in equation (3) using the simulated data:

$$\Delta_h y_{it} = \alpha_i + \beta_h \mathbb{1}(m_{it} > 0) + \Gamma' Z_{it} + u_{ith}, \tag{35}$$

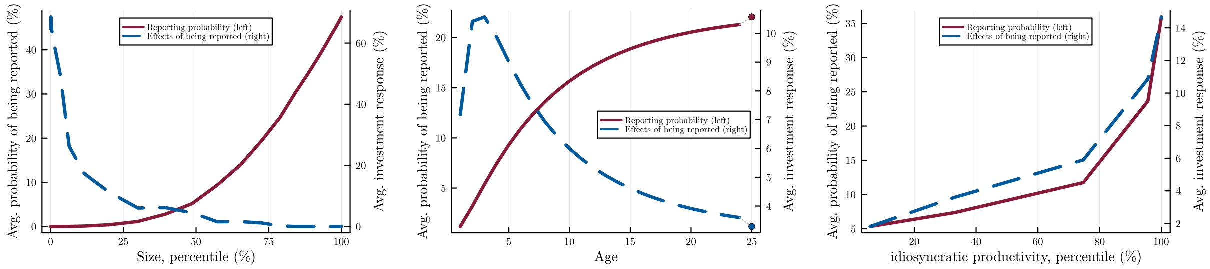
where, as in Appendix Figure A.3, the explanatory variable is $\mathbb{1}(m_{it} > 0)$, a binary variable for whether firm i receives media coverage in quarter t. We use this binary measure for its transparency and simplicity, and omit sector-by-year fixed effects since the model does not include aggregate shocks.

Figure 7 reports the model-implied local projection results in blue, alongside their empirical counterparts in gray, repeated from Figure A.3. The model closely replicates both the magnitudes and the dynamics of the empirical responses, particularly for investment surges in panel (b). While it somewhat under-predicts investment response at longer horizons in panel (a), the estimates remain within the 90% confidence intervals of the empirical estimates.

Importantly, these impulse responses were not targeted in our calibration, so they rep-

Figure 8: Cross-sectional pattern of media reporting and its effects on firms' investments

(a) By size **(b)** By age **(c)** By idio. productivity



Notes: This figure plots the variation of the quarterly average probability of being reported (red solid lines) and the effects of being reported (blue dash lines) along size (capital stock), idiosyncratic productivity, and age. In this figure, the "effects of being reported" refers to the log-difference in a firm's investment between when it is reported and when it is not. The dots in Panel (b) represent firms aged ≥ 25.

resent a useful validation of the model's ability to match our empirical evidence. Having verified the fit of the model, we proceed in the next subsections to quantify (*i*) the selection in media reporting, (*ii*) the effects of media reporting on firms' investment and financing, and (*iii*) the aggregate importance of the joint distribution between the two.

4.3. Distribution of media coverage and the effects of media reports

We begin by examining how firm characteristics influence the probability of receiving media coverage: the selection in media reporting.

Figure 8 presents the cross-sectional variation in the probability of media coverage under our calibration, shown as red solid lines, along three dimensions: size, age, and idiosyncratic productivity. Panels (a) and (b) indicate that larger and older firms are more likely to be reported, with the concentration being more pronounced along the size dimension. This pattern is consistent with the stylized facts documented in Figure 3. The model also predicts a higher likelihood of media coverage for firms with greater idiosyncratic productivity, as shown in Panel (c). These qualitative relationships follow from equation (31). Newsworthiness scales with firm size and productivity because both are positively correlated with market value. Since firms, on average, grow in size and productivity over time, the probability of media coverage also rises with firm age.

Having examined how firm characteristics influence the likelihood of media coverage, we now turn to study how media coverage affects firm behavior. Specifically, we assess the causal impact of coverage on investment, holding firm characteristics constant and isolating this effect from the endogenous selection into coverage.

Figure 8 plots the effect in blue dashed lines, showing how the investment response to media coverage varies across firm size, age, and idiosyncratic productivity. We measure this effect as the log difference in a firm's investment between two scenarios: when it is reported and when it is not. This, therefore, isolates the causal effect of media on firms from the endogenous selection into coverage.

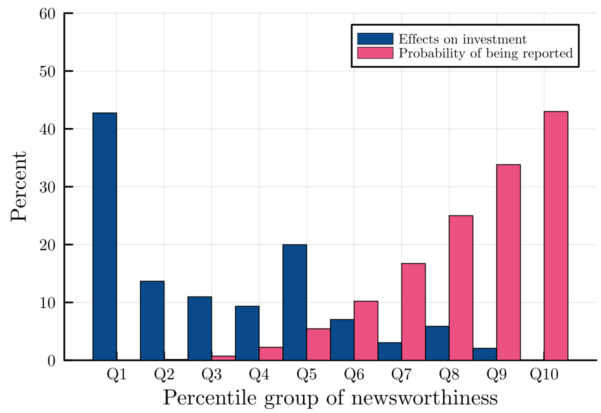
The effect of media coverage on investment decreases with firm size and age, but increases with firm productivity. This pattern arises because, as discussed in Section 3.3.1, media coverage can reduce information frictions related to equity issuance. The effects of media reports, therefore, depend on a firm's reliance on external funding. Smaller and younger firms, with less internal financing, rely more heavily on external equity markets, making their investment more sensitive to media reports. Similarly, more-productive firms, with greater investment needs, also depend more on external financing than less-productive firms of similar size.

These patterns imply a misalignment between the distribution of media reports and their impact on firm-level investment. To illustrate this misalignment more directly, Figure 9 plots the average investment responses to reporting alongside the probability of coverage across newsworthiness percentiles. Firms whose investment is most responsive to news reports are concentrated at the lower end of the newsworthiness distribution, receiving little coverage. In other words, the covariance term in the decomposition in equation (1) is strongly negative. This suggests that reallocating media coverage could generate a larger real effect on the economy. Building on this observation, the next subsection quantifies the magnitude of this distributional effect, using a counterfactual experiment.

4.4. Aggregate effects of media-coverage distribution

News reports affect firms' financing and investments by mitigating information asymmetries. To assess the aggregate relevance of media-coverage allocation, we first compare two counterfactual economies: one with no information asymmetry (symmetric-information economy) and another with information asymmetry but no media sector (no-media economy). The difference between the no-media economy and the symmetric-information economy captures the maximum potential loss from information asymmetry. We then consider an alternative

Figure 9: Mis-allocation of media reporting



Notes: This figure reports the probability of media reporting and the effects of media reporting. The "effects on investment" refers to the log-difference in a firm's investment between two scenarios: when it is reported and when it is not. Firms are sorted into deciles of newsworthiness, with "Q1" representing the 10% least newsworthy firms and "Q10" representing the 10% most newsworthy firms. For each decile, we report the average probability of the firms being reported and the average effects, of media coverage, on their investment.

media sector in which a portion of the space in media outlets is available for firms to purchase in a competitive news market. This allows us to evaluate the aggregate effect of reallocating media coverage towards firms that would benefit the most.

Limited role of the media in the baseline economy We first evaluate by how much the media alleviates the loss from asymmetric information in our baseline model. In Table 5, we measure the role of the media in a given economy by the relative reduction in the output loss from asymmetric information between this economy and the no-media economy. Without the media, asymmetric information depresses aggregate investment and capital accumulation, resulting in a 5.3% loss in output. While the media helps to alleviate this loss, its impact is modest, reducing the output loss by 0.7 percentage points (equivalent to 13% of the output loss in no-media economy).

Quantifying the aggregate effects of media-coverage distribution. To understand the aggregate impact of the news-coverage distribution, we conduct a counterfactual experiment that reallocates a portion of the news coverage through a competitive news market while holding constant the number of firms that get reported.

In all of these counterfactuals, as in the baseline economy, 13.7% of firms are reported each quarter. Since 18.2% of firms will increase their investment after being reported, if the

Table 5: Aggregate effects of information asymmetry (%)

	No-media	Baseline
Investment	-6.7	-5.9
Capital stock	-4.7	-4.2
Output	-5.3	-4.6

Notes: This table summarizes the effects of asymmetric information on aggregate investment, the capital stock, and output within the no-media economy and our baseline economy with selective-reporting media. To evaluate the effects of asymmetric information, we first solve a model that shares the same setup and calibration with the baseline model but features no information asymmetry. Then we compute the relative difference of the various aggregate quantities between each economy and the economy with symmetric information.

media allocated coverage exclusively to these "responsive firms," 75% of them would receive coverage.[26] In fact, in the baseline economy just 6% of the media coverage is allocated to these responsive firms, implying that 95% are not reported.

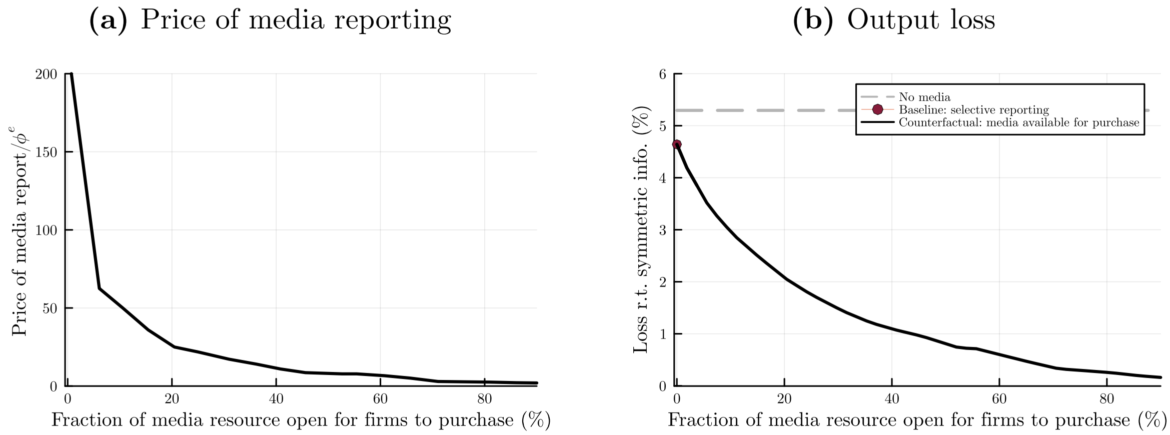
For the counterfactuals, we assume that the media outlets sell a portion (α_m) of their reporting resources to firms in a competitive market, allocating the remainder using the same news-reporting rule as in the baseline model. Firms not selected for coverage can purchase it before the equity market opens. The price of the media coverage is determined such that the total media coverage purchased by firms equals the coverage sold by the media in a competitive market. Appendix C.2 provides further details for this experiment.

Panel (a) of Figure 10 reports the price of the media reports across a series of counterfactual economies, characterized by different values of α_m. The horizontal axis represents α_m, the share of the media resource that is allocated through a competitive market out of the total media resources. The vertical axis represents the equilibrium price of the media reporting in each economy. Prices are high when the purchasable fraction of the media resources is small, with only the firms benefiting the most from news reporting willing to pay for being reported. As more media resources become purchasable, prices decline substantially.

Panel (b) shows how the output loss relative to the symmetric information economy varies with α_m. When $\alpha_m = 0$, all of the media resources are allocated following the baseline reporting policy, so the output loss coincides with the results of our baseline economy. While reallocating the media coverage cannot completely eliminate the output loss, because the

[26] Based on the variance decomposition $\mathbb{V}[\Delta x_{jt}] = \mathbb{E}\left[\mathbb{V}[\Delta x_{jt}|\mathbb{1}_{\Delta x_{jt}>0}]\right] + \mathbb{V}\left[\mathbb{E}[\Delta x_{jt}|\mathbb{1}_{\Delta x_{jt}>0}]\right]$, where $\Delta x_{jt} \equiv \frac{\partial \log x_{jt}}{\partial m_{jt}}$, the extensive margin responses explain 65% of the overall variation ($\frac{\mathbb{V}\left[\mathbb{E}[\Delta x_{jt}|\mathbb{1}_{\Delta x_{jt}>0}]\right]}{\mathbb{V}[\Delta x_{jt}]}$) in firms' investment responses to media coverage.

Figure 10: Aggregate relevance of media allocation



Notes: Panel (a) reports the equilibrium prices firms pay for media coverage in various counterfactual economies. In each counterfactual economy, we keep the total fraction of the reported firms at 13.7%, as in the baseline model, but allow a fraction of the media resource to be allocated through a competitive market. To facilitate the interpretation of the magnitude, we report the prices that are normalized by the fixed cost of issuing equity ϕ^e. Panel (b) shows the output loss in the counterfactual economies, measured by the relative difference in the aggregate output between each counterfactual economy and the economy with symmetric information.

total capacity of the media is insufficient to cover all constrained firms, it can substantially reduce this loss. Notably, reallocating just 5% of the media resources for firms to purchase doubles the media's effect in reducing the output loss. A 10% reallocation can already eliminate half of the overall output loss from information asymmetry.[27]

This substantial improvement from the media-reporting market stems from firms' self-selection. When media resources become available for purchase, firms that benefit the most from this coverage have the highest willingness to pay. Media reporting significantly boosts these firms' financing and investments, resulting in a considerable reduction in aggregate output loss.[28] Our counterfactual analysis shows that the aggregate effects of the media depend crucially on the distribution of the news coverage.

[27] Figure C.1 in Appendix C.3 reports the results for investment and capital losses, which also show substantial improvements.

[28] In Appendix C.3, we also study the aggregate effects of a "uniform"-reporting media that simply allocates coverage resources equally among firms and reports all firms with the same probability. This alternative allocation only generates a minor improvement from the baseline, due to the absence of firms' self-selection.

5. Conclusion

News outlets provide valuable information to their readers, but constraints on space and journalistic resources mean they have to make judgments on which firms are most newsworthy. We find that these judgments overwhelmingly favor reporting on the largest firms in the economy—firms that benefit the least from media coverage. This selectivity has important effects on firm dynamics and aggregate investment. Reallocating a small fraction of limited media reports away from large firms substantially increases the role the media can play in alleviating information frictions.

Both cross-time and cross-sectional variations in the media's production of firm news are endogenously determined, and the way the media reports firms' news has important implications for the macroeconomy. Our findings suggest that large firms that dominate their markets, or "superstar" firms, (e.g., Covarrubias et al., 2020; De Loecker et al., 2020; Autor et al., 2020) do so not only with better information technology (Kwon et al., 2024) but also with superior media coverage. The interaction between information provision and corporate finance highlights an intangible form of market power enjoyed by these large firms, which warrants closer investigation in future studies.

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Online Appendices

A. Additional Details for the Empirical Analysis

A.1. Data construction

This section describes the firm-level variables used in the empirical analysis of the paper, based on quarterly Compustat data. The definition follows standard practices in the firm dynamics literature (e.g., Kahle and Stulz, 2017; Ottonello and Winberry, 2020).

Variable definitions

1. *Size*: the log of total real assets (`atq`), deflated using the BLS implicit price deflator.

2. *Age*: the number of years since the CRSP listing.

3. *Leverage*: the sum of the debt in current liabilities and the long-term debt (`dlttq+dlc`) over the sum of total assets and the market valuation minus the common equity (`atq-ceqq+cshoq*prccq`)

4. *Investment*: defined as $\Delta \log k_{it}$, where k_{it} denotes the capital stock of firm i at the end of quarter t. Following Ottonello and Winberry (2020), for each firm, we set the first value of k_{it} to be gross plant, property, and equipment (`ppegtq`) in the first period in which this variable is reported in Compustat and the subsequent value of k_{it} to be the changes in the net value of the plant, property, and equipment (`ppentq`). If a firm has a missing observation for `ppentq` located between two periods with non-missing observations, we estimate its value using a linear interpolation with the values of `ppentq`; if two or more consecutive observations are missing, we do not do any imputation.

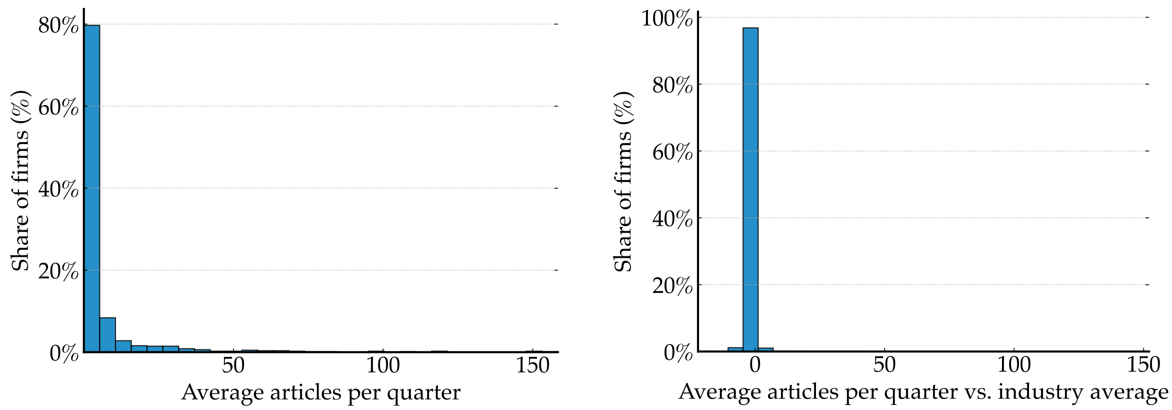
5. *Equity issuance*: defined as the sale of common and preferred stock (`sstky` in the first fiscal quarter and changes in the `sstky` for the second to fourth fiscal quarters). Following McKeon (2015), we classify equity issuance that are smaller than 3% of a firm's market capitalization as zero issuance.

6. *Cumulative equity issuance probability*: an indicator variable that takes the value of one if a firm has issued new equity between quarters t and $t+h$ (i.e., the cumulative equity issuance probability $E_{it+h} = 1$ if $e_{it-1} = 0$ and $\sum_{\tau=0,\cdots,h} e_{it+\tau} > 0$, where e_{it} denotes firm i's equity issuance in quarter t); and zero otherwise.

A.2. Additional tables and figures

Figure A.1: Distribution of corporate news coverage: Non-zero coverage and within industry

(a) Non-zero coverage **(b)** Within industry



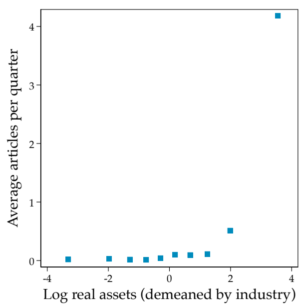
Notes: Panel (a) reports the distribution of average articles per quarter for firms that receive non-zero coverage over the sample period. Panel (b) reports the distribution of average articles per quarter compared to industry average, which is equivalent to the residual from regressing average articles per quarter on 4-digit NAICS fixed effects.

Table A.1: Top 10 firms ranked by total media coverage in the sample period

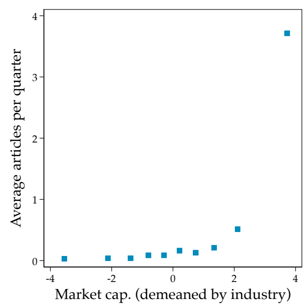
Rank	**Firm**	**Articles**
1	BlackRock	36,455
2	AT&T	22,775
3	General Motors	18,380
4	Microsoft	15,314
5	Apple	13,995
6	Time Warner	11,708
7	Alphabet	10,402
8	Citigroup	9,844
9	Merrill Lynch	9,070
10	Boeing	8,965
Total articles on top 10 firms		156,908
Total articles on remaining firms		228,790

Figure A.2: Media coverage and within-industry firm characteristics

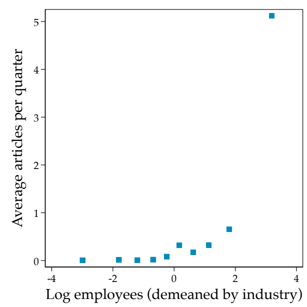
(a) Size (assets)



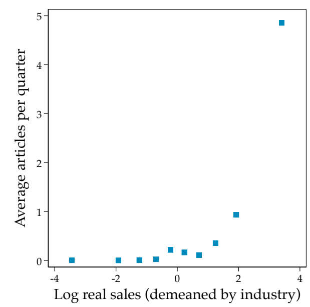
(b) Size (market cap.)



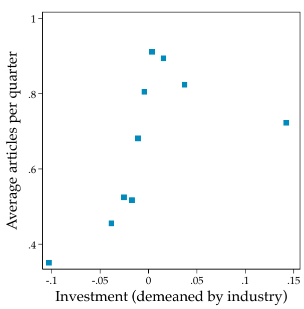
(c) Size (employees)



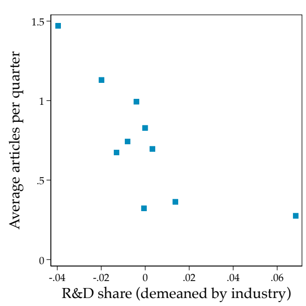
(d) Size (sales)



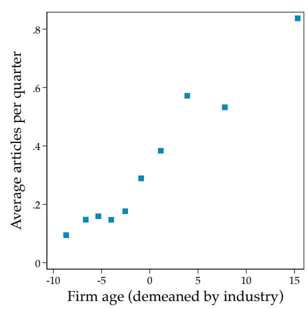
(e) Investment



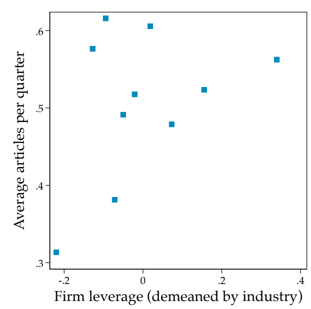
(f) R&D



(g) Age



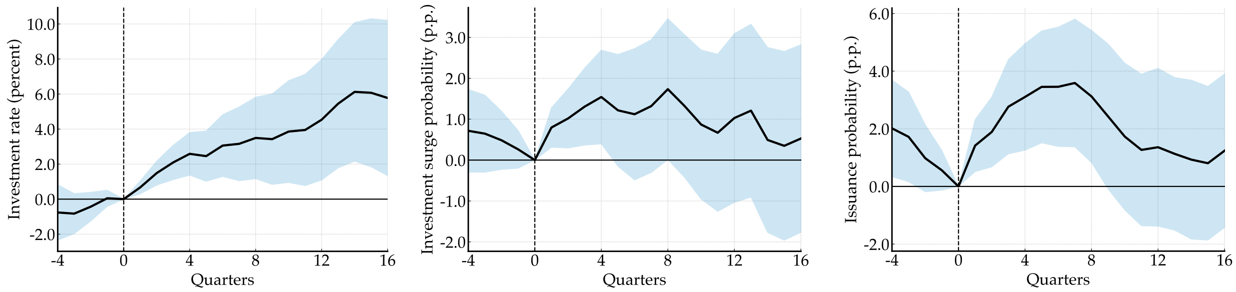
(h) Leverage



Notes: This figure reports binned scatterplots of average news articles per quarter.Each dot represents a decile of firms by firm characteristics relative to the industry (4-digit NAICS) average, sorted from the smallest to largest. The top panel reports the relationship between news coverage and firm size, measured by log real assets in panel (a), market capitalization (prices per share times shares outstanding) in panel (b), log employee numbers in panel (c), and log real sales in panel (d). The bottom panel reports the relationship between news coverage and other firm characteristics, including investment rate in panel (e), and research and development expenses as a share of assets in panel (f), firm age (years since the IPO) in panel (g), and market leverage in panel (h).

Figure A.3: Alternative media coverage measure: coverage indicator $\mathbb{1}(\nu_{it} > 0)$

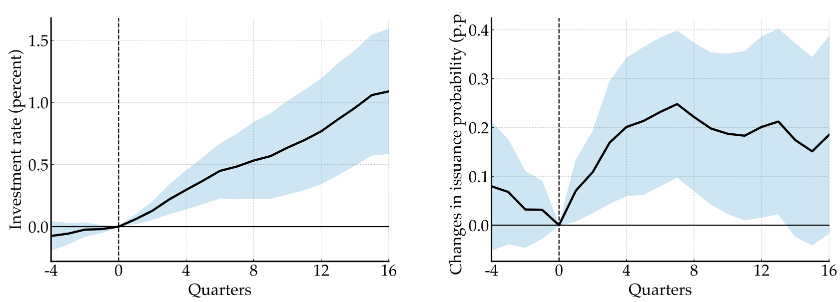
(a) Investment rate **(b)** Investment surge **(c)** Equity Issuance



Notes: This figure reports variants of the baseline local projections in equation (3) using an alternative media coverage measure, for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \mathbb{1}(\nu_{it} > 0) + \Gamma' Z_{it-1} + u_{ith}$, where α_{st} denotes a sector-by-quarter fixed effect (with sectors defined at the 4-digit NAICS level); α_i denotes firm a fixed effect; $\mathbb{1}(\nu_{it} > 0)$ is an indicator variable which takes the value of 1 if firm i has any coverage in major U.S. newspapers in quarter t, and 0 otherwise; and Z_{it-1} is a vector of firm controls including size, age, and real sales growth. The dependent variable y_{it} includes (a) the investment rate, defined as the log change in the book value of the firm's tangible capital stock; (b) the cumulative probability of investment surge, defined as an indicator variable that takes the value of 1 if a firm has quarter investment rate higher than 20% between quarters t and $t+h$, and zero otherwise; and (c) the cumulative probability of equity issuance, defined as an indicator variable that takes the value of 1 if a firm issues new equity between quarters t and $t+h$, and zero otherwise. Standard errors are double clustered by firm and quarter. 90% confidence intervals are reported.

Figure A.4: Excluding firms that share common ownership with media outlets

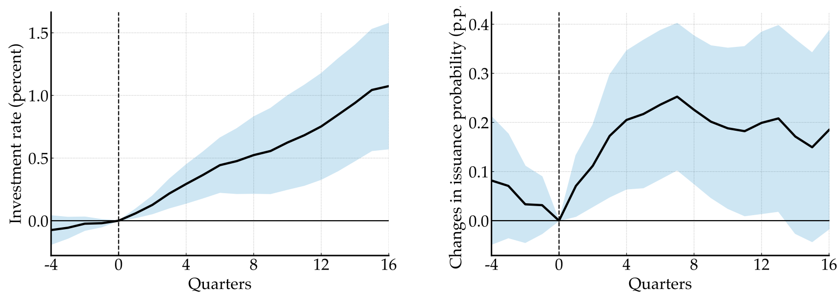
(a) Investment **(b)** Equity issuance



Notes: This figure reports variants of the baseline local projections in equation (3), where firms that share common owners with the media outlets in our sample (The Wall Street Journal, New York Times, and USA Today) are excluded.

Figure A.5: Excluding firms in the media sector

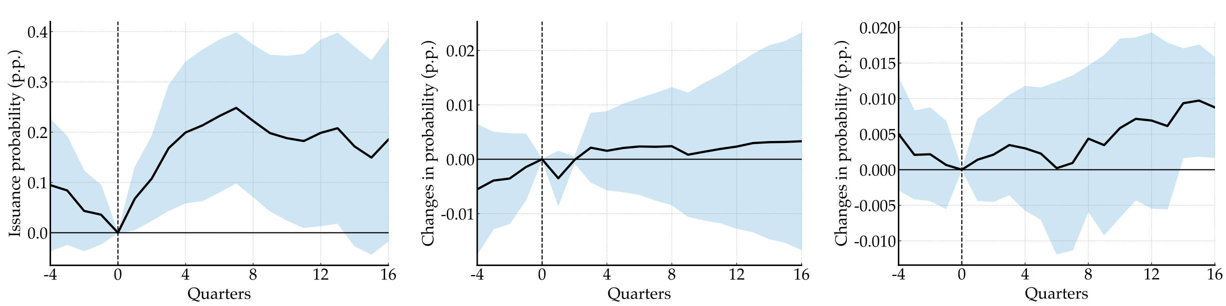
(a) Investment **(b)** Equity issuance



Notes: This figure reports variants of the baseline local projections in equation (3), where firms in the media sector (NAICS 5418) are excluded.

Figure A.6: The effects of media coverage on different forms of firm financing

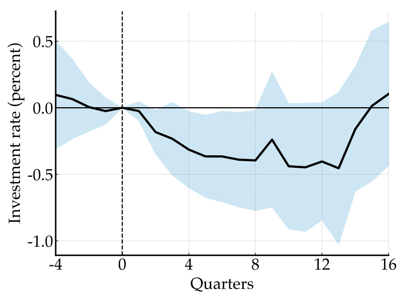
(a) Equity financing **(b)** Debt financing **(c)** Cash holdings



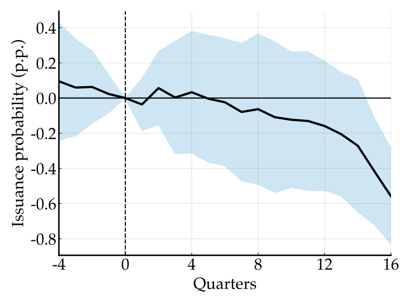
Notes: This figure reports variants of the baseline local projections in equation (3): $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it} - \mathbb{E}_i\,\nu_{it}) + \Gamma' Z_{it-1} + u_{ith}$, where α_{st} denotes a sector-by-quarter fixed effect; α_i denotes a firm fixed effect; ν_{it} denotes the number of mentions of firm i in major U.S. newspapers quarter t; $\mathbb{E}_i\,\nu_{it}$ denotes the average number of mentions of the firm over the sample; and Z_{it-1} is a vector of firm controls including size, age, and real sales growth. The dependent variable y_{it} includes (a) the cumulative probability of equity financing, repeated from the baseline estimates in Figure 4; (b) the cumulative probability of debt financing, defined as an indicator variable that takes the value of 1 if a firm increases debt financing between quarters t and $t+h$, and zero otherwise; and (c) the cumulative probability of increasing cash holdings, defined as an indicator variable that takes the value of 1 if a firm increases cash holdings between quarters t and $t+h$, and zero otherwise. We have standardized $(\nu_{it} - \mathbb{E}_i\,\nu_{it})$ across the entire sample. Standard errors are double clustered by firm and quarter. 90% confidence intervals are reported.

Figure A.7: Effects of Twitter coverage

(a) Investment



(b) Equity financing



Notes: This figure reports the results from estimating the local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h(\tau_{it} - \mathbb{E}_i\,\tau_{it}) + \Gamma' Z_{it} + u_{ith}$, where the dependent variables y_{it} include (a) the cumulative investment rate and (b) the cumulative probability of equity financing, defined in the main text; α_{st} denotes the sector-by-quarter fixed effect; α_i denotes the firm fixed effect; τ_{it} denotes the number of firm mentions on Twitter in quarter t; $\mathbb{E}_i\,\tau_{it}$ denotes the average number of firm mentions on Twitter over the sample; and Z_{it} is a vector of firm controls including size, age, and real sales growth. We have standardized $(\tau_{it} - \mathbb{E}_i\,\tau_{it})$ over the entire sample. Standard errors are double clustered by firm and quarter. Standard errors are double clustered by firm and quarter. 90% confidence intervals are reported.

A.3. Topics in news articles

To analyze the content of the news coverage, we employ latent Dirichlet allocation (LDA) to extract 20 distinct "topics" that represent the text of these newspaper articles. LDA, a generative probabilistic model from natural language processing, assumes that each article is a mixture of topics and each topic is a mixture of words. By analyzing the co-occurrence patterns of words within the articles, the model identifies the underlying topics that best represent the content.

We use the `gensim` library in Python to estimate the LDA model. The pre-processing of texts includes removing stop words, numbers, cases, and single-letter words, and then lemmatizing. We specify uniform Dirichlet priors. To select the model hyperparameter that governs the number of topics, we take a data-driven approach and perform a grid search of 200 topics in increments of 20. Through this procedure, we choose 20 as the number of topics as this generates the highest topic coherence.

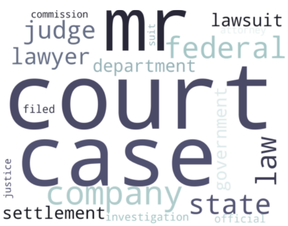
The estimated topics are reported in Appendix Figure A.8. To construct the measure of media coverage purged of coverage on investment or financing, we compute the share of a firm's quarterly news coverage containing any articles that have any positive loadings on topics related to firm investment and financing—topic 5 ("investment"), topic 16 ("financing"), and topic 8 ("financing from international markets") in Appendix Figure A.8—and exclude it from the baseline coverage measure.

We use this purged coverage measure to estimate a variant of the baseline local projection in (3):

$$y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it}^{\text{purged}} - \mathbb{E}_i\, \nu_{it}^{\text{purged}}) + \Gamma' Z_{it-1} + u_{ith},$$

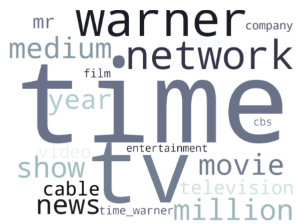
where the dependent variables y_{it} include (a) the cumulative investment rate and (b) the cumulative probability of equity financing, defined in the main text; $\{\alpha_{st}, \alpha_i\}$ denote the sector-by-quarter and firm fixed effects; ν_{it}^{purged} denotes the number of mentions of firm i in major U.S. newspapers quarter t excluding any articles with positive LDA loadings on topics related to investment and equity financing; $\mathbb{E}_i\, \nu_{it}^{\text{purged}}$ denotes the average of the firm's ν_{it}^{purged} over the sample; and Z_{it-1} is a vector of firm controls including size, age, and real sales growth. Estimates are reported in Appendix Figure A.9.

Figure A.8: Topics in firm news coverage



(a) Litigation

(b) Stock market

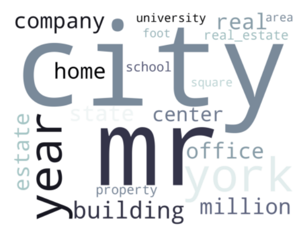


(c) Media sector

(d) China

(e) Investment

(f) Retail



(g) Real estate

(h) Financing (intl.)

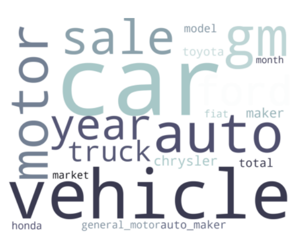
(i) Earnings

(j) Technology sector

(k) Airline sector

(l) Social media

(m) Energy sector



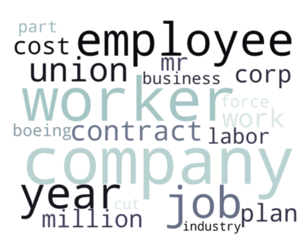
(n) Automobile sector

(o) Pharma. sector

(p) Financing

(q) Telecom sector

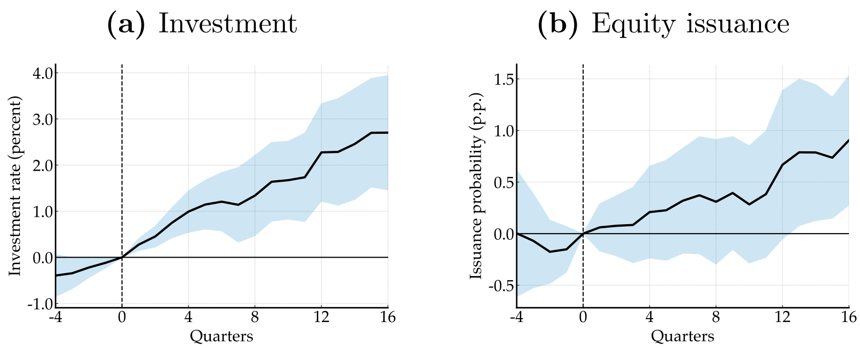
(r) Advertising sector



(s) Employees

(t) Executives

Figure A.9: News coverage, firm investment, and financing: Excluding the coverage in investment and financing articles



Notes: This figure reports variants of the baseline local projections in equation (3). We estimate $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h(\nu_{it}^{\text{purged}} - \mathbb{E}_i\, \nu_{it}^{\text{purged}}) + \Gamma' Z_{it-1} + u_{ith}$, where the dependent variables y_{it} include (a) the cumulative investment rate and (b) the cumulative probability of equity financing, defined in the main text; $\{\alpha_{st}, \alpha_i\}$ denote the sector-by-quarter and firm fixed effects; ν_{it}^{purged} denotes the number of mentions of firm i in major U.S. newspapers quarter t excluding any articles with positive LDA loadings on topics related to investment and equity financing; $\mathbb{E}_i\, \nu_{it}^{\text{purged}}$ denotes the average of the firm's ν_{it}^{purged} over the sample; and Z_{it-1} is a vector of firm controls including size, age, and real sales growth. Standard errors are double clustered by firm and quarter. Standard errors are double clustered by firm and quarter. 90% confidence intervals are reported.

A.4. Sentiment of news articles

This section describes the construction of the news sentiment measure. For each news article k, we compute three sentiment measures:

1. Keyword-based measure, $\mathrm{sent}_{\mathrm{k}}^{\mathrm{LM}} = (\mathrm{N}_{\mathrm{k}}^{+} - \mathrm{N}_{\mathrm{k}}^{-})/\mathrm{N}_{\mathrm{k}}$, where N_k^+, N_k^-, and N_k denote the number of positive, negative, and total words in article k, respectively, according to the dictionary constructed by Loughran and McDonald (2011).

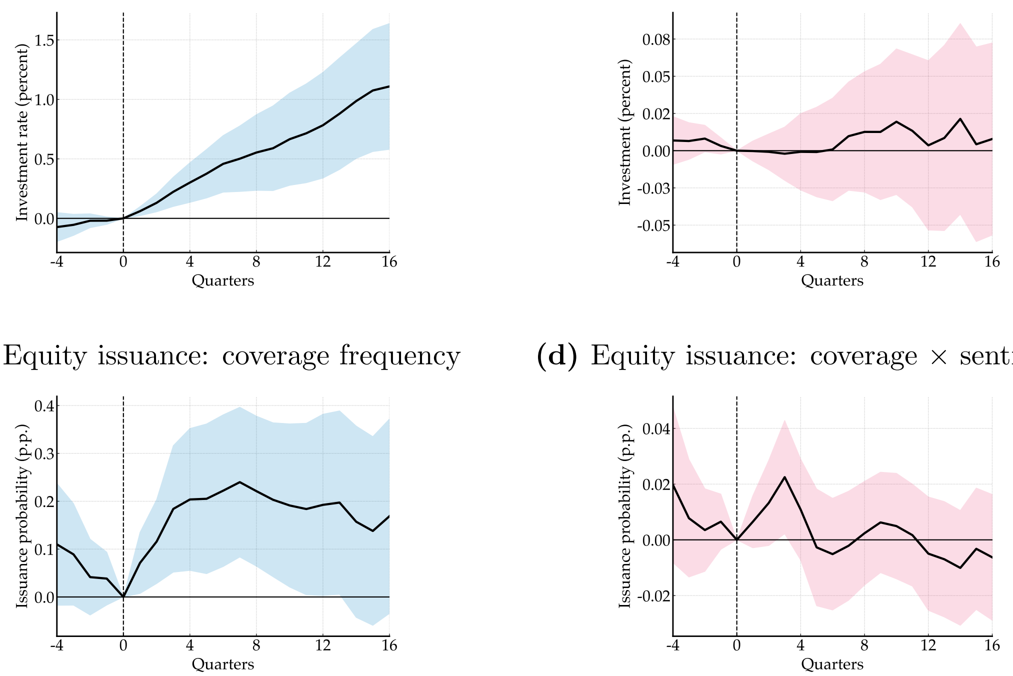
2. FinBERT-based measure, $\mathrm{sent}_{\mathrm{k}}^{\mathrm{BERT}} = (\mathrm{N}_{\mathrm{k}}^{+} - \mathrm{N}_{\mathrm{k}}^{-})/\mathrm{N}_{\mathrm{k}}$, where N_k^+, N_k^-, and N_k denote the number of positive, negative, and total sentences in article k, respectively. Sentiment is classified at the sentence level using FinBERT (Araci, 2019), a version of BERT pre-trained on financial texts.

3. GPT-based measure, $\mathrm{sent}_{\mathrm{k}}^{\mathrm{GPT}} \in \{-1, 0, 1\}$. We query GPT 3.5 (Ye et al., 2023) for the sentiment of an article and classify an article as negative (-1), neutral (0), or positive (1). The prompt used is: "Classify the sentiment of this news article. Return 'positive' if the sentiment of the article is positive, return 'negative' if the sentiment of the article is negative, and return 'neutral' if the sentiment of the article is neutral."

To match the frequency of the empirical analysis, we compute the sentiment of firm i's coverage in quarter t as the average sentiment of the firm's news articles within the quarter. Since each sentiment measure has its strength and limitations, we take the first principal component across the three measures as our sentiment measure, $\mathrm{sent}_{\mathrm{it}}$.

Figure A.10 reports the local projection results for which the frequency of news coverage is interacted with the sentiment of the coverage.

Figure A.10: News coverage sentiment



(a) Investment: coverage frequency

(b) Investment: coverage × sentiment

(c) Equity issuance: coverage frequency

(d) Equity issuance: coverage × sentiment

Notes: This figure reports results from estimating $\Delta_h y_{it} = \alpha_{st} + \alpha_i + \beta_{\nu h}(\nu_{it} - \mathbb{E}_i\, \nu_{it}) + \beta_{sh}\mathrm{sent}_{\mathrm{it}} + \beta_{\nu \mathrm{sh}}(\nu_{\mathrm{it}} - \mathbb{E}_{\mathrm{i}}\, \nu_{\mathrm{it}}) \times \mathrm{sent}_{\mathrm{it}} + \Gamma' \mathrm{Z}_{\mathrm{it}} + \mathrm{u}_{\mathrm{ith}}$, where $\mathrm{sent}_{\mathrm{it}}$ denotes the average sentiment of firm i's media coverage in quarter t, and the sentiment measure is defined in Appendix Section A.4. Panels (a) and (c) report estimated $\beta_{\nu h}$, and panels (b) and (d) report estimated $\beta_{\nu sh}$. 90% confidence bands are reported.

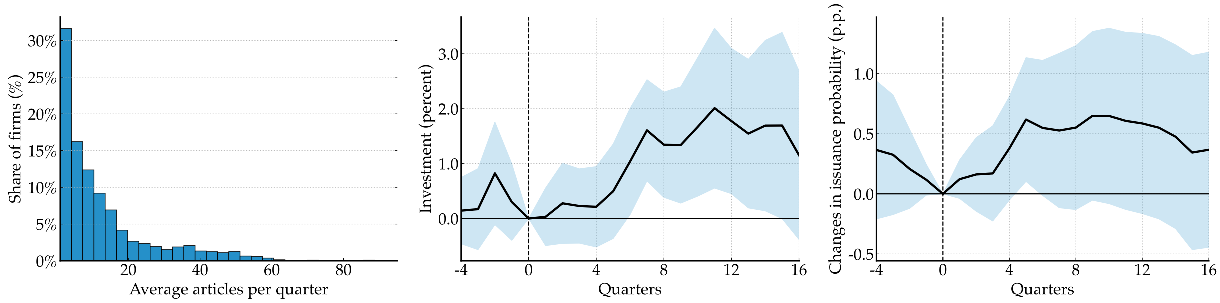
A.5. News coverage in France

Figure A.11: Media coverage and firm outcomes in France

(a) Distribution of news coverage

(b) Investment responses after media coverage

(c) Equity issuance responses after media coverage



Notes: Panel (a) reports the distribution of corporate news coverage in major French newspapers from 2005 to 2022, including *Les Echos*, *Le Monde*, *La Tribune*, and *Le Figaro*. Panels (b) and (c) report estimates from the local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it} + u_{ith}$, where $\{\alpha_{st}, \alpha_i\}$ denote the sector-by-quarter and firm fixed effects; ν_{it} denotes the news coverage of firm i in major French newspapers in quarter t, demeaned at the firm level and standardized; and Z_{it} is a vector of firm controls including size, age, and real sales growth. The dependent variable y_{it} includes the investment rate ($\Delta \log k_{it}$) in panel (b), defined as the log change in capital expenditures, and the cumulative probability of equity issuance (E_{it}) in panel (c), defined as an indicator variable that takes the value of 1 if a firm issues new equity between quarters t and $t+h$, and zero otherwise. Standard errors are double clustered by firm and quarter. 90% confidence intervals are reported.

Table A.2: National media strikes in France

Quarter	Date	Description
2005Q4	October 4, 2005	Unions of journalists and technicians in public broadcasting striked as part of a national day of action.
	October 20, 2005	The Agence France-Presse journalists' unions striked to oppose the announced closure of a regional office.
2008Q1	February 13, 2008	Workers in public broadcasting striked to protest President Nicolas Sarkozy's media reform.
2008Q4	November 25, 2008	Public broadcaster workers striked to protest bill passed reforming public broadcasting by President Sarkozy.
2013Q1	February 1, 2013	The Agence France Presse journalists' unions striked to call for the withdrawal of the "France Region" project.
2018Q2	April 1, 2018	National strikes, including by broadcasters, against President Emmanuel Macron's reforms to the public sector.

Notes: Information on national media strikes in France from 2005 to 2021 was found by searching Factiva using the search words "strike or grève" and "journalist or journaliste" or "strike or grève" and "broadcaster or diffuseur" and restricting the region to France, the industry to Media/Entertainment, the subject to Labor Dispute, and by excluding strikes against individual newspapers.

Table A.3: Descriptive statistics of strikes and nonstrikes

	Media strikes	**Nonstrikes**	**Total**
Number of quarters	5	9	68
Avg number of firm news	2,814	3,155	2,337
Avg share of firm news	8.87%	10.12%	8.25%

Notes: "Media strikes" includes 2005Q4, 2008Q1, 2008Q4, 2013Q1, and 2018Q2. "Nonstrikes" refers to quarters adjacnent of strikes which do not include a media strike. "Total" refers to all quarters in the French sample from 2005 to 2021.

Table A.4: Equity issuance and media strikes

	(1)	(2)	(3)
	Equity issuance probability		
Strike indicator	0.005	-0.002	-0.002
	(0.018)	(0.016)	(0.017)
Size		0.002**	0.002**
		(0.001)	(0.001)
Age		-0.013***	-0.014***
		(0.004)	(0.004)
Real sales growth		-0.000***	-0.000***
		(0.000)	(0.000)
rGDP growth			-0.000
			(0.001)
Aggregate investment			-0.000
			(0.000)
Observations	36454	33348	28493
R^2	0.019	0.025	0.026
Industry FE	yes	yes	yes
Double-clustered SE	yes	yes	yes

Notes: This table reports estimates from $E_{it} = \alpha_{st} + S_t + \Gamma' Z_{it} + u_{it}$, where E_{it} is an indicator variable that equals 1 if firm i issues equity in quarter t; α_{st} is a sector-by-fiscal-quarter fixed effect; S_{it} is an indicator variable which equals 1 if there is a media strike in quarter t; and Z_{it} is a vector of controls including firm size, age, real sales growth, real GDP growth, inflation, and aggregate investment. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

B. Additional Details for the Theoretical Analysis

B.1. Proofs

B.1.1. Proof of Proposition 1

Proof. We show that there is a unique reporting policy that can be sustained as a symmetric equilibrium. To find this, we begin by considering an arbitrary candidate reporting policy. We then show that there is a unique candidate reporting policy from which no outlet would find it optimal to deviate.

The candidate reporting policy is characterized by a vector of reporting choices $\boldsymbol{m}_t = \{m_{jt}\}_{j=0}^{1}$, which satisfies the space constraint (20). Without loss of generality, assume that $\boldsymbol{m}_t$ involves all outlets reporting on firm j and all outlets not reporting on firm j'.

Optimal forecasts For a firm j that is reported on by outlet i, forecaster i can forecast the market value precisely as they observe all of that firm's state variables

$$\text{Pred}_t(k_{jt}, z_{jt}, 1, \mathcal{I}_{it}^{\text{news}} | m_{ijt}^o = 1) = \text{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1). \tag{36}$$

Substituting this forecast into equation (26) reveals that when $m_{ijt}^o = 1$, forecaster i makes no forecast errors.

For a firm that is not reported by outlet i, the optimal forecast by forecaster i is given by

$$\text{Pred}_t(k_{jt}, z_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}} | m_{ijt}^o = 0) = \mathbb{E}\left[(\text{MV}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}) | k_{jt}, z_{jt}, m_{jt}\right]. \tag{37}$$

The forecast in (37) is uncertain because the forecaster is uncertain about a_{jt}. In general, this will lead forecaster i to make non-zero forecast errors when $m_{ijt}^o = 0$.[29]

[29] If $m_{jt} = 1$, forecaster i is aware that investors know a_{jt}, but they do not themselves observe this as their outlet did not report it. If instead $m_{jt} = 0$, forecaster i knows that no outlet reported a_{jt} and so it is not part of the investors' information set. However, there is still uncertainty in that case, because the realized a_{jt} can still affect the realized market value, indirectly, through firm j's equity issuance (see Section 3.3.1). Since forecasters make predictions before equity markets open, they cannot observe equity issuance. They do not therefore know what the investors' posteriors $g(a_{jt})$ will be and so cannot be certain about the realization of the market value.

Forecaster utility at equilibrium Since we consider a symmetric reporting policy, all outlets make the same reporting decisions. This means all forecasters have the same information set and make the same forecast errors. As a result,

$$\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{it}) = \overline{\mathrm{FE}}_{-it}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{-it}), \tag{38}$$

and thus $U_{it} = 0$.

Outlet deviations A minimal deviation from $\boldsymbol{m}_t$ consists of an outlet i ceasing to report on firm j and, instead, reporting on firm j'. $\boldsymbol{m}_t$ can only be sustained in equilibrium if no outlet finds it optimal to deviate in this way. Since in the absence of any deviation we have obtained that $U_{it} = 0$ with certainty, a sufficient condition for $\boldsymbol{m}_t$ to be an equilibrium is that

$$\mathbb{E}\,\hat{U}_{it}(j, j') + \kappa_{jt} - \kappa_{j't} \leq 0,, \tag{39}$$

where $\hat{U}_{it}(j, j')$ is the utility of forecaster i if outlet i deviates. If this condition holds for all pairs of the reported and unreported firms, j, j', the news outlets never deviate and $\boldsymbol{m}_t$ is an equilibrium.

We now proceed to find an expression for $\mathbb{E}\,\hat{U}_{it}(j, j')$. First, notice that the deviation would have no effect on firms other than j and j'. From the definition of the forecaster's utility in equation (25), we therefore have

$$\begin{aligned} \mathbb{E}\,\hat{U}_{it}(j, j') = &- \mathbb{E}\left[\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{it}) - \overline{\mathrm{FE}}_{-it}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{-it})\right] \\ &- \mathbb{E}\left[\mathrm{FE}_t(k_{j't}, z_{j't}, a_{j't}, m_{j't}, \mathcal{I}^{\text{news}}_{it}) - \overline{\mathrm{FE}}_{-it}(k_{j't}, z_{j't}, a_{j't}, m_{j't}, \mathcal{I}^{\text{news}}_{-it})\right]. \end{aligned} \tag{40}$$

The first two terms give the utility change from no longer reporting on firm j. Other forecasters are still reporting on j and so it remains the case that $m_{jt} = 1$ and the realized market value of firm j is unchanged. The average forecast error of the other forecasters $\overline{\mathrm{FE}}_{t-i}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{-it})$, therefore, remains unchanged at 0. However, forecaster i's forecast does change, as their information set no longer contains a_{jt}. Specifically,

$$\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}}) = \left[\mathrm{Pred}_t(k_{jt}, z_{jt}, 1, \mathcal{I}_{it}^{\text{news}} | m_{ijt}^o = 0) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\right]^2. \quad (41)$$

Substituting out for the optimal forecast using equation (28), and taking the expectations, we obtain

$$\begin{aligned}\mathbb{E}[\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}_{it}^{\text{news}})] = \mathbb{E}\big[\,&\mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1) | k_{jt}, z_{jt}, m_{jt} = 1) \\ &- \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\big]^2, & (42) \\ = \mathbb{V}[&\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1) | k_{jt}, z_{jt}], & (43)\end{aligned}$$

where $\mathbb{V}[.]$ denotes the variance with respect to a_{jt}.

The second two terms of equation (40) give the utility change due to reporting on firm j'. Recall that investors observe a firm's asset quality if at least one outlet reports it (equation (24)). Since outlet i has reported on firm j', that firm's asset quality $a_{j't}$ is transmitted to investors and so $m_{j't} = 1$. As a result, forecaster i observes all of the determinants of firm j''s market value and is able to make an accurate forecast (equation (36)). Forecaster i therefore makes no forecast error about firm j'.

However, although forecaster i makes no forecast error about j' under this deviation, the same is not true of the other forecasters. Their outlets have not reported on j' ($m_{i'j't}^o = 0$) and so they do not have sufficient information to precisely infer that firm's market value. This generates a forecast error, given by

$$\overline{\mathrm{FE}}_{-it}(k_{j't}, z_{j't}, a_{j't}, 1, \mathcal{I}_{-it}^{\text{news}}) = \int_{i' \neq i} \left[\mathrm{Pred}_t(k_{j't}, z_{j't}, \mathcal{I}_{i',t}^{\text{news}} | m_{i'jt}^o = 0) - \mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1)\right]^2 di' \quad (44)$$

All outlets, i', are identical, so when using the same steps as those used to derive equation (43), the expectation of this average forecast error becomes

$$\mathbb{E}\left[\overline{\mathrm{FE}}_{-it}(k_{j't}, z_{j't}, a_{j't}, 1, \mathcal{I}_{-it}^{\text{news}})\right] = \mathbb{V}[\mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1) | k_{j't}, z_{j't}]. \quad (45)$$

Substituting these results into equation (40), the utility of deviating in this way is

$$\mathbb{E}\,\hat{U}_{it}(j,j') = \mathbb{V}[\mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1)|k_{j't}, z_{j't}] - \mathbb{V}[\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)|k_{jt}, z_{jt}]. \tag{46}$$

Condition (39) is therefore satisfied, and the candidate, $\boldsymbol{m}_t$, can be sustained as a symmetric equilibrium, if and only if

$$\mathbb{V}[\mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1)|k_{j't}, z_{j't}] - \kappa_{j't} \leq \mathbb{V}[\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)|k_{jt}, z_{jt}] - \kappa_{jt} \tag{47}$$

for all pairs of reported and unreported firms j, j'. The reporting policy for which this condition holds is the one described in equations (30)-(32).

□

B.1.2. Invariance of reporting probability ratios

For any given firm j, suppose the probability of this firm being reported by a newspaper is $\bar{p}_j$, then the probability of this firm being reported by n newspaper will be $p_{j,n} = 1 - (1 - \bar{p}_j)^n$, which implies that

$$\frac{\ln(1-\bar{p}_j)}{\ln(1-\bar{p}_{j'})} = \frac{\ln(1-p_{j,n})}{\ln(1-p_{j',n})} \approx \frac{p_{j,n}}{p_{j',n}}, \quad \forall n.$$

Since $\frac{p_{j,n}}{p_{j',n}}$ is independent of the number of newspaper n, we use the ratio of different firm groups' average reporting probability observed in our data sample as the target moment for model calibration.

B.2. Alternative assumptions on outlets and forecasters

We consider two plausible alternative assumptions to the media-reporting policy in Section 3.3.2. Even though the resulting newsworthiness function differs slightly from equation (31), the qualitative properties remain unchanged.

B.2.1. Outlet objective function

In Section 3, we assumed that the media outlets maximize the expected utility of their forecasters. However, the media outlets observe all realizations of a_{jt} and the reporting decisions of the other outlets. These outlets are therefore able to predict the *realized* utility of their forecasters when they make their reporting decisions. If we allow the outlet to maximize this realized utility, their problem is as in Section 3.1.3, except that the objective function changes to

$$\max_{m^o_{ijt}} - \int_0^1 \left[\mathrm{FE}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{it}) - \overline{\mathrm{FE}}_{-it}(k_{jt}, z_{jt}, a_{jt}, m_{jt}, \mathcal{I}^{\text{news}}_{-it})\right] dj - \int_0^1 \kappa_{jt} m^o_{ijt} dj \tag{48}$$

subject to equations (22)-(23) and optimal predictions (28).

In this case, a vector $\boldsymbol{m}_t$ can be sustained as a symmetric reporting equilibrium in pure strategies if and only if

$$\hat{U}_{it}(j, j') + \kappa_{jt} - \kappa_{j't} \leq 0 \tag{49}$$

for all pairs of reported and unreported firms j, j'. This differs from equation (39) in that there is no longer an expectation operator present.

The results on the realized forecast errors derived in Section 3.3.2 continue to hold, as nothing has changed in the forecaster's problem. $\hat{U}_{it}(j, j')$ is therefore given by

$$\begin{aligned}\hat{U}_{it}(j, j') = & \left[\mathbb{E}(\mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1) | k_{j't}, z_{j't}, m_{j't} = 1) - \mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1)\right]^2 \\ & - \left[\mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1) | k_{jt}, z_{jt}, m_{jt} = 1) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\right]^2. \end{aligned} \tag{50}$$

The unique symmetric pure strategy reporting equilibrium is therefore as in Section 3.3.2, except that the newsworthiness function is modified to

$$\mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) = \left[\mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1) | k_{jt}, z_{jt}, m_{jt} = 1) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\right]^2. \tag{51}$$

Like the form in equation (31), this is increasing in the firm size. The key difference is that the newsworthiness function now also depends on the realized a_{jt}.

B.2.2. Forecaster information

In Section 3.1, we assumed that forecasters can observe the reporting decisions of outlets other than their own. This allowed for a simple characterization of the equilibrium reporting policy, but it is not essential for our results. In this subsection, we derive the equilibrium reporting policy under the alternative assumption that forecaster i does not observe the reporting decisions of other outlets, as in, for example, Nimark and Pitschner (2019). We continue to assume, as in the previous derivation, that the outlet maximizes the realized utility of their forecaster. The outlet problem is therefore unchanged: their objective is as in equation (48), and the constraints are as in equations (22)–(23). A vector $\boldsymbol{m}_t$ can be sustained as a symmetric pure strategy equilibrium if and only if condition (49) holds for all pairs of reported and unreported firms j, j'. The key way this alternative assumption changes the model is that forecasters no longer necessarily observe the aggregate media indicator m_{jt}.

As in Section 3.1, if outlet i reports on a firm, j, then $m_{jt} = 1$. Moreover, forecaster i can infer that $m_{jt} = 1$ for certain: they see that their outlet has reported on firm j, which is sufficient to imply $m_{jt} = 1$ (equation (24)). As in Appendix B.1.1, if an outlet deviates to report on firm j', while other outlets report on j, we therefore have

$$\mathrm{FE}_t(k_{j't}, z_{j't}, a_{j't}, m_{j't} = 1, \mathcal{I}^{\text{news}}_{it}) = \overline{\mathrm{FE}}_{t-i}(k_{jt}, z_{jt}, a_{jt}, m_{jt} = 1, \mathcal{I}^{\text{news}}_{-it}) = 0 \tag{52}$$

The utility change from deviating therefore reduces to

$$\begin{aligned}\hat{U}_{it}(j, j') =& \big[\, \mathbb{E}(\mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, m_{j't}) | k_{j't}, z_{j't}, m^o_{i'j't} = 0) - \mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1)\big]^2 \\ & - \big[\, \mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt}) | k_{jt}, z_{jt}, m^o_{ijt} = 0) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\big]^2.\end{aligned} \tag{53}$$

This differs from equation (50) because the expectations are formed without the knowledge of the true $m_{jt}, m_{j't}$. In both cases, all the forecasters know is what their own outlets have published. In the first of the expectations, this is the expected market value of firm j' formed by forecasters other than forecaster i, whose outlet did not report on j' ($m^o_{i'j't} = 0$). In the second expectation, the expected market value of firm j is formed by forecaster i, whose outlet has deviated and is not reporting on firm j ($m^o_{ijt} = 0$). In both cases, the true aggregate reporting indicator is $m_{jt} = m_{j't} = 1$: outlet i reports on firm j', and all other outlets report on firm j. As the outlets can still observe each others' reporting choices, each outlet is aware of this fact; only the forecasters who are not.

The law of iterated expectations implies

$$\begin{aligned}
&\mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, m_{jt})|k_{jt}, z_{jt}, m^o_{ijt} = 0) \\
&\qquad = \Pr(m_{jt} = 1|k_{jt}, z_{jt}, m^o_{ijt} = 0)\, \mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)|k_{jt}, z_{jt}, m^o_{ijt} = 0, m_{jt} = 1) \\
&+ (1 - \Pr(m_{jt} = 1|k_{jt}, z_{jt}, m^o_{ijt} = 0))\, \mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 0)|k_{jt}, z_{jt}, m^o_{ijt} = 0, m_{jt} = 0), \quad (54)
\end{aligned}$$

where $\Pr(m_{jt} = 1|k_{jt}, z_{jt}, m^o_{ijt} = 0)$ is the perceived probability that forecaster i attaches to $m_{jt} = 1$, conditional on their observations.

The term $\Pr(m_{jt} = 1|k_{jt}, z_{jt}, m^o_{ijt} = 0)$ represents, for a forecaster observing that their outlet *did not* report on a firm, the probability that some other outlet *did* report on that firm during the period. Under rational expectations, although forecaster i does not observe the reporting decisions of the outlet belonging to forecaster i' (and vice versa), they are able to understand the policy function that is driving that other outlet's decisions and, thus, the process for determining m_{jt}.

Under rational expectations, forecasters also understand that they are in a symmetric media equilibrium, which implies

$$\Pr(m_{jt} = 1|k_{jt}, z_{jt}, m^o_{ijt} = 0) = 0. \quad (55)$$

That is, when forecasters observe that their own outlet has not reported on a particular firm, they infer that no outlet has done so.

There is one nuance here that is noteworthy. Forecasters infer that $m_{jt} = m^o_{ijt}$ because they have rational expectations, so they have full knowledge of the equilibrium. In equilibrium, their inference on m_{jt} is therefore correct. However, in equation (53) we are considering a deviation from that equilibrium, implicitly assuming that if such a deviation were to happen, forecasters would not be able to identify that it had happened. As a result, they would continue to forecast $m_{jt} = m^o_{ijt}$ with certainty, even though this would have been incorrect under the deviation. This assumption is consistent with rational expectations: In any equilibrium, such a deviation is a probability-zero event, so it is rational to attach no weight to it. All the forecaster observes is k_{jt}, z_{jt} and m^o_{ijt}, and none of this reveals that a deviation is occurring. This is one key reason why deviations create forecast errors, as they lead forecasters to make errors about m_{jt}. The utility change from deviating in equation (53), therefore, becomes

$$\begin{aligned}\hat{U}_{it}(j,j') = & \big[\,\mathbb{E}(\mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 0)|k_{j't}, z_{j't}) - \mathrm{MV}_t(k_{j't}, z_{j't}, a_{j't}, 1)\big]^2 \\ & - \big[\,\mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 0)|k_{jt}, z_{jt}) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\big]^2 \end{aligned} \tag{56}$$

The unique symmetric pure strategy reporting equilibrium is the same as in Section 3.3.2, except that the newsworthiness function is modified to

$$\mathrm{N}_t(k_{jt}, z_{jt}, a_{jt}) = \big[\,\mathbb{E}(\mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 0)|k_{jt}, z_{jt}) - \mathrm{MV}_t(k_{jt}, z_{jt}, a_{jt}, 1)\big]^2. \tag{57}$$

A firm is more newsworthy if its news coverage would substantially alter the beliefs of forecasters and investors and would lead to a large change in market valuations. Newsworthiness is increasing in firm size (as in equation (31)) and depends on realizing a_{jt} (as in equation (51)).

B.3. Equity market equilibrium under asymmetric information

Given the equity issuance price specified by (18), the optimal equity issuance decision problem for firms being reported by the media is specified by

$$\mathrm{V}_t(k, z, a, 1) = \max_{e \geq 0} \mathrm{W}_t(k, z, a, e) - e, \tag{58}$$

The equity issuance price of an unreported firm is not determined by its asset quality but by its issuance, because the asset quality is unobservable by investors. Given this property, we can rewrite the equity issuance price function as $\mathrm{P}_t(k, z, e)$. For each set of firms with common observable characteristics (k, z), their equity issuance is determined by the equity market equilibrium characterized as follows.

For a given value function $\mathrm{W}_t(k, z, a, e)$ and a prior on firms' asset quality $\mathcal{G}(a)$: $\{a_1 < a_2 < \cdots < a_N\} \to (0, 1)$, the equilibrium is defined as a collection of the equity issuance policy function $\mathbf{e}_t(k, z, a)$, the equity issuance price function $\mathrm{P}_t(k, z, e)$, and the investors' beliefs $\mathcal{B}_t(a|k,z,e)$, such that

1. given the equity issuance price $\mathrm{P}_t(k,z,e)$, firms make their equity issuance decisions $\mathbf{e}_t(k,z,a)$ based on the optimization problem

$$\mathrm{V}_t(k,z,a) = \max_{e\geq 0} \frac{\mathrm{P}_t(k,z,e)}{\mathrm{P}_t(k,z,e)+e} \cdot \mathrm{W}_t(k,z,a,e); \tag{59}$$

2. given the firms' optimal equity issuance choices $\mathbf{e}_t(k,z,a)$, the investors' beliefs on the firms' asset quality must satisfy Bayes' rule

$$\mathcal{B}_t(a|k,z,e) = \frac{\mathcal{G}(a)\mathbb{1}_{\mathbf{e}_t(k,z,a)=e}}{\int \mathcal{G}(\tilde{a})\mathbb{1}_{\mathbf{e}_t(k,z,\tilde{a})=e} d\tilde{a}} \tag{60}$$

for equity issuance e on equilibrium paths and the Divinity criteria as specified in Banks and Sobel (1987) for the issuance off the equilibrium path;

3. given the investors' beliefs $\mathcal{B}_t(a|k,z,e)$, the equity issuance price $\mathrm{P}_t(k,z,e)$ has to satisfy the investors' break-even condition:

$$\int \frac{e}{e+\mathrm{P}_t(k,z,e)} \mathrm{W}_t(k,z,a,e)\mathcal{B}_t(a|k,z,e)da = e, \ \forall e > 0. \tag{61}$$

Guo et al. (2024) show that whenever the value function $\mathrm{W}_t(k,z,a,n)$ satisfies $\frac{\partial \mathrm{W}_t(k,z,a,e)}{\partial e} > 0$, $\frac{\partial^2 \mathrm{W}_t(k,z,a,e)}{\partial e^2} < 0$ and $\frac{\partial^2 \mathrm{W}_t(k,z,a,e)}{\partial e \partial a} \leq 0$, a pooling equilibrium does not exist. The following theorem characterizes a separating equilibrium through a sequential algorithm. For notational simplicity, we abstract from the time subscript t in the equations below.

Proposition 2. *The equilibrium issuance choices of firms that share the same publicly observable information (k,z) can be determined by the following sequential algorithm:*

0. *Denote the equity issuance of firms with quality a under symmetric information as $\mathbf{e}^*(k,z,a)$, that is, $\mathbf{e}^*(k,z,a) \equiv \arg\max_{e\geq 0} \mathrm{W}(k,z,a,e) - e$.*

1. *The optimal equity issuance of the firms with the lowest asset quality is $\mathbf{e}(k,z,a_1) = \mathbf{e}^*(k,z,a_1)$ and the associate equity issuance price is*

$$\mathrm{P}(k,z,\mathbf{e}(k,z,a_1)) = \mathrm{W}(k,z,a,\mathbf{e}(k,z,a_1)) - \mathbf{e}(k,z,a_1).$$

2. *Given the equity issuance of a firm with asset quality a_ι as $\mathbf{e}(k,z,a_\iota) > 0$ and its associated issuance price $P(k,z,\mathbf{e}(k,z,a_\iota))$, the upper bound of the equity issuance for firms with $a_{\iota+1}$, denoted as $\bar{e}_{\iota+1}$, such that lower-quality firms have no incentive to mimic, is solved by*

$$\mathrm{W}(k,z,a_\iota,\mathbf{e}(k,z,a_\iota)) - \mathbf{e}(k,z,a_\iota) = \mathrm{W}(k,z,a_\iota,\bar{e}_{\iota+1}) - \bar{e}_{\iota+1}\frac{\mathrm{W}(k,z,a_\iota,\bar{e}_{\iota+1})}{\mathrm{W}(k,z,a_{\iota+1},\bar{e}_{\iota+1})}. \quad (62)$$

Then the equity issuance of firms with $a_{\iota+1}$ is

$$\mathbf{e}(k,z,a_{\iota+1}) = \begin{cases} \min\{\mathbf{e}^*(k,z,a_{\iota+1}),\ \bar{e}_{\iota+1}\} & \textit{if } \mathrm{W}(k,z,a_{\iota+1},\bar{e}_{\iota+1}) > \mathrm{W}(k,z,a_{\iota+1},0) \\ 0 & \textit{otherwise.} \end{cases}$$

When $\mathbf{e}(k,z,a_{\iota+1}) > 0$, the associated equity issuance price is

$$\mathrm{P}(k,z,\mathbf{e}(k,z,a_{\iota+1})) = \mathrm{W}(k,z,a,\mathbf{e}(k,z,a_{\iota+1})) - \mathbf{e}(k,z,a_{\iota+1}).$$

3. *If firms with asset quality a_ι choose not to issue equity, that is, $\mathbf{e}(k,z,a_\iota) = 0$, then all firms with asset quality $a > a_\iota$ will not issue equity either.*

The belief that supports support this equilibrium outcome is

$$\mathcal{B}(a|k,z,e) = \begin{cases} \mathbb{1}_{a=a_1} & \textit{if } e > \mathbf{e}(k,z,a_2) \\ \mathbb{1}_{a=a_{\iota-1}} & \textit{if } e \in (\mathbf{e}(k,z,a_\iota), \mathbf{e}(k,z,a_{\iota-1})] \\ \frac{\mathcal{G}(a)}{\int_{\tilde{a}:\{\mathbf{e}(k,z,\tilde{a})=0\}}\mathcal{G}(\tilde{a})d\tilde{a}} & \textit{if } e \le \mathbf{e}(k,a,a_{\bar{\iota}}), \end{cases} \quad (63)$$

and the associated equity issuance price is

$$\mathrm{P}(k,z,e) = \begin{cases} \mathrm{W}(k,z,a_1,e) - e & \textit{if } e > \mathbf{e}(k,z,a_2) \\ \mathrm{W}(k,z,a_{\iota-1},e) - e & \textit{if } e \in (\mathbf{e}(k,z,a_\iota), \mathbf{e}(k,z,a_{\iota-1})] \\ \frac{\int_{\tilde{a}:\{\mathbf{e}(k,z,\tilde{a})=0\}} W(k,z,\tilde{a},e)\mathcal{G}(\tilde{a})d\tilde{a}}{\int_{\tilde{a}:\{\mathbf{e}(k,z,\tilde{a})=0\}}\mathcal{G}(\tilde{a})d\tilde{a}} - e & \textit{if } e \le \mathbf{e}(k,a,a_{\bar{\iota}}), \end{cases}, \quad (64)$$

where $a_{\bar{\iota}}$ denotes the highest asset quality of the firms that issue equity.

Proof. Before proceeding, we state four helpful results:[30]

[30] See Guo et al. (2024) for further details of the proof. Since the analysis is conditional on each pair of

1. Under symmetric information, the optimal equity issuance of a firm is not smaller than that of the firms with higher qualities, that is, $\mathbf{e}^*(a) \geq \mathbf{e}^*(a')$ for any $a' > a$ if $\mathbf{e}^*(a') > 0$.

2. Under asymmetric information, the upper bound of the equity issuance for the type-$a_{\iota+1}$ firm $\bar{e}_{\iota+1}$ that is imposed by the lemon threat from type-a_ι and specified by (62) exists and this upper bound is decreasing with respect to the firms' capital quality, that is, $\bar{e}_{\iota'} < \bar{e}_\iota$ for any $\iota' > \iota$.

3. Under asymmetric information, the existing shareholders' value is increasing by the firms' capital quality, that is, $\mathrm{V}(a_\iota) < \mathrm{V}(a_{\iota+1})$ for any $\iota \in \{1, 2, 3, \ldots, n\}$.

4. There exists a unique $e_\iota \in (\mathbf{e}^*(a_\iota), \bar{e}_\iota)$ that satisfies $\frac{\mathrm{W}(\eta_\iota, \bar{e}_\iota)}{\mathrm{W}(\eta_\iota, e^*_\iota) - e^*_\iota} = \frac{\mathrm{W}(\eta_{\iota-1}, \bar{e}_\iota)}{\mathrm{W}(\eta_{\iota-1}, e^*_{\iota-1}) - e^*_{\iota-1}}$, when $e^*_\iota < \bar{e}_\iota$.

Proving Proposition 2 requires showing three parts:

1. The equity issuance contract $P(e)$ specified in (64) is consistent with the belief $\mathcal{B}(a|e)$ specified in (63).

2. The firms' choices $\{e^*_\iota\}_{\iota=1}^n$ are the firms' optimal choices under the contract $P(e)$.

3. The belief $\mathcal{B}(a|e)$ is consistent with the firms' choices for the equilibrium outcomes of the issuance and satisfies the Divinity criteria for the off-equilibrium outcomes of the issuance.

Consistency between $P(e)$ and $\mathcal{B}(a|e)$ Given the belief $\mathcal{B}(a|e)$, the conditional expectation of the firms' value is

$$\mathbb{E}[\mathrm{W}(a,e)|\mathcal{B}^*(a;e)] = \begin{cases} \mathrm{W}(a_1, e) & \text{if } e > \mathbf{e}(a_2) \\ \mathrm{W}(a_{\iota-1}, e) & \text{if } e \in (\mathbf{e}(a_\iota), \mathbf{e}(a_{\iota-1})] \\ \frac{\sum_{\iota \geq \bar{\iota}} \mathrm{W}(a_\iota, e) \cdot \mathcal{G}(a_\iota)}{\sum_{\iota \geq \bar{\iota}} \mathcal{G}(a_\iota)} & \text{if } e \leq \mathbf{e}(a_{\bar{\iota}}), \end{cases},$$

which directly implies that $\frac{e}{\mathrm{P}(e)+e} \cdot \mathbb{E}[\mathrm{W}(a,e)|\mathcal{B}(a|e)] = e$ for any $e > 0$.

(k, z), for simplicity of notation, we omit these two publicly observable characteristics in the proof. We also express $\mathbf{e}^*(a_\iota)$ as e^*_ι.

Optimality of $\{e_\iota^*\}_{\iota=1}^n$ We can show that e_ι^* is the optimal choice of firm type-a_ι under contract $\mathrm{P}(e)$, $\forall \iota = 1, 2, 3, \ldots, N$, in the following steps:

0. For notational simplicity, we use $e \succeq_a (\succ_a) e'$ to denote that equity issuance e dominates (strictly dominates) e' for type-a firms under the issuance contract $\mathrm{P}(e)$.

1. $e_\iota^* \succeq_{a_\iota} e$, $\forall e \in (\bar{e}_{\iota+1}, \bar{e}_\iota]$, that is, when a firm is priced based on its true type, it has no incentive to deviate.

2. $e_\iota^* \succeq_{a_\iota} e$, $\forall e \in (\bar{e}_{\iota+2}, \bar{e}_{\iota+1})$, that is, type-$a_\iota$ firms have no incentive to lower their equity issuance and, thus, to let the investors perceive them as type-$a_{\iota+1}$ firms under the contract $\mathrm{P}(e)$.

3. $e_\iota^* \succeq_{a_\iota} e$ $\forall e \leq \bar{e}_{\iota+1}$, that is, the type-$a_\iota$ firm has no incentive to issue less equity and let investors perceive it as a firm with higher capital quality under contract $\mathrm{P}(e)$.

4. Similarly, we can also prove that $e_\iota^* \succeq_{a_\iota} e$ $\forall e \in (\bar{e}_\iota, \bar{e}_{\iota-1}]$, that is, type-$a_\iota$ firms have no incentive to increase their equity issuance and let investors perceive them as type-$a_{\iota-1}$ firms under contract $\mathrm{P}(e)$.

5. Now, we can prove that $e_\iota^* \succeq_{a_\iota} e$, $\forall e > \bar{e}_\iota$, that is, the type-$a_\iota$ firm has no incentive to increase its issuance and let investors perceive it as a firm with lower capital quality under contract $\mathrm{P}(e)$.

6. Combining results 1, 3, and 5, e_ι^* is type-a_ι firms' optimal equity issuance under contracts $\mathrm{P}(e)$.

Consistency of belief $\mathcal{B}(a|e)$ In our context, the Divinity Criterion requires that for any equity issuance $e > 0$, investors assign positive probability only to the firms who are most likely to benefit from deviating from their current equilibrium issuance to e. Definition 1 provides the formalization.

***Definition* 1** (Divinity Criterion)**.** *Let $\Theta(e, a)$ denote the set of investors' requested shares that makes a type-a firm better off by deviating to an off-equilibrium issuance $e > 0$:*

$$\Theta(e, a) \equiv \left\{ s \in \left[\frac{\mathrm{W}(a_N, e) - e}{\mathrm{W}(a_N, e)}, \frac{\mathrm{W}(a_1, e) - e}{\mathrm{W}(a_1, e)} \right] : \frac{1}{1+s} \mathrm{W}(a, e) > V(a_\iota) \right\}.$$

Then, the set of firm types that are most likely to deviate, denoted by $\mathcal{A}(e)$, is defined as

$$\mathcal{A}(e) \equiv \{a : \Theta(e, a') \subseteq \Theta(e, a),\ \forall a' \neq a\}.$$

The Divinity Criterion requires that for any off-equilibrium equity issuance $e > 0$, investors' belief satisfies:

$$\mathcal{B}(a|e) = 0\ \forall a \notin \mathcal{A}(e).$$

Now we first prove that the firm type most likely to deviate to a signal $e \in (\bar{e}_{\iota+1}, \bar{e}_{\iota})$ is a_{ι}, i.e., $\mathcal{A}(e)$ only has one element a_{ι}. For a given signal e, we define $\bar{s}(a_{\iota}, e) \equiv \frac{\mathrm{W}(a_{\iota},e)}{V(a_{\iota})} - 1$ as the upper bound of the required number of new shares to be issued that can motivate type-a_{ι} firms to deviate from their equilibrium choices and choose to issue e. Then, we can prove the following results:

1. $\bar{s}(a_{\iota}, e) > \bar{s}(a_{\iota-1}, e)$ for any $e < \bar{e}_{\iota}$, that is, type-a_{ι} firms are more likely to deviate to $e < \bar{e}_{\iota}$, compared with type-$a_{\iota-1}$ firms.

2. $\bar{s}(a_{\iota}, e) > \bar{s}(a_{\iota+1}, e)$ for any $e > \bar{e}_{\iota+1}$, that is, type-a_{ι} firms are more likely to deviate to e, compared with type-$a_{\iota+1}$ firms.

3. $\bar{s}(a_{\iota}, e) > \bar{s}(a_{\iota'}, e)$ for any $e \in (\bar{e}_{\iota+1}, \bar{e}_{\iota})$ if $\iota \neq \iota'$, that is, type-a_{ι} firms are more likely to deviate to $e \in (\bar{e}_{\iota+1}, \bar{e}_{\iota})$ than any other type of firm.

Based on the above proof, investors will believe that the equity issuance $e \in (\bar{e}_{\iota+1}, \bar{e}_{\iota})$ can only be a signal from firm type a_{ι}, i.e., $\mathcal{B}(a|e) = \mathbb{1}_{a=a_{\iota}}$, which is how we specify the off-equilibrium belief in (63). □

C. Additional Details for the Quantitative Analysis

C.1. Definitions and measurements of target moments

This section describes the construction of target moments reported in Table 4b, based on firms in the Compustat sample from 1990 and 2021.

1. Cash flow

(a) *Operating cash flow*: defined as net cash flow, measured by the operating activities (`oancfy` in the first fiscal quarter and changes in `oancfy` for the second to fourth fiscal quarters

(b) *Operating cash flow rate*: defined as operating cash flow normalized by capital stock (measured by lagged total assets `atq`).

(c) *Idiosyncratic TFP*: defined as the log of revenue rate divided by its cross-firm average, where the revenue rate is measured by the total revenue (`saleq`) normalized by lagged total assets (`atq`).

2. Investment

(a) *Investment*: defined as the capital expenditure (`capxy` in the first fiscal quarter and changes in `capxy` for the second to fourth fiscal quarters).

(b) *Investment rate*: defined as the investment normalized by capital stock

(c) *Measurement of investment rate dispersion*: Following Sterk et al. (2021), we measure the cross-sectional variation in firms' investment rates by first estimating

$$y_{jt} = \gamma_j + \gamma_{st} + \epsilon_{jt},$$

where y_{jt} denotes investment rate of firm j in quarter t, and $\{\gamma_j, \gamma_{st}\}$ denote firm and sector-by-quarter fixed effects; and then computing the dispersion of investment rate as the standard deviation of ϵ_{jt}.

3. Life-cycle dynamics

(a) *Age*: the number of years since the CRSP listing.

(b) *Young and mature firms*: young firms are defined as firms aged less or equal to 5 years; mature firms are defined as firms aged more than 25 years.

(c) *Growth rate*: the log-difference of the total assets (`atq`).

(d) *Measurement of age group difference*: To compute the target moment for the life-cycle differences between mature (age > 25) and young (age ≤ 5) firms, we use the coefficient β_5 estimated from

$$\begin{aligned} y_{jt} = &\gamma_j + \gamma_{st} + \beta_1 \cdot \mathbb{1}[5 < Age_{jt} \leq 10] + \beta_2 \cdot \mathbb{1}[10 < Age_{jt} \leq 15] \\ &+ \beta_3 \cdot \mathbb{1}[15 < Age_{jt} \leq 20] + \beta_4 \cdot \mathbb{1}[20 < Age_{jt} \leq 25] + \beta_5 \cdot \mathbb{1}[Age_{jt} > 25] + \epsilon_{jt}, \end{aligned}$$

where y_{jt} denotes growth rate or idiosyncratic TFP of firm j in quarter t, Age_{jt} denotes the age of firm j in quarter t, and $\{\gamma_j, \gamma_{st}\}$ denote firm and sector-by-quarter fixed effects.

4. Equity financing

   (a) *Equity issuance*: defined as the sale of common and preferred stock (`sstky` in the first fiscal quarter and changes in the `sstky` for the second to fourth fiscal quarters). Following McKeon (2015), we classify equity issuance that are smaller than 3% of a firm's market capitalization as zero issuance.

   (b) *Issuance fee ratio*: defined as the fixed issuance cost normalized by the issuance quantity. We use the reported mean in Table 4 of Lee and Masulis (2009) as our target moment.

   (c) *Selling concession ratio*: defined as the log difference between a firm's stock price before announcing its issuance decision and its post-issuance stock price. We use the reported mean in Table 4 of Lee and Masulis (2009) as our target moment.

5. Media reporting

   (a) *Reporting probability*: measured as the fraction of firms reported by media within each firm group of each quarter

C.2. Setup for the counterfactual studies

In this counterfactual, firms can purchase the option to be reported if they are not chosen by media to report. This induces two changes in these firms' problem. First, firms have one more choice to make, that is, whether to purchase the media coverage, $b(k, z, a) \in \{0, 1\}$.

When a firm is chosen by the media to report, its value function is

$$\mathrm{V}_t(k,z,a,1) = \max_{e\geq 0} \mathrm{W}_t(k,z,a,e) - e, \tag{65}$$

and when it is not chosen, its value function is

$$\begin{aligned}\mathrm{V}_t(k,z,a,0) = \max_{b\in\{0,1\}} \; & b\cdot\left(\max_{e\geq 0}\mathrm{W}_t(k,z,a,e-\phi^m) - e\right) \\ & + (1-b)\cdot\left(\max_{e\geq 0}\frac{\mathrm{P}_t(k,z,a,0,e)}{\mathrm{P}_t(k,z,a,0,e)+e}\cdot \mathrm{W}_t(k,z,a,e)\right),\end{aligned} \tag{66}$$

where ϕ^m is the price of the media coverage. Second, the media allocate a fraction of their coverage resource based on their baseline news-reporting policy and allocate the rest for firms to purchase. The associated clearing condition for the media-coverage resource is

$$\begin{aligned}&\underbrace{\int \mathrm{R}_t^{\text{baseline}}(k,z)\mathcal{G}(a)\mathcal{F}_t^{\text{baseline}}(k,z)dkdzda}_{\text{Total capacity of media coverage}} \\ = &\underbrace{\int \mathbf{b}_t(k,z,a)\cdot\left(1-(1-\alpha_m)\mathrm{R}_t(k,z,a)\right)\mathcal{G}(a)\mathcal{F}_t(k,z)dadkdz}_{\text{Total media coverage purchased by firms}} \\ + & \underbrace{(1-\alpha_m)\cdot\int \mathrm{R}_t(k,z,a)\mathcal{G}(a)\mathcal{F}_t(k,z)dkdzda}_{\text{The total media coverage allocated based on the baseline news-reporting policy}}\end{aligned} \tag{67}$$

This market clearing condition will determine the price of being reported by the media ϕ^m.

C.3. Additional quantitative results

Uniform reporting We evaluate the role of the media within a counterfactual economy with uniform media reporting, where the media allocates the total reporting resources equally and reports firm with equal probability. As summarized in Table C.1, compared with the selective-reporting baseline economy, equally allocating the media-coverage resource across firms can further alleviate the loss from asymmetric information. This improvement arises mainly because more firms that benefit from being reported receive media coverage under this allocation. However, the magnitude of this improvement is relatively small, because there is still a large fraction of the media-coverage resource allocated to financially unconstrained firms, which are unaffected by media reports.

Table C.1: Aggregate effects of information asymmetry (%)

	No-media	Baseline reporting	Uniform reporting
Investment	-6.7	-5.9	-.5.5
Capital stock	-4.7	-4.2	-3.9
Output	-5.3	-4.6	-4.4

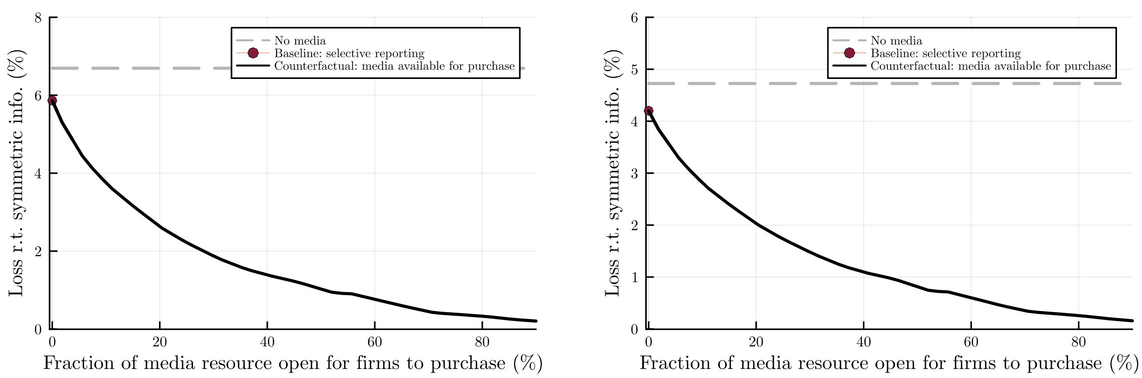
Notes: This table summarizes the effects of asymmetric information on aggregate investment, capital stock, and output within the no-media economy, our baseline economy with selective-reporting media, and a counterfactual economy with the media reporting every firm with equal probability. To evaluate the effects of asymmetric information, we first solve a model that shares the same setup and calibration with the baseline model but features no information asymmetry. Then we compute the relative difference of the various aggregate quantities between each economy and the symmetric-information economy.

Additional results for the aggregate relevance of the media-coverage allocation

In Section 4.4, we report the aggregate relevance of the media-coverage allocation measured by how much of the loss in aggregate output from asymmetric information is alleviated. In Figure C.1, we present the corresponding results measured by the aggregate capital and investment loss, which show a similar pattern as discussed in Section 4.4.

Figure C.1: Aggregate relevance of media allocation

(a) Investment loss **(b)** Capital



Notes: Panels (a) and (b) summarize the aggregate investment and capital loss in various counterfactual economies. In each counterfactual economy, we fix the total fraction of firms to be reported by the media but allow a fraction of the media resource to be allocated through a competitive market for firms to purchase the option to be reported by media. The investment (capital) loss is measured by the relative difference of aggregate investment (capital) between each counterfactual economy and the symmetric-information economy.

D. A Model with Investor-Led Media Demand

In this section, we provide an alternative microfoundation for the media's reporting policy. We incorporate a media sector in a variant of the static Grossman and Stiglitz (1980) model. Unlike our main quantitative model, noise traders prevent the perfect aggregation of information in asset prices. This causes investors to value information coming from the media. To solve this model, we abstract from the firm block of our quantitative model. Instead, a firm's equity generates a payoff that is independent of media decisions but initially unknown to investors.

D.1. Environment

Assets There is a risk-free asset with fixed return r and a price of 1 (the numeraire). There are N firms. The firms' equities consist of risky assets with payoffs given by the $N \times 1$ vector $f \sim N(\bar{f}, \Sigma_f)$, where Σ_f is diagonal (firm payoffs are independent). The prices of these risky assets are collected in the $N \times 1$ vector p. f is exogenous, but p will be determined in equilibrium by investors' behavior.

Media There is a representative media outlet, which observes the realization of f before the market opens. The outlet produces a publication in which they report the realized payoffs from a subset of firms' equities. As in Section 3, the outlet has a space constraint

$$\sum_{j=1}^{N} m_j \leq N_r \tag{68}$$

where m_j is an indicator equal to 1 if the outlet reports on firm j, and $N_r < N$. The outlet sells this publication to investors at a price $c > 0$.

Investors There is a unit mass of investors indexed by i, with exponential utility over final wealth, W_i, net of the costs of any information acquired, cL_i.

$$U_i = -\exp(-\rho(W_i - cL_i)), \tag{69}$$

where $\rho > 0$ governs the risk aversion and $L_i \in \{0, 1\}$ is an indicator for whether the investor purchased the media publication.

Each investor has an endowment of W_0 units of the risk-free asset. Let q_i be the $N \times 1$ vector of the quantities of each risky asset purchased by investor i. To buy this portfolio, they must sell $q_i'p$ units of the risk-free endowment. Their end-of-period wealth is therefore

$$W_i = (W_0 - q_i'p)r + q_i'f. \tag{70}$$

Investors can observe which firms are reported before they choose whether to purchase the media publication, but they can only see the information in the publication if they purchase it. If an investor purchases the publication, they can only process a limited amount of information from its contents. We model this fixed information capacity with the constraint

$$|\Sigma_i^{-1}| \leq e^{2K}|\Sigma_f^{-1}|, \tag{71}$$

where Σ_i is the variance-covariance matrix of investor i's beliefs after processing the information found in the publication, but before observing p. The constant $K > 0$ determines the investor's information capacity.[31]

Market clearing The supply of each risky asset is constant. The demand for risky assets comes from investors and noise traders, who add a random component x to the asset demand. Market clearing therefore requires

$$\int_0^1 q_i di + x = \bar{x}, \quad x \sim N(0, \sigma_x^2 I), \tag{72}$$

where $\bar{x}$ and x are $N \times 1$ vectors of the asset supplies and the noise trader shocks, respectively. The noise trader shocks have a common variance $\sigma_x^2 \geq 0$.

Timing The model consists of five stages:

1. f is realized. The media outlet observes this and chooses which firms to report.

[31] With Gaussian priors and posteriors (verified below), this constraint implies that the mutual information between the priors and the posteriors is $\leq K$, as is standard in rational inattention models (Maćkowiak et al., 2023).

2. Investors decide whether they wish to purchase the publication and, (conditional on purchasing), how to allocate their information capacity.

3. Investors observe the realization of their chosen signals.

4. Asset markets open. Investors observe the asset prices and choose among the portfolios. Simultaneously, prices are determined as a function of investor demand.

5. Payoffs are realized.

D.2. Equilibrium with given information sets

We begin by solving for the asset demand and equilibrium for any given information set. In stage 4 of the model timing, equilibrium is a set of asset demands, q_i, and prices, p, such that

1. q_i maximizes investor i's expected utility, conditional on the information they processed and any information contained in p.

2. p is such that asset markets clear.

Portfolio choice When the asset market opens, investors observe p. We summarize any other information they may have obtained from the media in $\mathcal{I}_i$. Their expected utility at this point, after substituting out for W_i using the budget constraint (70) and simplifying, is

$$\mathbb{E}_i[U_i|p,\mathcal{I}_i] = -\exp(-\rho r W_0)\exp(\rho c L_i)\,\mathbb{E}_i[\exp(-\rho q_i'(f-pr))|p,\mathcal{I}_i]. \tag{73}$$

The first two exponential terms are known positive constants, so they do not affect the portfolio choice problem. Since f is normally distributed, $\exp(-\rho q_i'(f-pr))$ has a log-normal distribution. Assuming all signals from prices and purchased information preserve this distribution (we will verify later), the expectation in equation (73) can be written as

$$\mathbb{E}_i[U_i|p,\mathcal{I}_i] \propto -\mathbb{E}_i[\exp(-\rho q_i'(f-pr))|p,\mathcal{I}_i] = -\exp\left(-\rho q_i'(\mathbb{E}_i[f|p,\mathcal{I}_i]-pr)+\frac{\rho^2}{2}q_i'\mathbb{V}_i[f|p,\mathcal{I}_i]q_i\right) \tag{74}$$

where $\mathbb{V}_i[f|p,\mathcal{I}_i]$ is the $(N\times N)$ posterior variance of investor i's beliefs about f.

Maximizing this with respect to q_i gives the asset demand equation

$$q_i = \frac{1}{\rho}(\mathbb{V}_i[f|p, \mathcal{I}_i])^{-1}(\mathbb{E}_i[f|p, \mathcal{I}_i] - pr) \tag{75}$$

Prior information All investors know the distribution of f. If investors have paid for information, then they also observe a vector of noisy signals, before the markets open, of the form

$$s_i = f + \varepsilon_i, \quad \varepsilon_i \sim N(0, \Sigma_{\varepsilon i}), \tag{76}$$

where the noise ε_i is idiosyncratic to investor i and independent of f.

For simplicity we restrict our attention to cases where $\Sigma_{\varepsilon i}$ is diagonal (i.e., the signal noise is independent across assets). Incorporating these signals using Bayes' rule, investor i's beliefs about f before the market opens are normally distributed, with

$$\mathbb{V}_i[f|\mathcal{I}_i] \equiv \Sigma_i = (\Sigma_f^{-1} + \Sigma_{\varepsilon i}^{-1})^{-1} \tag{77}$$

$$\mathbb{E}_i[f|\mathcal{I}_i] \equiv \mu_i = \Sigma_i(\Sigma_f^{-1}\bar{f} + \Sigma_{\varepsilon i}^{-1}s_i). \tag{78}$$

If investor i does not purchase the (media) information, they do not observe the signals, so $\Sigma_{\varepsilon i}^{-1}$ is a matrix of 0s. If an asset j is not reported by the media, then the j, j'th element of $\Sigma_{\varepsilon i}^{-1}$ is 0 for all investors, as no one is able learn about asset j.

Information in prices We solve for the prices, p, by guessing and verifying that they are a linear function of the payoffs and the shocks, where

$$p = A + Bf + Cx \tag{79}$$

for some diagonal $N \times N$ matrices A, B, C.

We split the assets into two groups, depending on whether or not they are reported in the media. Without loss of generality, we index the assets that are reported in the media by $n \in \{1, ..., N_r\}$ and those that are unreported by $n \in \{N_{r+1}, ..., N\}$.

(a) <u>Unreported firms</u>: Since no investors have information on the realized f_n for unreported firms, the prices are uninformative and the final $N - N_r$ rows and columns of B contain only 0s. As a result, the beliefs about f_n depend on the underlying payoff distribution only. The demand for the equity of an unreported firm is therefore identical across investors and is given by

$$q_{ni} = \frac{\bar{f}_n - rp_n}{\rho\sigma_{fn}^2}, \tag{80}$$

where σ_{fn}^2 is the nth diagonal element of Σ_f. Substituting this into the market clearing in equation (72) for firm n's equity and rearranging yields

$$p_n = \frac{\bar{f}_n - \rho\sigma_{fn}^2\bar{x}_n}{r} - \frac{\rho\Sigma_{fn}}{r}x_n \tag{81}$$

This is of the form in equation (79), with the nth diagonal element of B equal to 0.

(b) Reported firms: The asset prices of the reported firms contain some information. Let z_r denote a $1 \times N_r$ vector consisting of the first N_r elements of any vector z, that is, f_r denotes the payoffs of the reported assets; similarly, A_r, B_r, C_r, Σ_{rf}, and Σ_{ri} denote $N_r \times N_r$ matrices, consisting of the first N_r rows and columns of A, B, C, Σ_f, and Σ_i, respectively.

From the price law of motion, investors can construct an unbiased signal about f_r as

$$B_r^{-1}(p_r - A_r) = f_r + B_r^{-1}C_r x \sim N(f_r, \Sigma_{rp}), \tag{82}$$

$$\Sigma_{rp} \equiv \sigma_x^2 B_r^{-1}C_r(B_r^{-1}C_r)'. \tag{83}$$

After incorporating this signal, investors' posteriors are normally distributed, with

$$\mathbb{V}_i[f|p, \mathcal{I}_i] \equiv \hat{\Sigma}_{ri} = (\Sigma_{ri}^{-1} + \Sigma_{rp}^{-1})^{-1}, \tag{84}$$

$$\mathbb{E}_i[f|p, \mathcal{I}_i] \equiv \hat{\mu}_{ri} = \hat{\Sigma}_{ri}(\Sigma_{ri}^{-1}\mu_{ri} + \Sigma_{rp}^{-1}B_r^{-1}(p_r - A_r)). \tag{85}$$

Substituting $\hat{\mu}_{ri}$ and $\hat{\Sigma}_{ri}$ into equation (75) we obtain the asset demand

$$q_{ri} = \frac{1}{\rho}\Sigma_{ri}^{-1}\mu_{ri} + \frac{1}{\rho}(\Sigma_{rp}^{-1}(B_r^{-1} - rI_r) - r\Sigma_{ri}^{-1})p_r - \frac{1}{\rho}\Sigma_{rp}^{-1}B_r^{-1}A_r. \tag{86}$$

Substituting out for μ_{ri}, Σ_{ri} using equations (77) and (78) and aggregating across investors, the market clearing becomes

$$\frac{1}{\rho}(\Sigma_{rf}^{-1}\bar{f}_r - \Sigma_{rp}^{-1}B_r^{-1}A_r) + \frac{1}{\rho}\bar{\Sigma}_{r\epsilon}^{-1}f_r + \frac{1}{\rho}(\Sigma_{rp}^{-1}(B_r^{-1} - rI_r) - r\Sigma_{rf}^{-1} - r\bar{\Sigma}_{r\epsilon}^{-1})p + x_r = \bar{x}_r, \tag{87}$$

where $\bar{\Sigma}_{r\epsilon}^{-1} = \int_0^1 \Sigma_{r\epsilon i}^{-1} di$ is the average precision of the investors' signals. This rearranges to the form in equation (79), confirming our guess. Matching the coefficients yields solutions for A, B, C.

D.3. Information choice

We now go back a step and solve for the information choices, taking the media reporting as given.

Indirect expected utility Equation (73) defines the expected utility conditional on observing $p, \mathcal{I}$. Substituting out for the expectation, using (74), and for q_i using (75), this becomes

$$\mathbb{E}_i[U_i|p, \mathcal{I}_i] = -\exp(-\rho r W_0)\exp(\rho c L_i)\left[\exp\left(-\frac{1}{2}(\mathbb{E}_i[f|p,\mathcal{I}_i] - pr)'\mathbb{V}_i[f|p,\mathcal{I}_i]^{-1}(\mathbb{E}_i[f|p,\mathcal{I}_i] - pr)\right)\right]. \tag{88}$$

When the investor makes their information choice, they have not yet observed $p, \mathcal{I}$. We therefore need to take the expectation of equation (88) over these objects, or equivalently over the posterior expectation $\mathbb{E}_i[f|p, \mathcal{I}_i]$.[32] This is an expectation of an exponential of a squared Gaussian distribution, which is given by (see Veldkamp, 2023, ch. 7.3)

$$\begin{aligned}\mathbb{E}_i[U_i] = -\exp(-\rho r W_0)\exp(\rho c L_i)\left(\frac{|\mathbb{V}_i[f|p,\mathcal{I}_i]|}{|\Sigma_f|}\right)^{\frac{1}{2}} \\ \cdot\left[\exp\left(-\frac{1}{2}\mathbb{E}_i[\mathbb{E}_i[f|p,\mathcal{I}_i] - pr]'\Sigma_f^{-1}\mathbb{E}_i[\mathbb{E}_i[f|p,\mathcal{I}_i] - pr]\right)\right].\end{aligned} \tag{89}$$

The final bracketed term of this expression consists of investors' expectations of posterior

[32] The posterior variance $\mathbb{V}_i[f|p, \mathcal{I}_i]$ is unaffected by the realization of the signals or the prices. When they make that decision, investors know the $\mathbb{V}_i[f|p, \mathcal{I}_i]$ they will face with and without purchasing the information.

beliefs and prices. Investors know that information will make their beliefs more precise, but ex-ante they do not expect it to make their beliefs systematically more or less optimistic. Whether or not they purchase this information, this final term is therefore constant. As a result, only the terms in L_i and $(|\mathbb{V}_i[f|p,\mathcal{I}_i]|/|\Sigma_f|)^{-\frac{1}{2}}$ are affected by the information choice.

The expected utility for informed investors who purchase media and for uninformed investors who do not is therefore (respectively) proportional to

$$\mathbb{E}_i[U_i] \propto -e^{\rho c}\left(\frac{|\mathbb{V}_i[f|p,\mathcal{I}_i]|}{|\Sigma_f|}\right)^{\frac{1}{2}}, \quad \mathbb{E}_U[U_U] \propto -\left(\frac{|\mathbb{V}[f|p]|}{|\Sigma_f|}\right)^{\frac{1}{2}}, \tag{90}$$

where $\mathbb{V}_i[f|p,\mathcal{I}_i]$ may differ across informed investors, i, depending on how they choose to allocate their information capacity.

Information capacity allocation An investor who purchases the media publication chooses the properties of their noisy signals (76) to maximize their expected utility (89) subject to their capacity constraint (71). Since the priors are Gaussian, equation (76) is the optimal signal structure, and investors only have to choose the noise variance matrix $\Sigma_{\varepsilon i}$.

The important step here is to note, as shown in e.g., Veldkamp (2023), that the objective function is convex, implying there are gains to specialization. The optimal information capacity allocation is for the investor to devote all of their capacity to learning about a single firm's equity. In other words, the investor's signal is such that all elements of $\Sigma_{\varepsilon i}^{-1}$ are zero except for one. If an investor learns about firm n^*, the capacity constraint implies

$$\sigma_{\varepsilon i n^*}^{-2} = (e^{2K}-1)\sigma_{fn^*}^{-2}, \tag{91}$$

where $\sigma_{\varepsilon i n^*}^{2}, \sigma_{fn^*}^{2}$ are the n^*th diagonal elements of $\Sigma_{\varepsilon i}$ and Σ_f, respectively.

Since Σ_f and $\mathbb{V}_i[f|p,\mathcal{I}_i]$ are diagonal, $\mathbb{E}_i[U_i]$ from equation (90) can be written as

$$\mathbb{E}_i[U_i] \propto -e^{\rho c}\prod_{n=1}^{N}\left(\frac{\mathbb{V}_i[f_n|p_n,\mathcal{I}_i]}{\sigma_{fn}^2}\right)^{\frac{1}{2}} = -e^{\rho c}\prod_{n=1}^{N_r}\left(\frac{\sigma_{fn}^{-2}+\sigma_{\varepsilon in}^{-2}+\sigma_{pn}^{-2}}{\sigma_{fn}^{-2}}\right)^{-\frac{1}{2}} \tag{92}$$

$$= -e^{\rho c}\left(\frac{|\mathbb{V}[f|p]|}{|\Sigma_f|}\right)^{\frac{1}{2}}\left(\frac{\sigma_{fn^*}^{-2}e^{2K}+\sigma_{pn^*}^{-2}}{\sigma_{fn^*}^{-2}+\sigma_{pn^*}^{-2}}\right)^{-\frac{1}{2}}. \tag{93}$$

The first of these equalities uses the observation that for all unreported firms, $\mathbb{V}_i[f_n|p_n,\mathcal{I}_i] =$

σ_{fn}^2. The second uses the fact that investor i uses all of their information capacity to learn about a single firm, denoted n^*, with the information precision given in equation (91).

Investors therefore learn about the firm with the highest "learning index," $\mathcal{L}_n$, defined as

$$\mathcal{L}_n \equiv \frac{\sigma_{fn}^{-2} e^{2K} + \sigma_{pn}^{-2}}{\sigma_{fn}^{-2} + \sigma_{pn}^{-2}}. \tag{94}$$

This is strictly increasing in σ_{fn}^{-2} and strictly decreasing in the precision of the information contained in the prices, σ_{pn}^{-2}. We show below that if more investors learn about asset n, σ_{pn}^{-2} rises. Investors therefore prefer to learn about the assets that other investors are not learning about.

Mixed strategy equilibrium We follow Van Nieuwerburgh and Veldkamp (2010) and look for an equilibrium in mixed strategies. Since investors wish to learn about that assets that other investors are not learning about, ex-ante identical investors specialize by randomizing the use of their information capacity.

Suppose that conditional on buying the publication, investors devote their information capacity to learning about asset n with probability π_n. For such a strategy to be optimal, investors must be indifferent between learning about all firms in the publication, given all other investors are playing the same mixed strategy. From equation (93), this implies[33]

$$\mathcal{L}_n = \mathcal{L}_{n'} \quad \text{for all} \quad (n, n') \quad \text{such that} \quad \pi_n, \pi_{n'} > 0. \tag{95}$$

Learning indices in equilibrium Let λ_n be the fraction of investors who process information about firm n, equal to π_n multiplied by the fraction of investors purchasing the media publication. The average precision of the investors' signals about firm n is then given by

$$\bar{\sigma}_{n\epsilon}^{-2} = \lambda_n (e^{2K} - 1)\sigma_{fn}^{-2}. \tag{96}$$

[33]This is exactly as in Van Nieuwerburgh and Veldkamp (2010), except for the extra constraint that investors can only learn about the assets that are reported in the media and only if they purchase the media publication.

Substituting this into row n of equation (87) and rearranging the leads to

$$p_n = (\sigma_{pn}^{-2}(b_n^{-1} - r) - r\sigma_{fn}^{-2}(1 + \lambda_n(e^{2K} - 1)))^{-1}\Big[(\rho\bar{x}_n + \sigma_{pn}^{-2}b_n^{-1}a_n - \sigma_{fn}^{-2}\bar{f}_n) \\ - \lambda_n\sigma_{fn}^{-2}(e^{2K} - 1)f_n - \rho x_n\Big]. \quad (97)$$

Matching the coefficients between equations (79) and (97), we obtain

$$b_n = -\frac{\lambda_n\sigma_{fn}^{-2}(e^{2K} - 1)}{\sigma_{pn}^{-2}(b_n^{-1} - r) - r\sigma_{fn}^{-2}(1 + \lambda_n(e^{2K} - 1))} \quad (98)$$

$$c_n = b_n \cdot \frac{\rho}{\lambda_n\sigma_{fn}^{-2}(e^{2K} - 1)}. \quad (99)$$

Equation (83), combined with the fact that all of the matrices here are diagonal, implies that the variance of the noise in the price of asset n is

$$\sigma_{pn}^2 = \sigma_x^2(b_n^{-1}c_n)^2 = \frac{\rho^2\sigma_x^2\sigma_{fn}^4}{\lambda_n^2(e^{2K} - 1)^2}, \quad (100)$$

which confirms our earlier statement that σ_{pn}^{-2} is increasing in λ_n. Substituting this into equation (94) and simplifying, we can express the learning index as

$$\mathcal{L}_n = 1 + \frac{e^{2K} - 1}{1 + \lambda_n^2\sigma_{fn}^{-2}\sigma_x^{-2}\rho^{-2}(e^{2K} - 1)^2}. \quad (101)$$

Many of the elements of this formula for the learning index are common across assets. Condition (95) is therefore satisfied if and only if

$$\frac{\lambda_n^2}{\sigma_{fn}^2} = \frac{\lambda_{n'}^2}{\sigma_{fn'}^2} \quad \text{for all} \quad (n, n') \text{ such that } \lambda_n, \lambda_{n'} > 0. \quad (102)$$

This is the key indifference condition for the mixed strategy equilibrium. For two assets with the same prior variance, the fraction of the informed investors λ_n must be equal. Otherwise, the assets with greater prior uncertainty will have a greater proportion of informed investors.

A final implication of these results is that the investors learn about all of the firms that are included in the media publication, with positive probability. To see this, suppose that no investor learns about firm n_0, so $\lambda_{n_0} = 0$. In equation (101), that firm's learning index would be $\mathcal{L}_{n_0} = \exp(2K)$, which is strictly greater than the learning index for any firm with a positive λ_n. As a result, if $\lambda_{n_0} = 0$, then an investor could always increase their expected utility by deviating from the mixed strategy of the other investors and from learning about n_0 with probability 1. It is therefore not possible for a mixed strategy equilibrium to entirely exclude some reported firms.

Media purchase Using equations (90) and (93), the expected utility gain from purchasing the media publication is given by

$$\mathbb{E}_i[U_i] - \mathbb{E}_U[U_U] = \left(\frac{|\mathbb{V}[f|p]|}{|\Sigma_f|}\right)^{\frac{1}{2}} (1 - e^{\rho c}\mathcal{L}_{n^*}^{-\frac{1}{2}}), \tag{103}$$

where $\mathcal{L}_{n^*}$ is the learning index of any of the assets over which investors mix.

Investors purchase the information if the expected utility gain is positive. The proportion of the investors who purchase the publication is such that investors are indifferent between purchasing or not purchasing the information, which occurs at $\mathcal{L}_{n^*} = e^{2\rho c}$. Therefore, a given value of c pins down a unique learning index.

Media-reporting decision The media outlet chooses which firms to report on to maximize their profits. Let Q be the proportion of investors who purchase the outlet's publication, so the latter's profits are revenues, cQ, minus costs, which we assume are independent of the outlet's reporting decisions. We take c as given, so the outlet chooses reporting to maximize its readership, Q.

To find the optimal reporting strategy, it is helpful to note that condition (102) implies that λ_n can be expressed as

$$\lambda_n = \lambda_0 \sigma_{fn}, \tag{104}$$

where λ_0 is identical for all firms, n. Substituting this into equation (101), we find that λ_0 is uniquely determined by the parameters that are common to all n and by the learning index $\mathcal{L}_n$, which in turn is fixed by c. We can therefore treat λ_0 as fixed.

Recall that λ_n is the proportion of investors who process information about firm n, which is given by the proportion who buy the media publication, multiplied by the probability an informed investor devotes their information capacity to that firm: $\lambda_n \equiv Q\pi_n$. Summing over all reported firms and using the fact that $\sum_{n=1}^{N_r} \pi_n = 1$, we therefore have

$$Q \sum_{n=1}^{N_r} \pi_n = \sum_{n=1}^{N_r} \lambda_n \implies Q = \lambda_0 \sum_{n=1}^{N_r} \sigma_{fn}. \tag{105}$$

Since λ_0 is fixed by c, the outlet maximizes Q by reporting on the N_r firms with the most volatile payoffs, that is, those firms with the highest σ_{fn}.

Relationship to the quantitative model To solve this model, we abstracted from firms' decisions. The variance of the payoffs from holding equity of firm n is thus fixed at σ_{fn}^2. In the quantitative model, media reporting affects firms' decisions and so affects that variance.

The appropriate analogue to the reporting policy derived here is that media outlets report on the firms with large payoff variances *conditional* on being reported. To see why, consider an outlet choosing between reporting on firms j and j'. If the outlet reports on firm j, investors observe that and evaluate the benefits of purchasing the outlet's publication, based on the resulting variance of asset j's payoff. If the outlet does not report on j but instead reports on j', then the value of the publication, to investors, is determined by the variance of asset j', given that j' was reported. The appropriate comparison is therefore between the variances of the payoffs conditional on the firm being reported. This is exactly the reporting policy derived in Section 3.3.2 in the quantitative model.