The (Mis)Allocation of Corporate News*

Xing Guo Bank of Canada

Alistair Macaulay University of Surrey

Wenting Song Bank of Canada

October 14, 2024

Abstract

This paper studies how the distribution of information supply by the news media affects the macroeconomy. We document three connected facts on media's reporting of firm news. First, media coverage is highly concentrated, particularly among the largest firms. Second, firms' equity financing and investment rise after media coverage. Third, these equity and investment responses are largest among small, rarely-covered firms. We then develop a heterogeneous-firm model with a media sector that matches these facts. Asymmetric information between firms and investors leads to financial frictions that constrain firms' financing and investment. Media's role in alleviating information frictions is limited by its focus on large and financially unconstrained firms. Re-allocating news coverage, or allowing firms to buy coverage from outlets in a competitive market, leads to substantial increases in aggregate investment and output. The aggregate effects of media coverage therefore depend crucially on how that coverage is allocated.

*Emails: Guo (xingguo@bank-banque-canada.ca), Macaulay (a.macaulay@surrey.ac.uk), and Song (wenting.w.song@gmail.com). We thank Yu-Ting Chiang, Oleksiy Kryvtsov, John Leahy, Kristoffer Nimark, Pablo Ottonello, Francisco Queirós, Víctor Ríos-Rull, Kjetil Storesletten, and participants at several conferences and seminars for helpful discussions. Maude Ouellet provided excellent research assistance. The views expressed herein are those of the authors and not necessarily those of the Bank of Canada.

1. Introduction

Information asymmetry between firms and potential investors distorts resource allocations and restricts firm growth (Myers and Majluf, 1984). At the same time, growing evidence suggests that news media serves as a key information source for investors (e.g., Dougal, Engelberg, García and Parsons, 2012; Peress, 2014; Hu, 2024). This raises the question: how does media coverage affect firm life cycles and aggregate investment?

In answering, we pay particular attention to how media coverage is allocated across firms. Like other types of news (Gentzkow and Shapiro, 2008; Nimark and Pitschner, 2019), firm-level media coverage is not randomly distributed; rather, editors and journalists selectively report on firms they consider most newsworthy. In this paper, we examine which firms receive media coverage and explore the macroeconomic implications of this selective, endogenous provision of information.

Empirically, we begin by constructing a new dataset of firm-level media coverage in the US, which captures the timing and frequency of coverage in major US newspapers for the universe of publicly traded firms over a 30-year period. Using this data, we document three connected facts on the distribution of news coverage: corporate news coverage is highly concentrated, particularly among the largest firms; firms' equity financing and investment rise after media coverage; and yet these responses are largest among small, rarely-covered firms.

First, we document that corporate news coverage is highly concentrated, and that 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.

Second, combining this news-coverage data with financial data from Compustat and CRSP, we document that media coverage is associated with subsequent changes in firm actions. In the quarters following media coverage, firms have a greater likelihood of raising equity financing and a higher rate of investment. The association between news coverage and investment increases with the financial focus of a newspaper, and is not present after social media coverage, which indicates that these relationships are not simply because the coverage makes a firm more salient to investors.[1]

We provide evidence on the mechanism behind this positive correlation. First, using detailed texts of news coverage, we identify and exclude articles discussing equity issuance and investment, which may be subject to a form of reverse causality in which imminent firm actions attract media coverage. Second, we complement the US evidence with evidence from France, where media strikes create variation in media coverage, which is unrelated to firm outcomes of interest. Among firms that have issued equity during media strikes, those with higher previous media coverage go on to invest less compared to other firms with less media exposure, consistent with firms relying on media to alleviate information frictions.

Lastly, we examine the conditional distribution of news coverage. Studies on firm heterogeneity indicate that the macroeconomic impact of micro-level heterogeneity depends heavily on its distribution (e.g., Alves, Kaplan, Moll and Violante, 2020; Sterk, Sedláček and Pugsley, 2021, and references therein). Ranking firms by size, we document that the correlation between news coverage and firm responses is strongest for small firms and almost negligible for large firms. Taken together, the empirical results are consistent with media reporting alleviating information asymmetries in financial markets.[2] The last result also implies that the firms who receive the most coverage are those who respond the least to it, which confirms the importance of considering the distribution of media coverage when evaluating its aggregate consequences.

To quantify the macroeconomic importance of corporate news reporting, we introduce a media sector to a macro-finance model with heterogeneous firms. Firm managers seek to maximize the firm value to existing shareholders and can raise external equity from retail investors to finance investments. However, retail investors face asymmetric information about firms' heterogeneous asset qualities. 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 report a subset of them. Once a firm appears in news reports, investors gain full information about the firm, which alleviates the asymmetric information in the equity market. However,

[1]As in Frydman and Wang (2020).

[2]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.

this effect is limited to the firms that news outlets choose to cover.

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, media outlets, therefore, disproportionately report on large firms in our calibrated model. Our key result is that this focus on large firms strongly limits media's effect on aggregate outcomes: Large firms—typically financially unconstrained in our model—are unaffected by fluctuations in investor beliefs induced by media coverage, since they do not need external funding to finance their optimal investment. In contrast, small and financially constrained firms do benefit from news reporting, because information asymmetries otherwise cause them to under-issue and under-invest. By concentrating coverage on firms least influenced by it, the media plays a limited role in alleviating the negative effects of asymmetric information on aggregate investment.

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 total media space constant. Specifically, we open a competitive market in which a fraction of media coverage is available for purchase by firms. Firms that stand to gain the most from coverage have the highest willingness to pay. Targeting media reporting to those firms significantly boosts their financing and investment, leading to a substantial reduction in aggregate output loss. A reallocation of just 5% of media resources towards firms with higher demand for coverage doubles 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.

Literature Our paper is related to four strands of literature. First, we contribute to the literature on the macroeconomic consequences of news media.[3] This literature has largely focused on the reporting of macroeconomic news: the selection of which stories get reported,

[3] A related but distinct strand of literature studies news shocks, in which 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).

and the manner in which they are reported, has been found to affect aggregate dynamics through a range of channels (e.g., Nimark, 2014; Larsen, Thorsrud and Zhulanova, 2021; Macaulay and Song, 2022). In addition, Bybee, Kelly, Manela and Xiu (2020) find that reports of macroeconomic stories can be used to effectively forecast a range of macroeconomic time series. Beyond this, Chahrour, Nimark and Pitschner (2021) show that variation in the reporting of sectoral news can drive business cycle fluctuations, and find that sectoral news patterns played a substantial role in the great recession. We contribute to this literature by studying the aggregate consequences of firm-level news, which we show varies substantially even within sectors.[4]

Second, we relate to the literature studying the importance of information frictions for firms' choices and resource allocations (Gorton and Ordonez, 2014; Asriyan, 2021; Coibion, Gorodnichenko and Ropele, 2020, 2023). We study the role of information supply by considering news media, whose reporting has been shown to affect equity markets (e.g., Cutler, Poterba and Summers, 1988; Chan, 2003; Engelberg and Parsons, 2011; Dougal et al., 2012), as a potential market for disseminating information and alleviating information frictions.

Third, we extend an emerging literature that studies the selectivity in media reporting, known as "gatekeeping" in journalism (Shoemaker and Vos, 2009). Within economics, selective reporting has been documented across political and other forms of news (Gentzkow and Shapiro, 2008; Nimark and Pitschner, 2019). We extend this literature by documenting a selectivity in firm-level corporate news reporting and characterizing which firms are most likely to be selected, consistent with recent theoretical work on incentives in the news industry (Chiang, 2022; Martineau and Mondria, 2022; Perego and Yuksel, 2022; Denti and Nimark, 2022, among others).

Finally, we contribute to the broader literature on the effects of financial frictions on firm dynamics, investment, and misallocation (e.g., Cooley and Quadrini, 2001, and see Brunnermeier, Eisenbach and Sannikov, 2012 for a survey). Our corporate finance model builds on Guo, Ottonello, Whited and Winberry (2024), who micro-found equity financing costs with asymmetric information. We extend the model to incorporate a media sector and study how media reporting can facilitate firms' financing and investment by alleviating their

[4] Hu (2024) also provides evidence on the consequences of firm-level news, but focuses on implications for the business cycle, while we consider how the distribution of news coverage across firms affects long-run outcomes.

financial friction; and how the allocation of media reporting resources can play an active 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, associated with real effects on firm outcomes, and allocated to the least responsive firms.

2.1. Illustrative framework: a decomposition

To begin with, we present a simplified version of our quantitative model, in which coverage from news outlets interacts with firms' financing costs. This simple model highlights that there are three moments needed to measure the aggregate consequences of media coverage: the average level of coverage, the average firm response to coverage, and the covariance between news coverage and firm 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. News coverage of the firm, $m_i \in \{0, 1\}$, is considered exogenous to the firm and interacts with financial frictions. The marginal costs of investment is given by $\log c_i = a + a_i m_i$, where $a \in \mathbb{R}$ denotes the component of financing costs that does not interact with media coverage (assumed constant across firms), and $a_i \in \mathbb{R}$ denotes the component of financing costs that does. 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 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' investment implies 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 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 media sector on aggregate investment can then be characterized as:

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

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

The decomposition in (1) shows that the aggregate effects of media depends not only on the average level of coverage, $\mathbb{E}\, m_i$ and the average investment responses to coverage $\mathbb{E}\,\frac{\partial I_i}{\partial m_i}$, but also on the distribution of media coverage, consistent with the broader literature on macroeconomic implications of micro-level heterogeneity (e.g., Alves et al., 2020; Sterk et al., 2021). Specifically, the covariance term indicates that media coverage negatively correlated with firm responsiveness dampens the aggregate investment response, whereas media coverage positively correlated with firm responsiveness amplifies it. Motivated by this decomposition, we now measure each component in (1) in turn.

2.2. Data

We collect the frequency of firm news coverage in three of the largest US newspapers by circulation—*The Wall Street Journal*, *The New York Times*, and *USA Today*—from Dow Jones Factiva, a news aggregator.[5] News coverage frequency is matched to firm financial data from CRSP/Compustat using a fuzzy match algorithm (Levenshtein et al., 1966), based on

[5] Factiva is a widely used database for measuring the frequency of news coverage (see, for example, Chahrour et al., 2021; Bui, Huo, Levchenko and Pandalai-Nayar, 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 in each quarter.

firm names.[6] With this procedure, we construct a dataset of firm-level media coverage for the universe of publicly traded firms in the US, consisting of 375,627 articles on 18,809 unique firms from 1990 to 2021. In the CRSP/Compustate data, we construct a number of firm-level financial variables following standard definitions (e.g., Kahle and Stulz, 2017; Ottonello and Winberry, 2020), which we detail in Appendix A.1.

We complement the main data on news frequency with three additional datasets. The first is the full texts of news articles obtained from Dow Jones Factiva DNA, which contains the detailed content of the subset of news articles that Dow Jones has the license to redistribute (representing 54% of the full coverage sample).

The second is firms' social media coverage on Twitter (now X), which allows us to compare the role of curated news coverage with social media coverage. We identify over 3,000 publicly traded firms that have official accounts on the social media platform and collect the frequency that a 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 media coverage. We use Factiva to collect the frequency of firm news coverage from 2005 to 2021 in four major French newspapers—*Les Echos*, *Le Monde*, *La Tribune*, and *Le Figaro*—and link it with firm variables from Compustat Global as in the U.S. analysis.

2.3. Frequency of news coverage

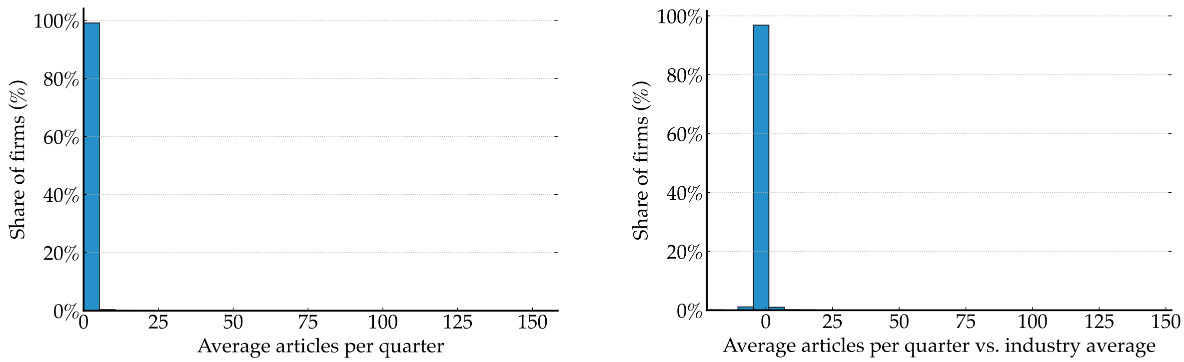
Panel (a) in Figure 1 reports the unconditional distribution of average firm article counts over the sample period. Most firms have zero coverage, while firms with the top 1% of coverage appear in an average of 23 articles per quarter in major newspapers.[7] The distribution is highly skewed, which shows that news coverage is concentrated in a small number of firms. To ensure that the pattern is not driven by firms with zero coverage, Appendix Figure A.1 restricts the sample to firms with positive coverage and finds a similarly skewed distribution.

[6] Factiva provides named entity tags identifying 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 firm names in Factiva with those of publicly traded US 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.

[7] Table A.1 in the Appendix lists the top 20 firms by total media coverage. The top firms are household names such as General Motors and Microsoft, whose brand recognition may attract attention from readers who do not necessarily have a specific interest in business news.

Figure 1: Distribution of corporate news coverage

(a) Average firm coverage **(b)** Within industry



Notes: This figure reports the distribution of average articles per quarter for firms in our sample. Panel (a) reports the share of firms with a certain average number of articles per quarter. Panel (b) reports the share of firms with a certain average number of articles relative to industry average, with industry measured at the 4-digit NAICS level.

Panel (b) in Figure 1 reports distribution of firm news coverage within industries. We demean news coverage by industries, measured by 4-digit NAICS, and report the residuals. Skewness in the coverage distribution is not driven by differences in industry-specific coverage. The top percentile of firms appear in an average of 21 more articles per quarter compare to remaining firms in the industry.

In light of the concentration in news coverage, we next study factors associated with media coverage. We first estimate a panel regression

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

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

Table 1 reports the results. The left panel shows that 69% of variation in media coverage can be accounted for by firm-specific characteristics. Industry explains 5% of the variation, while the time dimension plays little role. The right 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 28% of the variation in media coverage and 38% of the

Table 1: Variance Decomposition

	Mean	SD	R^2		Mean	SD	R^2
Articles per quarter	0.51	6.939	0.0000	Probability of news coverage	1.27%	0.112	0.0000
Time		6.938	0.0003			0.112	0.0000
Industry		6.763	0.0500			0.109	0.0665
Firm		3.889	0.6859			0.073	0.5728
Industry × Time + Firm		3.686	0.7214			0.070	0.6178

Notes: This table reports the standard deviation of ε_{it} and the R^2 from estimating (2): $h_{it} = \alpha_{st} + \alpha_i + \varepsilon_{it}$, where h_{it} is article counts containing firm i in major newspapers in quarter t, α_{st} is sector-by-time fixed effects, and α_i is firm fixed effects.

variation in the probability of coverage are unexplained by the aforementioned factors. This unexplained portion, which contains variation over time at the firm level, is the variation we use to study the relationship between media coverage and firm outcomes in the next section.

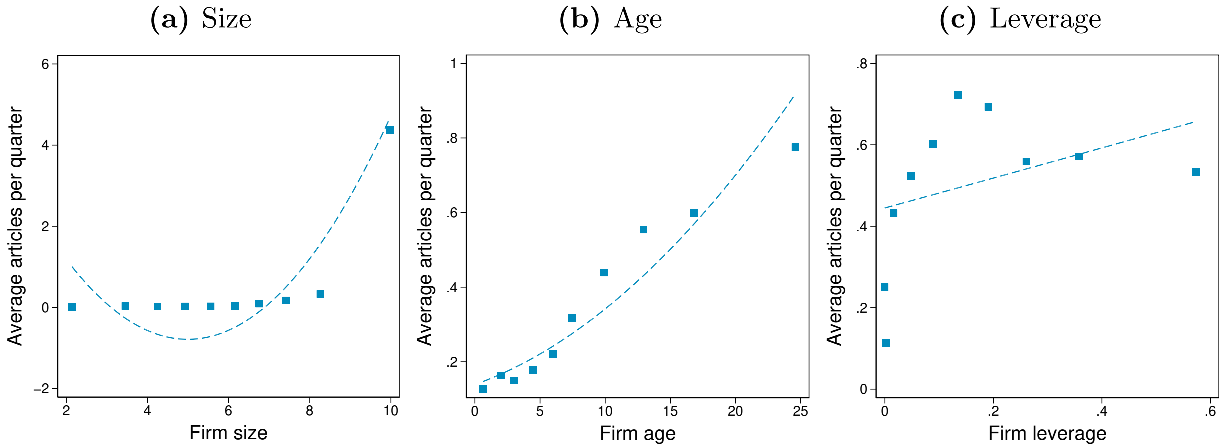
To understand the firm characteristics associated with media coverage, we next study variation in media coverage along three dimensions: size, age, and financial conditions.[8] Figure 2 reports binned scatter plots of news coverage by these firm characteristics. Each bin represents a decile of firm-quarter 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.

Panel (a) in Figure 2 reports the binned scatters by firm size, measured with log real assets. The relationship between news coverage and firm size is highly nonlinear. Media coverage is concentrated in the largest 10% of firms, while the remaining firms receive almost no coverage. Appendix Figure A.2a shows that this concentration is also present within 4-digit NAICS industries. Market capitalization is closely related to firm size, and because of its prevalence in popular press likely receives more attention from business readers. In Appendix Figure A.3, we alternatively measure firm size with market capitalization and find a similar concentration of media coverage in the top decile of largest firms.

This strong concentration of media coverage in the top decile is unique to firm size. Panel (b) reports the relationship between news coverage and firm age, measured with years since IPO. Unlike the pattern with firm size, media coverage increases linearly over the life

[8]These firm characteristics are considered important for business cycle fluctuations and the transmission of macroeconomic policy (e.g. Ottonello and Winberry, 2020; Cloyne, Ferreira, Froemel and Surico, 2023).

Figure 2: Firm characteristics and media coverage



Notes: This figure reports binned scatterplots of average news articles per quarter. Each dot represents a decile of firms. Dashed lines represent quadratic fit lines. Panel (a) sorts firms by size, measured by log real assets, from smallest to largest. Panel (b) sorts firms by age, measured by years since IPO. Panel (c) sorts firms by leverage, measured by market leverage.

cycle of a firm. Appendix Figure A.2b shows the relationship after conditioning for industry. In both cases, young and medium-aged public firms are also featured in the news, not just the oldest firms.

Panel (c) studies the role of firms' financial positions, reflected in their market leverage. News coverage increases with leverage for firms with low levels of leverage. However, for firms within a given industry, the relationship between leverage and news coverage is much weaker. Appendix Figure A.2c shows that after conditioning on industry, leverage is only weakly correlated with news coverage.

2.4. Firm responses to news coverage

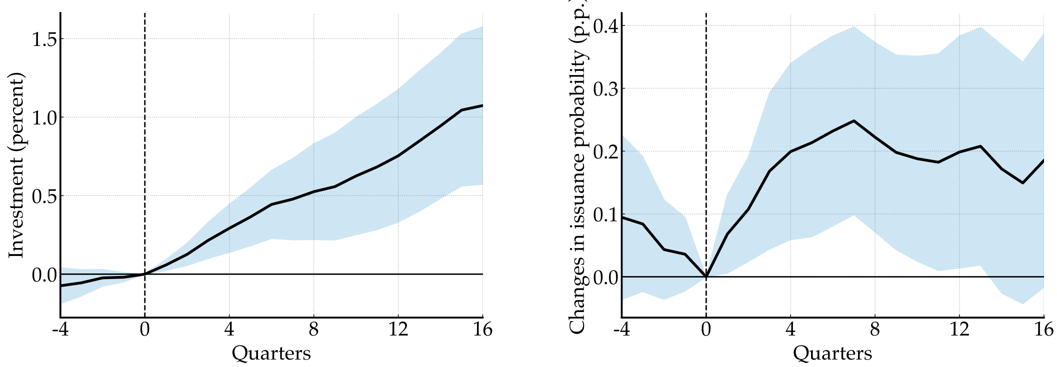
Next, we study the relationship between news coverage and firms' investment and financing. To do so, we estimate the local projections for firm i in quarter t for each horizon $-4 \leq h \leq 16$ with

$$y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it} + u_{ith}, \tag{3}$$

where y_{it} is the firm variable of interest for firm i in quarter t; ν_{it} is the number of mentions of that firm in major US newspapers that quarter, demeaned at the firm level and standardized so that the unit can be interpreted as one standard-deviation within-firm change in media

Figure 3: News coverage, firm investment, and financing

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



Notes: This figure reports results from estimating the local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it} + u_{ith}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 4-digit NAICS level); α_i denotes firm fixed effects; ν_{it} denotes news coverage of firm i in major US 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 (a), defined as the log change in the book value of the firm's tangible capital stock, and the cumulative probability of equity issuance (E_{it}) in panel (b), defined as an indicator variable that takes the value 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.

coverage; $\{\alpha_{st}, \alpha_i\}$ are sector-by-quarter and firm fixed effects; $Z_{i,t}$ is a vector of firm controls including sales growth, size, and current assets as a share of total assets; and u_{it+h} is a random error. Firm variables of interest include (i) the investment rate, $\Delta \log k_{it}$, defined as the log change in the book value of the firm's tangible capital stock, and (ii) the cumulative probability of equity issuance, E_{it}, defined as an indicator variable that takes the value 1 if a firm issues new equity between quarters t and $t+h$ and zero otherwise. We double cluster standard errors by firm and quarter.

Figure 3 reports our baseline findings. Panel (a) shows that higher coverage is associated with a higher rate of investment in quarters after the coverage. 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, to reach a peak effect of approximately 1%. Panel (b) shows that media coverage is also associated with a higher probability of raising financing from the equity market. The quarter after news coverage, one standard deviation higher media coverage is associated with 0.07% points greater probability of issuing equity. The effect rises gradually to a peak effect of around 0.2% points after 6 quarters.

Appendix A.3 presents three additional analyses that reveal the specialized role of the *curated* news featured in traditional news outlets. First, Appendix Figure A.4 shows that the effect of news coverage is specific to equity financing: the effects of coverage on 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 insensitive to information (Hoberg and Maksimovic, 2015; Gorton and Ordonez, 2014).

Second, we compare curated news 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. Appendix Figure A.5 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 firm outcomes is specific to curated news.

Third, the three newspapers differ markedly in the types of content that they specialize in and the audiences that they appeal to. Appendix Figure A.6 studies the effects of news coverage from each newspaper, repeating regression (3) but replacing ν_{it} with the frequency of coverage in each newspaper individually. Coverage in *The Wall Street Journal*, which specializes in financial news, has the largest positive association with firm investment and financing. Coverage in *The New York Times*, which maintains a dedicated section on business news, also displays a positive association. However, coverage in *USA Today*, which is the least finance-focused newspaper among the three, does not appear to have a significant association with firm financing. Overall, the effects of newspaper coverage increase with the degree of specialization in financial news, consistent with a mechanism in which the information contained in specialized coverage receives attention from financial market participants.

2.5. Distribution of news coverage

The decomposition in Section 2.1 highlights that the aggregate effects of corporate news depend critically on how news coverage is distributed across firms. Specifically, aggregate investment depends on whether coverage is correlated with firm-level responsiveness to news.

Motivated by this, we now study the conditional distribution of news coverage responsiveness in the data. We focus on the size dimension, the strongest observed driver of firms' news coverage.

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

$$\Delta y_{it} = \alpha_{st} + \alpha_i + \beta_q \cdot \mathbb{1}_{Q_{it}=q} \times \nu_{it} + \Gamma' Z_{it} + u_{it}, \tag{4}$$

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

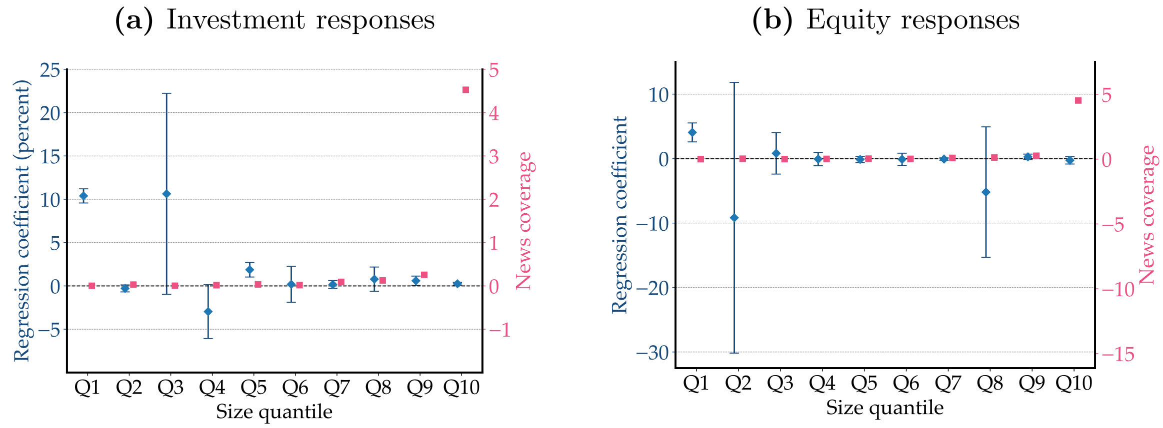
The estimates for β_q are reported in Figure 4 in blue, along with 90% confidence intervals. Firms are ordered from smallest to largest, with "Q1" denoting the smallest 10 percent firms and "Q10" denoting the largest 10 percent of firms. We overlay the estimated coefficients with the average level of media coverage from Figure 2a, reported in red on the right axis.

Panel (a) shows that the smallest 10 percent of firms are are the most responsive to media coverage. One standard deviation higher media coverage is associated with 10% 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 percent of firms receive substantial news coverage, but they do not respond to the media coverage through investment.

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

The conditional distribution in Figure 4 indicates that the correlation between firm news coverage and firm responses to news coverage is negative. The firms who receive the most

Figure 4: News coverage and firm responses: by firm size



Notes: This figure reports results from estimating equation (4): $\Delta y_{it} = \alpha_{st} + \alpha_i + \beta_q \cdot \mathbb{1}_{Q_{it}=q} \times \nu_{it} + \Gamma' Z_{it} + u_{it}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 4-digit NAICS level); α_i denotes firm fixed effects; $\mathbb{1}_{Q_{it}=q}$ is an indicator variable that takes the value 1 if a firm's size quantile within quarter, Q_{it}, belongs to the size quantile q; ν_{it} is the news coverage of firm i major US newspapers mention 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 hte 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 percent firms, and "Q10" denotes the largest 10 percent firms. 90% confidence intervals are reported.

coverage are the firms who respond the least to it, which is shown in equation 1 to reduce the aggregate effect of news coverage on firm investment. We quantify this effect in Section 4.

2.6. Evidence on the mechanism

Before turning to the model, we provide suggestive evidence on the causal mechanism behind our results so far. We have documented a positive relationship between news coverage and firms' investment and equity financing. The concern with interpreting the relationship as causal is that newspapers may report on firms because they are planning investment projects and equity issuance, in which case our estimates would partly reflect reverse causality. In this section, we present two sets of analyses aimed at addressing this concern. First, using the content of news articles, we identify whether news coverage is related to investment and financing and remove such articles from our sample; second, using international evidence from France, we study the effects of variation in news coverage that is unrelated to firms' outcomes.

2.6.1. Text of news articles

To analyze the content of news coverage, we employ latent Dirichlet allocation (LDA) to extract 20 distinct "topics" that represent the text of 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 underlying topics that best represent the content.[9]

The resulting topics are reported in Appendix Figure A.4. News coverage about firms falls into three broad categories: news related to overall financial conditions (e.g., stock markets), news related to firms' industries (e.g., technology and automobile), and firm-specific news (e.g., investment, financing, litigation, and employees).

We exclude any news articles that have nonzero loading 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.7. Using the frequency of news *excluding* this coverage of firm investment and financing, we re-estimate the baseline local projections in (3). The estimates in Figure 5 indicate that news coverage remains associated with a higher probability of equity issuance and a higher rate of investment in this restricted sample, with somewhat stronger effects than those estimated using the total news frequency in the baseline estimation in Figure 3.

2.6.2. Evidence from media strikes

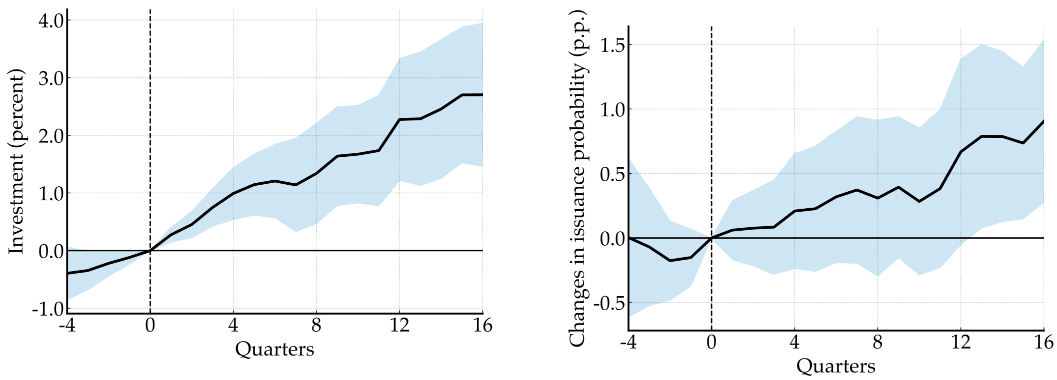
We now complement our US evidence with international evidence from France, where media strikes introduce variation in news coverage that is unrelated to firm choices.[10] During strikes, journalists stop reporting for their employers, reducing the amount of information provided by the media sector, for reasons that are unrelated to individual non-media firms (Peress, 2014).

[9] We take a data-driven approach to select the model hyperparameter that governs the number of topics, performing a grid search from 20 topics to 200 topics in increments of 20. Through this procedure, we choose the number of topics to 20, which generates the highest topic coherence.

[10] Appendix Figure A.8 reports the distribution of corporate news coverage in France, which displays a similar pattern of concentrated in coverage as the US. both similarities and differences with the US.

Figure 5: News coverage, firm investment, and financing: Excluding coverage on investment and financing articles

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



Notes: This figure reports results from estimating a variant of the baseline local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it-1} + u_{it+h}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 4-digit NAICS level); α_i denotes firm fixed effects; ν_{it} denotes news coverage of firm i major US newspapers in quarter t that excludes coverage on investment and equity financing, demeaned at the firm level and standardized; and Z_{it-1} 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 (a), defined as the log change in the book value of the firm's tangible capital stock, and the cumulative probability of equity issuance (E_{it}) in panel (b), defined as an indicator variable that takes the value 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.

Media strikes are rare in recent history in the US. However, in France we identify 6 episodes large-scale media strikes using the criteria developed by Peress (2014), detailed in Appendix Table A.2.[11] We focus on sector-wide strikes and exclude strikes by individual newspapers, to ensure that these strikes occur not because of individual newspaper or non-media firm factors, but rather as a response to government and policy changes (such as Nicolas Sarkozy's broadcasting-advertising reform and Emmanuel Macron's pension reform).

To facilitate comparison with the US evidence, we first estimate effects of media coverage using the same local projection as in (3).[12] Appendix Figure A.9 report estimates that are

[11] We search Factiva for keywords containing (i) "strike" and "journalist", or (ii) "strike" and "broadcaster", as well as their French translation. Using Factiva's tagging, we restrict the region to be France, the industry to be Media/Entertainment, and the subject to be Labor Dispute. We focus on national strikes and exclude strikes in individual newspapers. The 6 strike episodes are reported in Appendix Table A.2. They are concentrated in 5 quarters: 2005Q4, 2008Q1, 2008Q4, 2013Q1, and 2018Q2.

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

consistent with the US evidence: Greater media coverage in France is associated with higher equity issuance probability and investment.

We then test whether news reports affect firm outcomes by focusing on the subset of firms that have issued equity during the sample period, and estimating

$$\log k_{it+4} - \log k_{it} = \alpha_s + \beta S_t + \delta \theta_{it} + \gamma \theta_{it} S_t + \Gamma' Z_{it} + u_{it}, \tag{5}$$

where the dependent variable is firm i's cumulative investment a year after equity issuance, α_s is a sector fixed effect; S_t is an indicator for media strikes in quarter t; θ_{it} denotes firm i's average news coverage in the year before the strike; and Z_{it} is a vector of controls including firm sales growth, size, current assets as a share of total assets, fiscal year end, real GDP growth, and inflation.[13]

The parameter of interest is γ. Among firms that have issued equity during media strikes, γ measures the differential impact of the strike on a firm's investment depending on the firm's reliance on media coverage. If news media disseminates firm news to investors, firms that tend to receive more coverage are expected to suffer a bigger impact during strikes compared to their peers with little coverage to begin with. The specification in (5) allows for the possibility that strikes tend to happen in economic downturns by using the cross-sectional variation in firms' exposure to the same strike.

Table 2 report 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 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 (5) without any controls. Columns 3 and 4 add macro and firm controls iteratively. Column 5 excludes firms that share a common owner with a major newspaper, to account for a possible direct effect of the labor disputes behind media strikes on the investment of firms in our sample. Specifically, *Les Echos* and *Le Figaro* are owned by LVMH and Dassault Group respectively. These groups are also the parent companies of some of the non-media firms in our sample.[14] Strikes in newspapers

as a share of total assets.

[13] We retrieve GDP (CLVMNACSCAB1GQFR) and inflation (CPHPTT01FRM659N) series from FRED.

[14] In our sample, subsidiaries of Dassault group (parent of *Le Figaro*) include Dassault Aviation and

Table 2: Equity issuance during media strikes and exposure to media coverage

	(1)	(2)	(3)	(4)	(5)
	Investment after issuance (1yr)				
Strike	-0.140*	-0.173	-0.132	-0.135	-0.170*
	(0.078)	(0.106)	(0.087)	(0.083)	(0.099)
Past coverage		0.004	0.004	0.005	0.005
		(0.004)	(0.005)	(0.005)	(0.005)
Strike × Past coverage		-0.042*	-0.043**	-0.045**	-0.044**
		(0.021)	(0.021)	(0.022)	(0.021)
Observations	1072	1024	1024	1007	1006
R^2	0.029	0.039	0.041	0.043	0.042
Industry FE	yes	yes	yes	yes	yes
Macro controls	no	no	yes	yes	yes
Firm controls	no	no	no	yes	yes
Remove common ownership	no	no	no	no	yes
Double-clustered SE	yes	yes	yes	yes	yes

Notes: This table reports the coefficient γ from estimating: $\log k_{it+4} - \log k_{it} = \alpha_j + \beta S_t + \delta\theta_{it} + \gamma\theta_{it}S_t + \Gamma' Z_{it} + u_{it}$, where t is the quarter in which a firm issues equity, the dependent variable $\log k_{it+4} - \log k_{it}$ is the cumulative investment 4 quarters after 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, and inflation. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

can arise from disputes with their owners, which potentially affects the investment decision of their non-media subsidiaries for reasons other than media coverage. We account for this possibility by removing these subsidiaries.

We focus our discussion on Column 5 in Table 2, which provides the most conservative estimates. Firms that issue equity during media strikes invest 17% less compared to firms that issue during nonstrikes. Firms with higher historical coverage suffer more from the sudden loss of coverage. Compared to other firms that issue equity during strikes, a firm with one-standard-deviation higher historical coverage invests 4% less after the equity issuance. The economic magnitude is one-quarter of the average effects from the strike. The results suggest that firms who rely more on media coverage to disseminate firm news have to reduce their investment because of the strikes, consistent with the interpretation that media reports can alleviate the information friction firms face and facilitate their financing and investment.

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 individuals. *Le Monde* belongs to Groupe Le Monde, which does not have other subsidiaries in our sample.

The empirical evidence in this section suggests that news coverage has positive effects on firms' financing and investment. However, the large firms that news outlets focus on are the least responsive to the coverage. In the next section, we incorporate these features in a macro-finance model with news outlets to understand the aggregate importance of curated news reporting.

3. A Model of Corporate News Reporting

In this section, we construct a model of corporate news reporting to study its importance for corporate finance and firm life cycles. The model features firms that raise equity from retail investors in the equity market, with asymmetric information which may be mitigated by information provided by news outlets.

3.1. Environment

Time is discrete, and there is no aggregate uncertainty. The economy consists of four groups of agents: firms, investors, forecasters, and news outlets. The corporate finance block builds on Guo et al. (2024), who model firm decisions under asymmetric information. We extend the model to incorporate a media sector, allowing investors to learn about firms' private information not only from firm actions but also from media reporting.

3.1.1. Firms

There is a continuum of firms indexed by $j \in [0, 1]$, who are heterogeneous in 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 $k_{j,t}$ from the previous period. The firm also observes its idiosyncratic productivity $z_{j,t}$, which evolves according to

$$\ln z_{j,t} = \rho_z \cdot \ln z_{j,t-1} + \epsilon^z_{j,t}, \quad \text{where } \epsilon^z_{j,t} \overset{i.i.d}{\sim} \mathcal{N}(0, \sigma_z^2). \tag{6}$$

At this point, each firm receives an i.i.d. exit shock $\epsilon^{\texttt{exit}}_{j,t} \sim \texttt{Bernoulli}(\xi)$. 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 using capital as the input with the technology

$$y_{j,t} = Z \cdot z_{j,t} \cdot k_{j,t}, \tag{7}$$

where Z denotes aggregate productivity.

After the production stage, a firm receives an i.i.d. capital quality shock ($a_{j,t}$) to its assets in place and chooses its investment $x_{j,t}$. The i.i.d. assumption prevents investors from inferring $a_{j,t}$ using observable information from previous periods. A firm's capital evolves according to

$$k_{j,t+1} = (1-\delta) \cdot a_{j,t} \cdot k_{j,t} + x_{j,t}^{\theta}, \quad \text{where } a_{j,t} \overset{i.i.d}{\sim} \mathcal{G}(a). \tag{8}$$

Capital quality $a_{j,t}$ therefore affects the ability of a firm to transfer their assets-in-place to future periods (as in e.g., Bigio, 2015; Gertler, Kiyotaki and Prestipino, 2019).

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

$$div_{j,t} + x_{j,t} = y_{j,t} + e_{j,t} - \phi^e \mathbb{1}_{e_{j,t}>0}, \tag{9}$$

where $e_{j,t}$ denotes the funding raised from issue new equity and ϕ^e denotes a fixed cost of issuing equity.

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

$$\mathrm{V}_t(k, z, a, m) = \max_{e \geq 0} \frac{\mathrm{P}_t(k, z, a, m, e)}{\mathrm{P}_t(k, z, a, m, e) + e} \cdot \mathrm{W}_t(k, z, a, e) \tag{10}$$

Here, m is an indicator variable equal to 1 if the firm is covered by the news media, which the firm takes as given, and which will be specified below. $\mathrm{W}_t(k, z, a, e)$ is the firm's post-issuance value and will be defined below. $\mathrm{P}_t(k, z, a, m, e)$ is 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 existing shares to 1, a firm has to issue a further $\frac{e}{\mathrm{P}_t(k,z,a,m,e)}$ shares to external investors to raise funding e. Given this, the fraction $\frac{\mathrm{P}_t(k,z,a,m,e)}{\mathrm{P}_t(k,z,a,m,e)+e}$ is the fraction of firm value accruing to initial shareholders after any subsequent equity issuance.

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

$$\mathrm{W}_t(k,z,a,e) = \max_{div\geq 0, x\geq 0} div + \beta\mathbb{E}_t\left[\xi\hat{\mathrm{V}}_{t+1}(k') + (1-\xi)\mathrm{V}_{t+1}(k',z',a',\mathbf{m}_{t+1}(k',z',a',\kappa'))|z\right] \tag{11}$$

$$\text{s.t.} \qquad x = Z\cdot z\cdot k + e - \mathbf{1}_{e>0}\phi^e - div \tag{12}$$

$$k' = (1-\delta)\cdot ak + x^\theta \tag{13}$$

where $\hat{\mathrm{V}}_t(k) \equiv k$ denotes the capital's liquidation value and $\mathbf{m}_t(\cdot)$ is the aggregate media reporting function that will be described in later part of this section. In the remainder of the paper, we denote the firms' policy functions of equity issuance, dividend payment, and investment 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 return. Investors observe capital k and productivity z of each firm, along with equity issuance decisions e. They cannot, however, observe capital quality a and must make inference about it based on media reports and firm behavior.

When a firm is reported by the media outlets, its asset quality is fully revealed. When a firm is not reported by the media, investors must instead form a posterior belief on that firm's asset quality based on its equity issuance choice. Let $\mathcal{B}_t(a|k,z,e)$ denote the density function of investors' belief about a firm's asset quality when this firm is not reported. For equity issuance on the equilibrium path, investors' belief satisfies the Bayes rule

$$\mathcal{B}_t(a|k,z,e) = \frac{\mathcal{G}(a)\mathbf{1}_{\mathbf{e}_t(k,z,a,0)=e}}{\int\mathcal{G}(\tilde{a})\mathbf{1}_{\mathbf{e}_t(k,z,\tilde{a},0)=e}d\tilde{a}}, \tag{14}$$

and for equity issuance off the equilibrium path, investors' belief has to satisfy the Divinity

Criterion as specified in Banks and Sobel (1987).[15] Given investors' belief about firms' asset qualities, firms' equity issuance price has to satisfy the break-even condition for investors, i.e., the expected return from purchasing the newly issued equity has to match the risk-free interest rate: $\forall e > 0$,

$$\frac{e}{\mathrm{P}_t(k,z,a,1,e)+e} \cdot \mathrm{W}_t(k,z,a,m,e) = e, \tag{15}$$

and

$$\frac{e}{\mathrm{P}_t(k,z,a,0,e)+e} \cdot \int \mathrm{W}_t(k,z,a,m,e) \cdot \mathcal{B}_t(\tilde{a}|k,z,e)d\tilde{a} = e. \tag{16}$$

The implied equity issuance price is

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

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 value is determined by:

$$\mathrm{MV}_t(k,z,a,m) = \begin{cases} \mathrm{P}_t(k,z,a,m,\mathbf{e}_t(k,z,a,m)) & \text{if } \mathbf{e}_t(k,z,a,m) > 0 \\ \frac{\int \mathrm{V}_t(k,z,\tilde{a},m)\mathbf{1}_{\mathbf{e}_t(k,z,\tilde{a},m)=0}\mathcal{G}(\tilde{a})d\tilde{a}}{\int \mathbf{1}_{\mathbf{e}_t(k,z,\tilde{a},m)=0}\mathcal{G}(\tilde{a})d\tilde{a}} & \text{if } \mathbf{e}_t(k,z,a,m) = 0. \end{cases} \tag{18}$$

3.1.3. Media

There is a continuum of media outlets, indexed by $i \in [0,1]$, who have full information on all firm fundamentals including asset qualities $a_{j,t}$. Each outlet is owned by a corresponding forecaster, who reads the news in their outlet and does not read other outlets. A media outlet selects the set of firms to report on in order to maximize its forecaster's expected

[15] Strictly speaking, investors should also update their posteriors after observing that the firm has not been reported, analogously to the mechanism explored in Nimark (2014). However, 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 the decision of an editor to not report on firm j does not provide investors with any information about that firm's asset quality. For notational simplicity we therefore omit this aspect of posterior updating from the equations in the text.

utility.[16]

Let $m^o_{i,j,t} \in \{0,1\}$ denote the reporting decision of media outlet i of firm j. If $m^o_{i,j,t} = 1$, outlet i reports the exact $a_{j,t}$ to its associated forecaster in period t. If $m^o_{i,j,t} = 0$, outlet i does not report on firm j, and transmits no information about $a_{j,t}$. Throughout the paper, we differentiate between $m^o_{i,j,t}$—which denotes the reporting choices of an individual news outlet i—and $m_{j,t}$, which denotes the aggregate news reporting outcome for firm j, which we define in equation (23) below.

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

$$\int_0^1 m^o_{i,j,t} dj = r. \tag{19}$$

Outlet i's decision problem is to choose firms to report in order to maximize the expected utility of their forecaster, net of a firm and period-specific reporting cost $\kappa_{j,t} \sim \mathcal{H}(\kappa)$ which is independent of firm j's fundamentals.[17] Their problem is given by

$$\max_{m^o_{i,j,t}} \mathbb{E} \int_0^1 \mathrm{U}_{i,t}(\mathcal{I}^{\text{news}}_{i,t}) dj - \int_0^1 \kappa_{j,t} m^o_{i,j,t} dj \tag{20}$$

$$\text{s.t.} \qquad \mathcal{I}^{\text{news}}_{i,t} = \{a_{j,t} : m^o_{i,j,t} = 1\} \tag{21}$$

$$r = \int_0^1 m^o_{i,j,t} dj \tag{22}$$

where $\mathrm{U}_{i,t}(\mathcal{I}^{\text{news}}_{i,t})$ denotes forecaster i's utility, which we specify in the next subsection, and $\mathcal{I}^{\text{news}}_{i,t}$ is the information set communicated to the forecaster by their outlet.

Investors observe all information reported in all outlets.[18] Therefore, the investors' information set includes the *total* information reported in the media. We denote this total

[16]See Armona, Gentzkow, Kamenica and Shapiro (2024) for an example of another model with this feature, and a discussion of how such 'direct maximization' incentives may arise.

[17]These should be thought of as cognitive or effort costs, similar to the information processing costs in the rational inattention literature (Maćkowiak, Matějka and Wiederholt, 2023). These costs arise from the media outlets, and so are different from the 'attention capacity of readers' used to motivate the space constraint (19). Equivalently, $\kappa_{j,t}$ could also capture variation in media reporting preferences due to factors outside of our model.

[18]This assumption can be microfounded as follows. Since there is no noise in market prices in this model (unlike e.g., Grossman and Stiglitz, 1980), market prices perfectly aggregate information. If even one investor reads the news published by outlet i, they therefore use that information to trade, and market prices adjust to communicate that information to all other investors.

media information set as $\mathcal{I}_t^{\text{news}} = \{a_{j,t} : m_{j,t} = 1\}$, where the aggregate news reporting indicator $m_{j,t}$ is defined as

$$m_{j,t} = \begin{cases} 0 & \text{if } m^o_{i,j,t} = 0 \text{ for all } i \\ 1 & \text{otherwise.} \end{cases} \tag{23}$$

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

3.1.4. Forecasters

Forecaster i observes the information communicated by outlet i, which is denoted $\mathcal{I}_{i,t}^{\text{news}} = \{a_{j,t} : m^o_{i,j,t} = 1\}$, along with the observables $k_{j,t}$ and $z_{j,t}$. Forecasters make forecasts of firm market values before equity markets open each period, and so cannot observe equity issuance $e_{j,t}$. We assume that forecasters are able to observe the reporting decisions of other outlets ($m^o_{i',j,t}$), 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 $m_{j,t}$. The latter assumption implies that forecasters do not observe $a_{j,t}$ unless their own outlet reports on it.

Forecasters derive utility from making more accurate market value forecasts than their peers, as in the literature on forecaster incentives (reviewed by Marinovic, Ottaviani and Sorensen, 2013). As shown by (18), market value is a function of firm fundamentals $(k_{j,t}, z_{j,t}, a_{j,t})$ and the aggregate news reporting indicator $m_{j,t}$. Forecaster i's utility is therefore given by

$$\mathrm{U}_{i,t}(\mathcal{I}_{i,t}^{\text{news}}) \equiv -\int_0^1 \left[\mathrm{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}}) - \overline{\mathrm{FE}}_{-i,t}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}_{-i,t}^{\text{news}})\right] dj. \tag{24}$$

The first component of equation (24) represents the realized forecast errors that forecaster i has made about firm j, defined as

$$\mathrm{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}}) \equiv \left[\mathcal{P}_t\left(k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}}\right) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t})\right]^2, \tag{25}$$

where $\mathcal{P}_t(k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}})$ denotes the associated prediction by forecaster i. The second component of equation (24) represents the realized average forecast error from forecasters other than i, defined as

$$\overline{\mathrm{FE}}_{-i,t}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{-i,t}) \equiv \int_{i' \neq i} \left[\mathcal{P}_t\left(k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i',t}\right) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t})\right]^2 di'. \tag{26}$$

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 $\mathcal{P}_t\left(k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t}\right)$ to maximize expected utility, where the expectation is formed conditional on the forecaster's restricted information set. Since the forecaster's choice has no effect on realized market values, or the forecasts of others, this is equivalent to minimizing $\overline{\mathrm{FE}}_{i}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t})$, which is achieved by each forecaster setting predictions equal to the rational expectation of each firm's value, given that forecaster's information set

$$\mathcal{P}_t(k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t}) = \mathbb{E}\left[\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}) | k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t}\right]. \tag{27}$$

3.1.5. Model assumptions and robustness

Before proceeding to the definition of equilibrium, we now discuss our key assumptions regarding news reporting and examine the robustness of our model to altering them. First, our formulation of forecasters' utility assumes 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. While we take this objective as given, it is consistent with a model in which potential readers compare the quality of news outlets as information sources by comparing their previous forecast performance (as in, e.g., the contest model of Ottaviani and Sørensen, 2006).

Moreover, in Appendix B we show that the equilibrium news reporting function derived from these preferences is consistent with an alternative model of the media market, in which outlets respond to demand for news from investors rather than forecasters. To achieve this, we introduce noise traders as in Grossman and Stiglitz (1980), which prevents asset prices from perfectly aggregating information. This implies there is a non-degenerate demand for news from investors.[19] Solving this investor-led model of media requires us to abstract from much of the firm side of the model presented here, so we keep to the forecaster model presented in this section for our quantitative analysis. However, it is striking that the equilibrium predictions of the two models coincide. The alternative microfoundation of the equilibrium reporting function in Appendix B provides further support for our choice of forecaster objective and the resulting media equilibrium.

Second, outlet i's objective function depends on the reporting behavior of other outlets, both through $\overline{FE}_{-i,t}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{-i,t})$ and realized market values. We assume that when choosing reporting $m^o_{i,j,t}$, outlet i takes the reporting decisions of other outlets, $m^o_{-i,j,t}$, 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 e.g. Eliaz and Spiegler (2024), while others have used monopoly media supply (Martineau and Mondria, 2022) or restrictions on media demand (Gentzkow and Shapiro, 2010) to achieve the same removal of strategic reporting incentives. For an example where strategic interactions do occur, see Perego and Yuksel (2022).

Third, the media outlet objective depends on the expectation of $\mathrm{U}_{i,t}$, taken before the forecaster observes information and makes the prediction. The objective in (20) is, therefore, conditional on the information available to the forecaster when reporting decisions are made. Appendix C.2 conducts robustness by considering alternative assumptions on media outlets' objective functions, including the case when the outlets maximize *realized* utility. Under this assumption, media outlets observe all firm state variables before choosing reporting, and therefore have more information available than their forecasters. Appendix C.2 shows that while such a change has an effect on the exact form of the equilibrium reporting decisions of outlets, the key qualitative characteristics of the reporting functions are robust to these alternative assumptions.

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

3.2. Equilibrium

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

1. given the firm distribution $\mathcal{F}_t(k, z)$ and firms' stock market value $\mathrm{MV}_t(k, z, a, m)$, media outlets determine reporting choices $\{m^o_{i,j,t}\}$, which in turn determines aggregate media reporting $\mathbf{m}_t(k, z, a, \kappa)$;

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

3. given media reporting function $\mathbf{m}_t(k, z, a, \kappa)$ and firms' equity issuance policy $\mathbf{e}_t(k, z, a, m)$, investors form posterior beliefs $\mathcal{B}_t(a|k, z, e)$ on the asset quality of firms not reported that has to satisfy 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 (17);

5. given firm's value function $\mathrm{V}_t(k, z, a, m)$ and equity issuance price function $\mathrm{P}_t(k, z, a, m, e)$, firms' stock market value $\mathrm{MV}_t(k, z, a, m)$ is specified by (18);

6. firms' distribution evolves as

$$\begin{aligned}\mathcal{F}_{t+1}(k', z') =& \xi \cdot \mathcal{F}^{\text{entrant}}(k', z') \\ &+ (1-\xi) \cdot \int \Gamma^z(z'|z) \cdot \mathbf{1}_{\mathbf{k}'_t(k,z,a,\mathbf{m}_t(k,z,a,\kappa))=k'} \mathcal{F}_t(k, z, a)\mathcal{G}(a) dk dz da\end{aligned} \tag{28}$$

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

3.2.1. Equilibrium equity issuance

When a firm is not reported by the media, investors make inferences about its capital quality based on its equity issuance decision. Appendix C.3 characterizes the equity market equilibrium, in which firms' equity issuance is constrained by the "lemons threat" (Guo et al., 2024): a low-quality firm has the incentive to mimic high-quality firms' equity issuance quantity, so that investors would perceive it to be of higher asset quality and price its equity issuance more favorably. This lemon threat leads a higher-quality firm to under-issue equity in equilibrium, in order to credibly signal its asset quality to investors and avoid being mimicked by its lower-quality peers. When a firm is reported by media outlets, investors observe the firm's true capital quality and the firm can issue equity without facing the "lemon threat". As a result, news reports can relieve a firm from costly signaling efforts, encouraging greater equity issuance and increasing investment, particularly among high-quality firms.

3.2.2. Equilibrium news reporting function

We now characterize the reporting decisions of media outlets in equilibrium. We focus our analysis on symmetric equilibria in pure strategies for outlets,[20] in which all outlets make the same reporting decisions, so that $m^o_{i,j,t} = m^o_{i',j,t} = m_{j,t}$ for all outlets i, i' and all firms j.[21] Theorem 1 characterizes the equilibrium reporting decisions of media.

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

$$m_{j,t} = \mathbb{1}(\mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) - \kappa_{j,t} \geq \mathrm{N}^*_t), \tag{29}$$

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

$$\mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) = \mathbb{V}[\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)|k_{j,t}, z_{j,t}], \tag{30}$$

[20] Importantly, since all forecasters are identical ex-ante, the motives for media specialization studied in Nimark and Pitschner (2019) and Perego and Yuksel (2022) (among others) are absent in our setting.

[21] Under pure strategy equilibria, $m^o_{i,j,t}$ is entirely determined by firm j's state variables, and there is no randomness in outlet reporting decisions. Armona et al. (2024) similarly focus on pure-strategy reporting equilibria, with applications to macroeconomic and non-economic news.

and the threshold N_t^* *is determined by the space constraint* (19)*:*

$$\int_0^1 \mathbb{1}(\mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) - \kappa_{j,t} \geq \mathrm{N}_t^*)dj = r. \tag{31}$$

Proof. Appendix C.1.1 □

Appendix C.1.1 details the proof. To find 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.

Theorem 1 specifies media's reporting behavior, and equation (30) defines the equilibrium newsworthiness function that drives it. 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 (29) implies that the probability firm j is reported, denoted as $\mathrm{R}_t(k_{j,t}, z_{j,t}, a_{j,t})$, is given by

$$\mathrm{R}_t(k_{j,t}, z_{j,t}, a_{j,t}) = \Pr(\kappa_{j,t} \leq \mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) - \mathrm{N}_t^*) = \int_0^{\mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) - \mathrm{N}_t^*} \mathcal{H}(\kappa)d\kappa. \tag{32}$$

By choosing the distribution of reporting costs $\mathcal{H}(\kappa)$ appropriately, we can therefore calibrate the equilibrium reporting policy to the empirical facts documented in Section 2. We then use the calibrated model to study the macroeconomic consequences of selective firm media coverage. In the remainder of the paper, because (30) implies that a firm's newsworthiness is only determined by its publicly observable characteristics $(k_{j,t}, z_{j,t})$, we simplify the notation of the 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 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. Then, we use the calibrated model to examine how media reporting affects firms' investment and financing, and how the

Table 3: 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		
$\mu^{\text{entrant}}_{\ln z}$	Entrants, average (log) productivity	-0.175
$\mu^{\text{entrant}}_{\ln k}$	—, 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 and growth (annual, %)		
Investment rate, mean	6.00	6.10
–, std	5.53	5.58
Difference between matured (age$>$ 25) and young firms (age$\leq$5)		
Growth rate	-0.106	-0.105
Log revenue rate	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
News Reports		
$p_{\geq 80\%}/p_{\leq 20\%}$	175	176

Notes: ϕ^e has been normalized by the average annual profit of the firm population. Operating cash flow rate, revenue rate, and investment rate refer to firms' operating cash flow, revenue, and investment normalized by their capital. The issuance fee ratio is measured as the fixed cost paid by the issuing firms normalized by their issuance proceeds. The average selling concession when issuing equity is measured as the average log-difference between a firm's stock price before and after revealing its equity issuance decision. $p_{\geq 80\%}$ and $p_{\leq 20\%}$ denote the average reporting probability of the firms in the top 20% and bottom 20% of market capitalization percentile. When constructing the annual rate in the model, we first simulate a panel of the firms at a quarterly frequency, then we aggregate the quarterly data into annual data so our model-implied moments are directly comparable to our empirical moments. All the empirical moments are based on Compustat firms between 1990 and 2021.

distribution of media reports shapes the macroeconomic effects of media.

4.1. Calibration

We calibrate the model quarterly to match Compustat firms between 1990 and 2021. We first set the discount rate to be $\beta = 0.99$, which corresponds to a 4% annual real interest rate, and the exogenous exit probability to be $\xi = \frac{7.7\%}{4}$, which is consistent with an average exit rate of 7.7% in the Compustat sample. Then, we calibrate parameters listed in Table 3a to target the empirical moments in Table 3b. The calibrated parameters are divided into five groups. The first three groups (cash flow, investment technology, and life-cycle dynamics) include standard parameters on firm dynamics, which we calibrate following existing approaches. The last two groups of parameters govern financial and information frictions in the economy. Given their importance for gauging the role of 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 average operating cash flow rate. Since it determines firms' average level of internal financing, we calibrate it to match the average operating cash flow rate in the data. The idiosyncratic productivity shock, z, is the source of cash flow risk faced by the firms, which shapes firms' ex-post heterogeneity and their precautionary motives in investment decisions. We calibrate its 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' investment to capital profitability. We set $\theta = 0.81$ to target the cross-sectional standard deviation of firms' investment rates[22].

Life-cycle dynamics The ex-post heterogeneity among firms is shaped by the dynamics of firms' idiosyncratic productivity and the distribution of entrants. Two parameters of the entrant distribution, $\{\mu^{\text{entrant}}_{\log z}, \mu^{\text{entrant}}_{\log(k)}\}$, govern the variation across firms of different age groups.[23] Therefore, we calibrate them to match the differences in growth and revenue rates 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 explicit expenses related to 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

[22] As documented by Sterk et al. (2021), there is a strong component of ex-ante heterogeneity across firms, so we use the within-firm variation to measure the cross-sectional variation in firms' investment rate. See Appendix D.1 for more details of measurement.

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

the dispersion of capital quality shocks. We calibrate the dispersion to match the average selling concession of seasonal equity offering 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 cross-sectional distribution of media coverage, as documented in Section 2.

Parameterization of the media reporting policy Equation (32) implies that the probability of a firm being reported is an increasing function of 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 with the reporting probability directly, parametrizing it using the generalized hazard function

$$\mathrm{R}_t(k,z) = \frac{\lambda_p}{\lambda_p + (1-\lambda_p)(\frac{\lambda_\alpha}{\mathcal{Q}_t(k,z)})^{\lambda_\xi}}, \tag{33}$$

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

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 (32). 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 (33) in terms of 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 quantile regressions presented in Section 2.

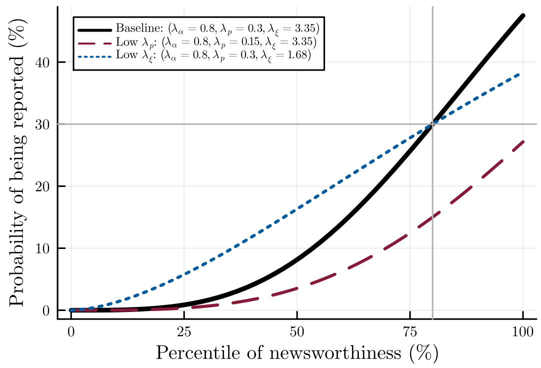
Each parameter of equation (33) captures a distinct aspect of how reporting probability depends on a firm's newsworthiness ranking. As shown in Figure 6a, $\{\lambda_\alpha, \lambda_p\}$ are the location

[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 empirical estimates for stock price drop associated with stock issuance (2%∼3%) as documented in the literature.

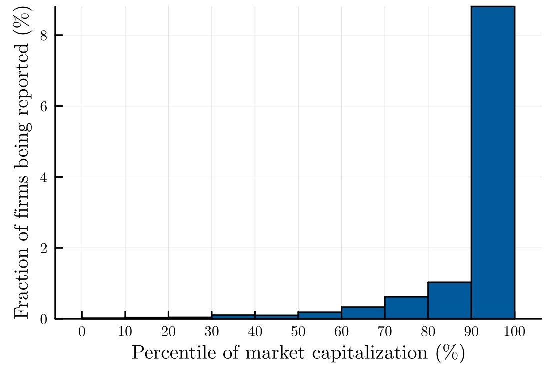
[25] This approach of working directly with hazard functions, rather than the underlying cost distributions, is common in the literature on "lumpy adjustments" of prices, investment, and other firm choices (Caballero and Engel, 1999; Alvarez, Lippi and Oskolkov, 2022).

Figure 6: Calibration of Media Reporting Policy

(a) Parameterization



(b) Data Moment



Notes: Figure 6b is based on the same sample as the empirical facts as presented in Section 2. We first divide the firms into ten decile groups based on their market capitalization in each quarter. Then we compute the share of firms being reported by the media in each decile group and report the cross-time average of these shares for each decile group.

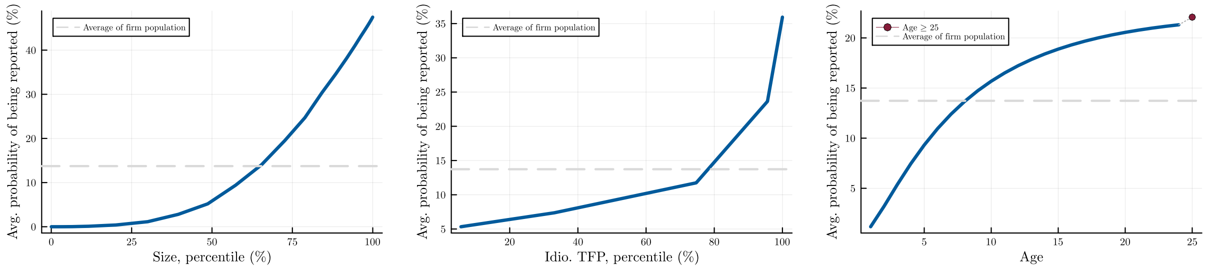
parameters: a firm with newsworthiness percentile of λ_α has a reporting probability of λ_p. Once the newsworthiness percentile exceeds λ_α, the probability of being reported increases rapidly. The rate of this increase is governed by the parameter λ_ξ: a higher λ_ξ implies a steeper increase in the 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 stock market value taken before equity markets open, conditional on that firm being reported in the media (equation (30)), which is neither directly observed nor priced in option contracts. Second, we do not observe a firm's probability of being reported, only the realization of reporting in the data (i.e., whether a firm is reported or unreported). 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 varies across market-capitalization percentiles. Figure 6b reports the empirical distribution from the data introduced in Section 2, which shows that the share of firms with coverage increases monotonically with market capitalization. Firms below the 80th percentile receive

Figure 7: Cross-sectional Pattern of Media Reporting

(a) By Size **(b)** By Idio. Productivity **(c)** By Age



Notes: This figure plots the variation of quarterly average probability of being reported along size (capital stock), idiosyncratic productivity, and age. The dash lines in each plot indicate the level of population average.

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. This approach uses the cross-sectional data patterns without focusing on the overall level of coverage, as our data provides a lower bound on the proportion of reported firms.

Second, we calibrate λ_p to match the average share of firms with equity issuance, since this parameter governs the average probability of firms being reported. With a given fixed cost of equity issuance and dispersion in capital quality, a higher probability of media coverage reduces information frictions, making 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.

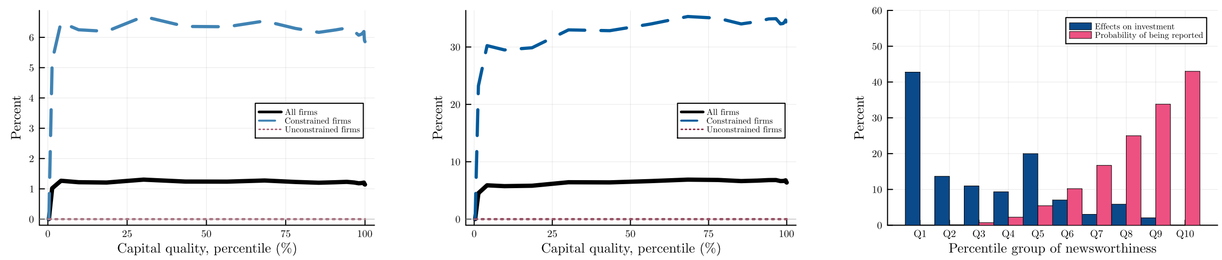
We use the average probability of issuance to calibrate λ_p, rather than the average proportion of firms reported in our dataset each quarter, because of the third issue highlighted above: our data comprises only a subset of all corporate news, and so would understate how many firms receive coverage. The key assumption behind our calibration is that despite this limitation, the *cross-sectional* patterns in our data are still relevant to discipline the cross-sectional patterns of media coverage in the model.

4.2. Patterns of corporate news reporting

Figure 7 reports the cross-sectional variation in the probability of media coverage under our calibration. We plot the cross-section of firms' coverage probability along three dimensions: their size, idiosyncratic productivity level, and age. Consistent with the stylized facts

Figure 8: Effects and Allocation of Media Coverage

(a) Effects on equity issuance **(b)** Effects on investment **(c)** Allocation vs. effects



Notes: Panel (a) and (b) summarize the average difference in equity issuance and investment for a firm conditional on its capital quality between two scenarios: when it is reported and when it is not. In panel (a), the reported number is the difference in annualized equity issuance rate, i.e., equity issuance scaled by firm size. In panel (b), the reported number is the relative difference in investment. In panel (c), we split the firms into ten equal-size groups based on their newsworthiness. For each group, we compute the average probability of the firms being reported and the average effects of being reported on their investment.

documented in Figure 2, larger and older firms are more likely to be reported, and the concentration is more pronounced along the size dimension. Our model also predicts that firms with higher idiosyncratic productivity have a higher probability of being reported by the media.

These qualitative relationships between news reporting and firm size, age, and productivity follow from equation (30). Newsworthiness scales with firm size and productivity because size and productivity are positively correlated with firms' market values. Since firms, on average, grow in size and productivity over time, the positive correlation of firm size and productivity with media-coverage probability extends to firm age as well.

4.3. The effects of media reporting on firm investment and financing

Using the calibrated model, we quantify the effects of media coverage on a firm's equity issuance and investment. Figure 8a and 8b report the average differences in firm outcomes between reported and unreported firms for each level of capital quality. Figure 8a shows that being reported increases firms' equity issuance rate by 1.2% on average. However, there is a large heterogeneity in terms of how much their equity issuance is affected by media coverage.

This heterogeneity arises along two key dimensions. First, media coverage affects firms differently depending on their capital quality. For firms with the lowest capital quality, media coverage has no impact on equity issuance. As explained in Section 3.2.1, news reporting can affect a firm's equity issuance because it fully reveals a firm's asset quality to investors, eliminating the need for firms to costly signal its type by issuing less equity than desired. Firms with the lowest capital quality are not subject to the "lemons threat" of being mimicked by lower-quality peers, so being reported does not change their equity issuance. In contrast, firms with higher capital quality benefits from media coverage, which enables them to issue more equity to their desired level.

Second, the impact of media coverage depends on whether a firm is financially constrained. A firm is considered financially constrained if there exist some firms with the same observable characteristics that would choose to issue equity after being reported, i.e., firm j is financially constrained if there exists an a such that $\mathbf{e}(k, z, a, 1) > 0$.[26] In Panel (a) of Figure 8, the blue dashed line represents the effects of media coverage on constrained firms, while the red dotted line represents those on unconstrained firms. Since unconstrained firms do not issue equity even after being reported, media coverage has no effect on their equity issuance. Panel (b) reports the effects of news reporting on investment and shows a similar pattern. Media coverage only affects the investment of financially constrained firms, especially those with high capital quality.

As discussed in Section 4.2, media coverage tends to focus on large and matured firms. Importantly, these firms are the least likely to be financially constrained. This implies a misalignment between the media's reporting incentives and a firm's benefit from coverage. A significant portion of media coverage is devoted to unconstrained firms with large stock market values that do not rely on external financing for investment. Figure 8c highlights this misalignment, plotting average investment responses to reporting and the probability of coverage across newsworthiness percentiles. Firms whose investment is most influenced by news reports receive little coverage, which suggests that reallocated news reporting would generate a larger real effect on the economy. In the next subsection, we quantify the magnitude of this distributional effect for aggregate financing, investment, and output with a counterfactual experiment.

[26] On average, 19.5% of firms are classified as constrained in each quarter under our definition. Our definition of financially constrained firms focuses on the friction from asymmetric information that deters firms from issuing equity. There could be some firms in our economy that refrain from issuing even after being reported because of the fixed costs of issuing equity. These firms are categorized as unconstrained under our definition.

4.4. Aggregate effects of media coverage distribution

News reports affect firms' financing and investment 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 symmetric-information economy captures the maximum potential loss from information asymmetry. We then consider an alternative 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 media in baseline economy We first evaluate how much media alleviates the loss from asymmetric information in our baseline model. In Table 4, we measure the role of media in a given economy by the relative reduction in output loss from asymmetric information between this economy and the no-media economy. Without media, asymmetric information depresses aggregate investment and capital accumulation, resulting in a 5.3% loss in output. While media helps to alleviate this loss, its impact is modest, reducing the output loss only by 0.7 percentage points (or 13% of the no-media output loss).

Table 4: Aggregate Effects of Information Asymmetry (%)

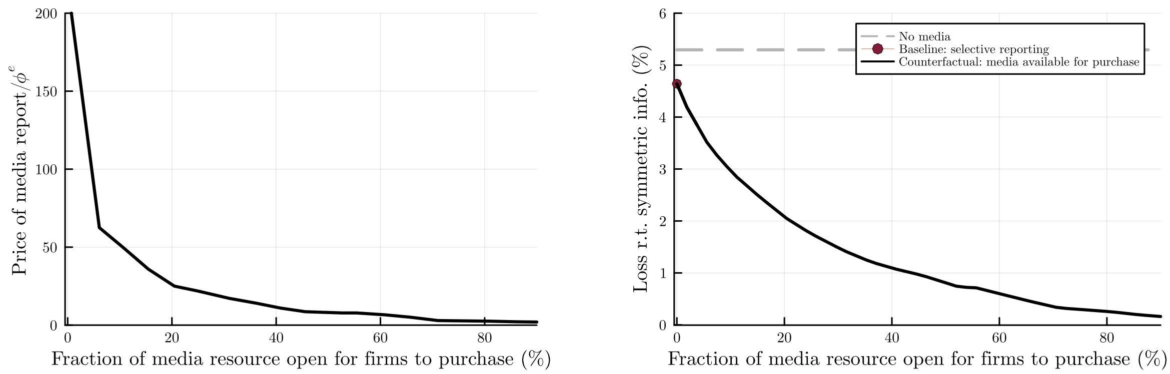
	No-media	Baseline
Investment	-6.7	-5.9
Capital stock	-4.7	-4.2
Output	-5.3	-4.6

Notes: This table summarizes the effects of asymmetric information on aggregate investment, 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 various aggregate quantities between each economy and the symmetric-information 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 news coverage through a competitive news market while holding constant the number of firms who get reported.

Figure 9: Aggregate Relevance of Media Allocation

(a) Price of media reporting **(b)** Output loss



Notes: Panel a reports the equilibrium price firms pay for media coverage in various counterfactual economies. In each counterfactual economy, we kept the total fraction of reported firms to be 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 normalized by the fixed cost of issuing equity ϕ^e. Panel b summarizes the output loss in counterfactual economies, where the output loss is measured by the relative difference of aggregate output between each counterfactual economy and the symmetric-information economy.

In all of these counterfactuals, as in the baseline economy, 13.7% of firms are reported each quarter. 19.5% of firms are classed as constrained, so if media allocated coverage exclusively to constrained firms, 70% of those constrained firms would receive coverage. In fact, in the baseline economy just 6% of media coverage is allocated to constrained firms, implying 96% of constrained firms are unreported.

For the counterfactuals, we assume that 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 media in the competitive market. Appendix D.2 provides further details for the counterfactual experiment.

Panel (a) of Figure 9 reports the price of media reports across a series of counterfactual economies, characterized by different values of α_m. The horizontal axis represents α_m, the share of media resource allocated through a competitive market out of total media resources. The vertical axis represents the equilibrium price of media reporting in each economy. Prices are high when the purchasable fraction of media resources is small, with only firms benefiting most from news reporting willing to pay for being reported. As more media resources become purchasable, prices decline substantially.

Panel (b) shows how output loss varies with α_m. When $\alpha_m = 0$, all media resources are allocated following the baseline reporting policy, so the output loss coincides with the result of our baseline economy. While reallocating media coverage cannot eliminate output loss completely because the total capacity of media is insufficient to cover all constrained firms, it can reduce it substantially. Notably, reallocating just 5% of media resources for firms purchase doubles media's effect in reducing 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 most from coverage have the highest willingness to pay. Media reporting significantly boosts these firms' financing and investment, 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 news coverage.

5. Conclusion

News outlets provide valuable information to their readers, but constraints on space and journalistic resources mean they have to make judgements of which firms are most newsworthy. We find that these judgements overwhelmingly favor reporting on the largest firms in the economy, and that this selectivity has important effects on firm dynamics and aggregate investment.

When a firm is reported in the media, their probability of issuing new equity in the subsequent quarters rises. They also see a rise in investment. Evidence from media strikes in France suggests that this is partly due to news coverage alleviating information asymmetries in financial markets. Consistent with this view, the effects of media coverage are strongest among small firms. The fact that coverage is systematically concentrated amongst the very largest firms, therefore, slows down firm growth and depresses aggregate investment.

In a quantitative model with heterogeneous firms, asymmetric information, and a media

[27] See Appendix D.3 for similar patterns for investment and capital losses.

[28] In Appendix D.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.

sector calibrated to our data, we find that selective media coverage increases average firm size and investment relative to a world with no media. But this improvement is fairly minor, because the coverage is concentrated among large firms whose investment and financing are not constrained by information asymmetry. If even a small fraction of the limited media reports were allocated with a market for coverage, the impact of media reporting would be substantially larger.

This highlights the importance of the allocation of media resources. Small and constrained firms benefit most from media coverage because media reporting can alleviate the information friction that constrains their investment. However, media outlets allocate their resources to reporting mostly large and unconstrained firms. This misalignment between the media's incentive to report and the firm's need to be reported substantially affects firm dynamics, financing markets, and business investment.

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Appendices

A. Additional Details of Empirical Analysis

A.1. Data construction

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

Variables

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

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

3. *Leverage*: the sum of debt in current liabilities and long-term debt (`dlttq+dlc`) over the sum of total assets and market valuation minus 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 of net plant, property, and equipment (`ppentq`). If a firm has a missing observation of `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.

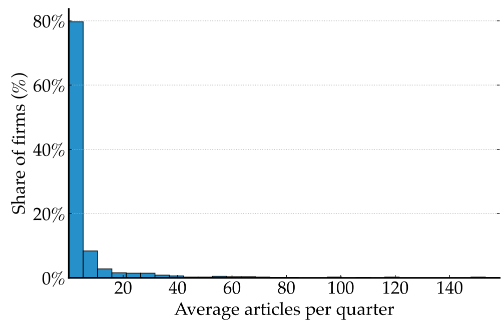
5. *Equity issuance*: defined as the sale of common and preferred stock (`sstky` in the first fiscal quarter and changes in `sstky` for the second to fourth fiscal quarters). Following McKeon (2015), we classify equity issuances that are smaller than 3% of a firm's market capitalization as zero issuance.

6. *Cumulative equity issuance probability*: an indicator variable that takes the value of one if a firm has issued new equity between quarter 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.

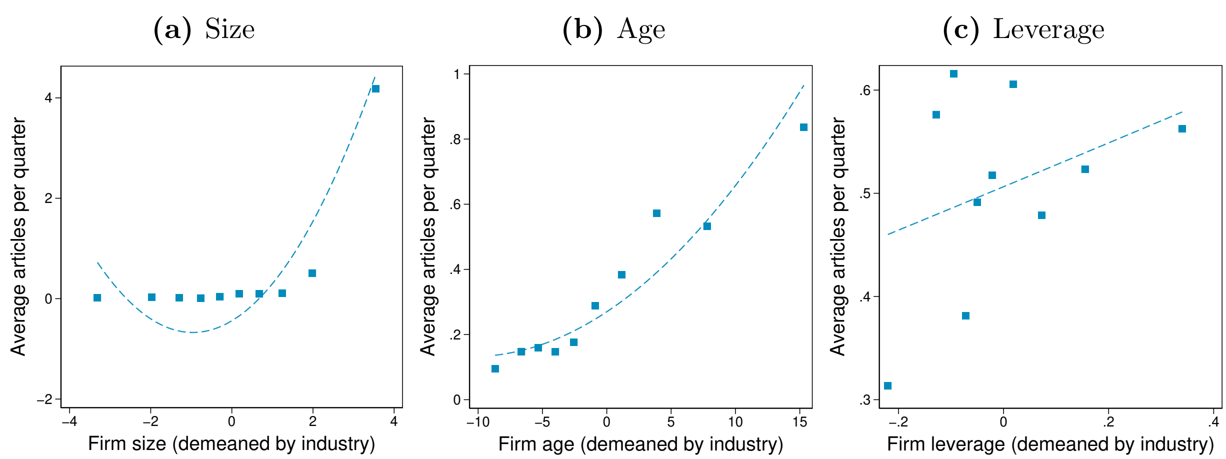
A.2. Additional tables and figures

Figure A.1: Distribution of corporate news coverage (firms with nonzero coverage)



Notes: This figure reports the distribution of firm news coverage for firms that appear in at least one news article in the sample.

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



Notes: This figure reports binned scatterplots of average news articles per quarter. Each dot represents a decile of firms. Dashed lines represent quadratic fit lines. Panel (a) sorts firms by size, measured by log real assets, relative to industry (4-digit NAICS) average. Panel (b) sorts firms by age, measured by years since IPO, relative to industry average. Panel (c) sorts firms by leverage, measured by market leverage, relative to industry average.

Figure A.3: Market capitalization and media coverage

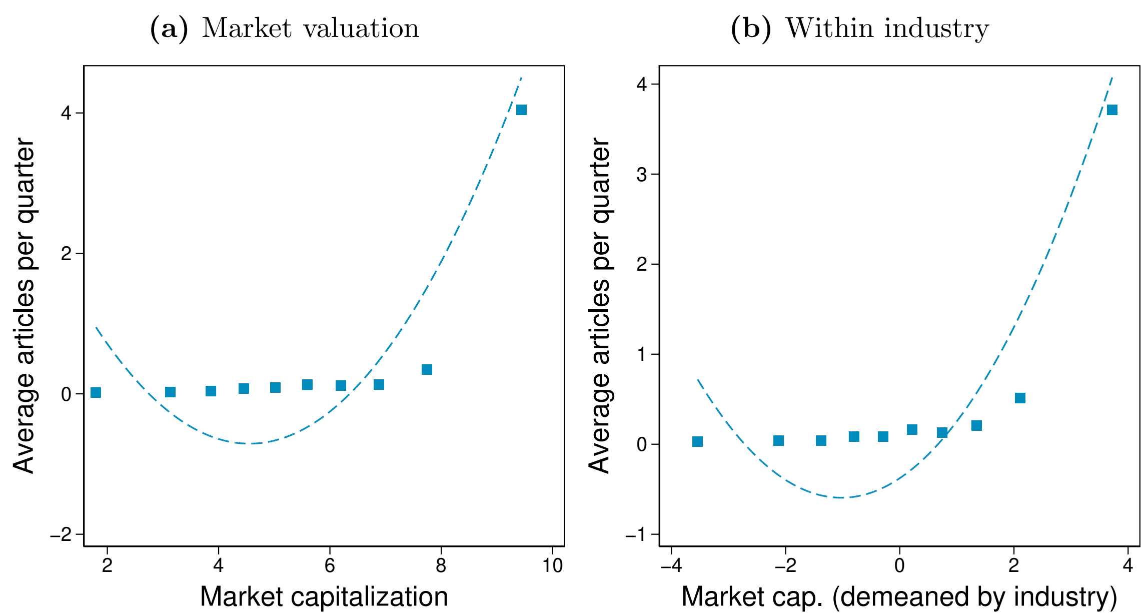


Table A.1: Top 20 firms with media coverage

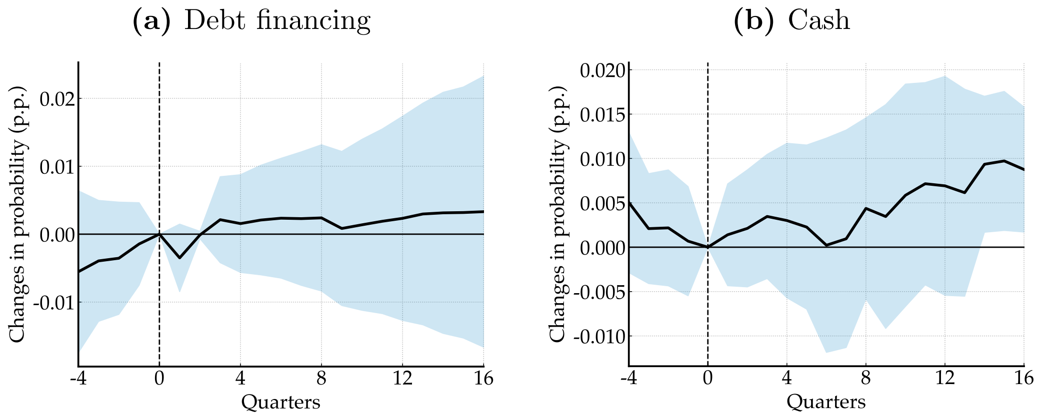
Rank	Firm	Articles	Rank	Firm	Articles
1	General Motors	18,380	11	Amazon	6,615
2	Microsoft	15,314	12	Bank of America	6,432
3	Apple	13,995	13	Merrill Lynch	6,169
4	Alphabet	10,402	14	Goldman Sachs	6,121
5	Citigroup	9,844	15	American Airlines	5,506
6	Boeing	8,965	16	HP	5,180
7	Time Warner	7,398	17	Delta Airlines	4,574
8	AT&T	7,244	18	US Airways	4,551
9	Walmart	6,887	19	Procter & Gamble	4,309
10	JPMorgan Chase	6,795	20	Altria Group	4,094
Total articles on top 20 firms					158,775
Total articles on remaining firms					216,852

Notes: This table lists the top 20 firms by total number of news articles from 1990 to 2021.

A.3. Specialized role of curated news

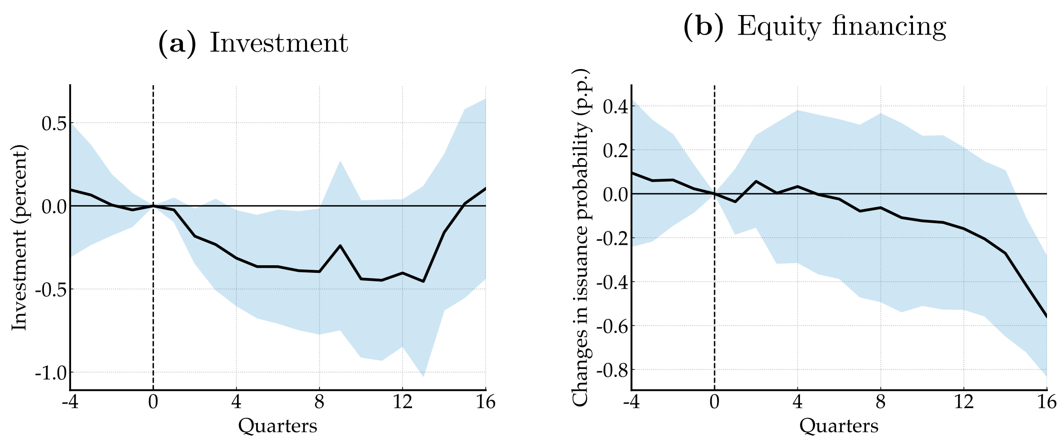
This subsection conducts additional analysis that provides evidence on the specialized role of curated news in newspapers for equity financing.

Figure A.4: News coverage and other forms of firm financing



Notes: This figure reports results from estimating a variant of the baseline local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it-1} + u_{it+h}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 4-digit NAICS level); α_i denotes firm fixed effects; ν_{it} denotes the Twitter mentions of firm i in quarter t, demeaned at the firm level and standardized; and Z_{it-1} 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 (a), defined as the log change in the book value of the firm's tangible capital stock, and the cumulative probability of equity issuance (E_{it}) in panel (b), defined as an indicator variable that takes the value 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.

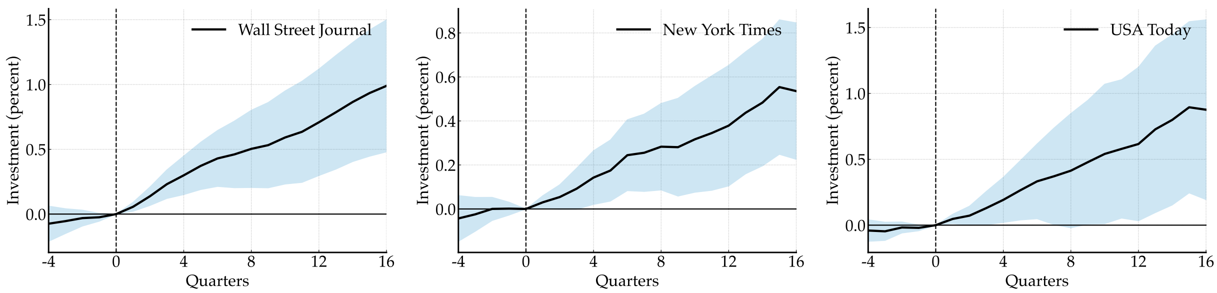
Figure A.5: Effects of Twitter coverage



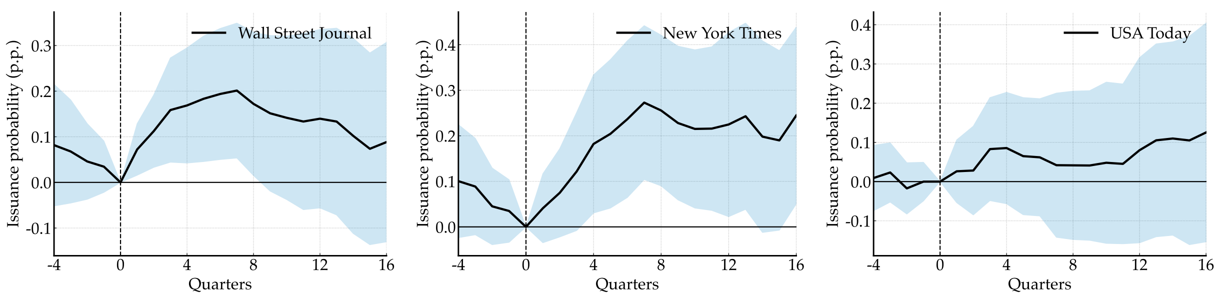
Notes: This figure reports results from estimating the local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it} + u_{it+h}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 4-digit NAICS level); α_i denotes firm fixed effects; ν_{it} denotes news coverage of firm i in major US 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 cumulative probability of debt financing in panel (a), defined as an indicator variable that takes the value 1 if a firm raises debt financing between quarters t and $t+h$ and zero otherwise, and the cumulative probability of increasing cash holdings in panel (b), defined as an indicator variable that takes the value 1 if a firm increases cash holdings 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.6: Effects of coverage by newspaper

(a) Investment



(b) Equity issuance



Notes: This figure reports results from estimating variants of the baseline local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it} + u_{it+h}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 4-digit NAICS level); α_i denotes firm fixed effects; ν_{it} denotes news coverage of firm i in each newspaper in quarter t (The Wall Street Journal, The New York Times, or USA Today), 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 (a), defined as the log change in the book value of the firm's tangible capital stock, and the cumulative probability of equity issuance (E_{it}) in panel (b), defined as an indicator variable that takes the value 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.

A.4. Topics in news articles

Figure A.7: 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.)

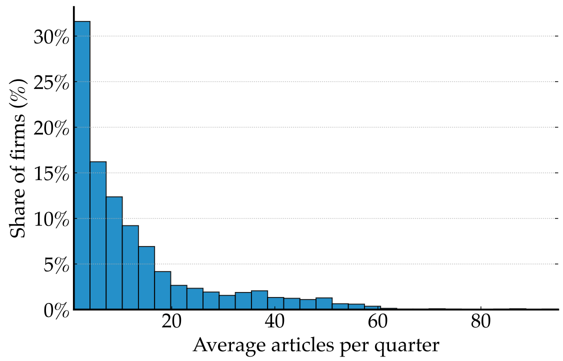
(i) Earnings (j) Technology sector (k) Airline sector (l) Social media

(m) Energy sector (n) Automobile sector (o) Pharma. sector (p) Financing

(q) Telecom sector (r) Advertising sector (s) Employees (t) Executives

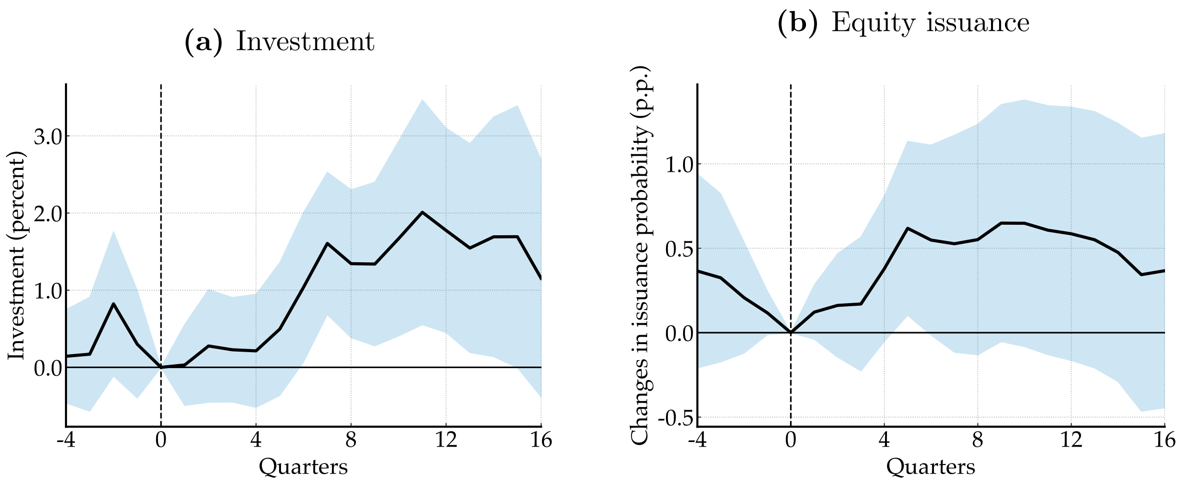
A.5. News coverage in France

Figure A.8: Distribution of corporate news coverage in major French newspapers



Notes: This figure reports the distribution of corporate news coverage in major French newspapers from 2005 to 2022, including *Les Echos*, *Le Monde*, *La Tribune*, and *Figaro*.

Figure A.9: Media coverage and firm outcomes in France



Notes: This figure reports results from estimating the local projections in equation (3) for quarters $-4 \leq h \leq 16$: $y_{it+h} - y_{it} = \alpha_{st} + \alpha_i + \beta_h \nu_{it} + \Gamma' Z_{it} + u_{it+h}$, where α_{st} denotes sector-by-quarter fixed effects (with sectors defined at the 2-digit NAICS level); α_i denotes firm fixed effects; ν_{it} denotes 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 (a), defined as the log change in capital expenditures, and the cumulative probability of equity issuance (E_{it}) in panel (b), defined as an indicator variable that takes the value 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 the 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	Public broadcaster workers 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: National media strikes in France from 2005 to 2021 through searching for "((strike or grève) and (journalist or journaliste)) or ((strike or grève) and (broadcaster or diffuseur))" in Factiva, restricting the region to France, industry to Media/Entertainment, subject to Labor Dispute, and excluding strikes in individual newspapers

B. A Model with Investor-Led Media Demand

We here derive a variant of the classic static Grossman and Stiglitz (1980) model with a media sector. A media outlet decides which firms to include in their publication. Unlike our main quantitative model, we now introduce noise traders, who prevent the perfect aggregation of information in asset prices. This causes investors to value information from media.

Investors choose whether to purchase the media publication. The publication contains a lot of information about many firms. Conditional on purchasing the publication, investors must decide how to allocate a limited capacity for processing information among those various signals. As in Van Nieuwerburgh and Veldkamp (2010), ex-ante identical investors specialize in gathering information about different firms. Unlike Van Nieuwerburgh and Veldkamp (2010), the set of firms investors can learn about is chosen endogenously by the media outlet, which responds to investor demand.

To solve this model, we abstract from the firm block of our quantitative model. Instead, holding each firm's equity has a payoff that is independent of media decisions, but which is initially unknown to investors.

B.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 equity of the firms are risky assets with payoffs given by the $N \times 1$ vector f, which is distributed according to:

$$f \sim N(\bar{f}, \Sigma_f) \tag{34}$$

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 investor 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, so can only report on $N_r < N$ of the firms. Letting m_j be an indicator equal to 1 if the outlet reports on firm j, and equal to 0 otherwise, the space constraint is:

$$\sum_{j=1}^{N} m_j \leq N_r \tag{35}$$

The outlet sells this publication to investors at a price $c > 0$. For the purposes of this model, we will hold c fixed, and consider only the choice of which firms to include in the publication.

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

$$U_i = -\exp(-\rho(W_i - cL_i)) \tag{36}$$

where $\rho > 0$ is the risk aversion parameter and $L_i \in \{0, 1\}$ is an indicator for if the investor purchased that 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 quantities of each risky asset purchased by investor i. To buy this portfolio, they must sell $q_i'p$ units of risk-free endowment. Their end-of-period wealth is therefore:

$$W_i = (W_0 - q_i'p)r + q_i'f \tag{37}$$

Investors can observe which firms are reported before they choose whether to purchase the media publication, but 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:

$$|\Sigma_i^{-1}| \leq e^{2K} |\Sigma_f^{-1}| \tag{38}$$

where Σ_i is the variance-covariance matrix of investor i's beliefs after processing information, but before observing asset prices. The constant $K > 0$ determines the investor's information capacity. With Gaussian priors and posteriors (verified below), this constraint implies that the mutual information between priors and posteriors cannot exceed K, as is standard in the rational inattention literature (Maćkowiak et al., 2023).

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

$$\int_0^1 q_i di + x = \bar{x} \tag{39}$$

where $\bar{x}$ and x are $N \times 1$ vectors of asset supplies and noise trader shocks respectively. Noise trader shocks are distributed according to

$$x \sim N(0, \sigma_x^2 I) \tag{40}$$

where $\sigma_x^2 \geq 0$ is a scalar.

Timing The model consists of a number of stages.

1. f is realized. The media outlet observes it, and chooses which firms to report.
2. Investors decide if 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 asset prices and choose portfolios. Simultaneously, prices are determined as a function of investor demand.
5. Payoffs are realized.

We solve this by working backwards. The first step is to solve for the asset demands that an investor would make for any given information set. Once we have that, we can then solve the information-choice problem, and finally the media reporting problem.

B.2. Equilibrium with given information sets

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 have processed and any information contained in p.

2. p is such that asset markets clear.

Portfolio choice When the asset markets open, investors observe p. They also potentially have other information, if they purchased it. We summarize that extra information in $\mathcal{I}_i$. Their expected utility at this point is

$$\mathbb{E}_i[U_i|p, \mathcal{I}_i] = -\mathbb{E}_i[\exp(-\rho(W_i - cL_i))|p, \mathcal{I}_i] \tag{41}$$

Substituting out for W_i using the budget constraint (37) and simplifying:

$$\mathbb{E}_i[U_i|p, \mathcal{I}_i] = -\exp(-\rho r W_0)\exp(\rho c L_i)\,\mathbb{E}_i[\exp(-\rho q_i'(f - pr))|p, \mathcal{I}_i] \tag{42}$$

The first two exponential terms are known positive constants, so do not affect the portfolio choice problem. The simplified objective is therefore

$$\mathbb{E}_i[U_i|p, \mathcal{I}_i] \propto -\mathbb{E}_i[\exp(-\rho q_i'(f - pr))|p, \mathcal{I}_i] \tag{43}$$

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 (43) can be written as

$$-\mathbb{E}_i[\exp(-\rho q_i'(f - pr))|p, \mathcal{I}_i] = -\exp\left(-\rho q_i'(\mathbb{E}_i[f|p, \mathcal{I}_i] - pr) + \frac{\rho^2}{2} q_i' \mathbb{V}_i[f|p, \mathcal{I}_i] q_i\right) \tag{44}$$

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

$$q_i = \frac{1}{\rho}(\mathbb{V}_i[f|p, \mathcal{I}_i])^{-1}(\mathbb{E}_i[f|p, \mathcal{I}_i] - pr) \tag{45}$$

Prior information All investors know the distribution of f (equation (34)). If investors have paid for information, they also observe a vector of noisy signals before markets open of the form

$$s_i = f + \varepsilon_i \tag{46}$$

where the noise vector ε_i is idiosyncratic to investor i, independent of f, and is distributed according to

$$\varepsilon_i \sim N(0, \Sigma_{\varepsilon i}) \tag{47}$$

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

$$\mathbb{V}_i[f|\mathcal{I}_i] \equiv \Sigma_i = (\Sigma_f^{-1} + \Sigma_{\varepsilon i}^{-1})^{-1} \tag{48}$$

$$\mathbb{E}_i[f|\mathcal{I}_i] \equiv \mu_i = \Sigma_i(\Sigma_f^{-1}\bar{f} + \Sigma_{\varepsilon i}^{-1} s_i) \tag{49}$$

If investor i does not purchase information, they do not observe signals, so $\Sigma_{\varepsilon i}^{-1}$ is a matrix of 0s, and their priors depend on the distribution of f only: $\Sigma_i = \Sigma_f$, $\mu_i = \bar{f}$. 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 Guess that prices are a linear function of payoffs and noise trader shocks:

$$p = A + Bf + Cx \tag{50}$$

for some $N \times N$ matrices A, B, C. Since there are no links between assets elsewhere in the model, guess that each of these matrices is diagonal.

At this point, it is useful to split assets into two groups depending on whether they are reported in the media or not. We then solve for equilibrium beliefs, asset demands, and the price coefficients A, B, C. Without loss of generality, index the assets that are reported in the media by $n \in \{1, ..., N_r\}$, and let $n \in \{N_r + 1, ..., N\}$ be the unreported firms.

Unreported firms Since no investors have information on realized f_n for unreported firms, prices cannot contain any such information. The final $N - N_r$ rows and columns of B must therefore contain only 0s.

As a result, beliefs about f_n depend on the underlying distribution (equation (34)) only. The demand for equity of an unreported firm is therefore identical across investors, and is given by:

$$q_{ni} = \frac{\bar{f}_n - rp_n}{\rho \sigma_{fn}^2} \tag{51}$$

where σ_{fn}^2 is the nth diagonal element of Σ_f. Substituting this into market clearing (equation (39)) for firm n's equity and rearranging yields

$$p_n = \frac{\bar{f}_n - \rho \sigma_{fn}^2 \bar{x}_n}{r} - \frac{\rho \Sigma_{fn}}{r} x_n \tag{52}$$

This is of the form in equation (50), with the nth diagonal element of B equal to 0.

Reported firms For reported firms, asset prices contain some information, so there is a further step in solving for equilibrium asset demand. Let z_r denote a $1 \times N_r$ vector consisting of the first N_r elements of any vector z, so e.g. f_r denotes the payoffs of reported assets. Similarly, Σ_{rf} and Σ_{ri} denote $N_r \times N_r$ matrices, consisting of the first N_r rows and columns of Σ_f and Σ_i respectively. A_r, B_r, C_r denote the first N_r rows and columns of A, B, C.

From the guessed law of motion for prices, investors can construct an unbiased Gaussian signal about f_r:

$$B_r^{-1}(p_r - A_r) = f_r + B_r^{-1} C_r x \sim N(f_r, \Sigma_{rp}) \tag{53}$$

where

$$\Sigma_{rp} \equiv \sigma_x^2 B_r^{-1} C_r (B_r^{-1} C_r)' \tag{54}$$

Investors use Bayes rule to incorporate this signal into their beliefs. Posteriors are normally distributed, with

$$\mathbb{V}_i[f|p,\mathcal{I}_i] \equiv \hat{\Sigma}_{ri} = (\Sigma_{ri}^{-1} + \Sigma_{rp}^{-1})^{-1} \tag{55}$$

$$\mathbb{E}_i[f|p,\mathcal{I}_i] \equiv \hat{\mu}_{ri} = \hat{\Sigma}_{ri}(\Sigma_{ri}^{-1}\mu_{ri} + \Sigma_{rp}^{-1}B_r^{-1}(p_r - A_r)) \tag{56}$$

Posterior expectations $\hat{\mu}_{ri}$ are therefore simply a weighted average of priors μ_{ri} and the signal $B_r^{-1}(p_r - A_r)$, with the weights determined by the signal to noise ratio. Substituting $\hat{\mu}_{ri}$ and $\hat{\Sigma}_{ri}$ into equation (45) we obtain the asset demand

$$q_{ri} = \frac{1}{\rho}\Sigma_{ri}^{-1}\mu_{ri} + \frac{1}{\rho}(\Sigma_{rp}^{-1}(B_r^{-1} - rI_r) - r\Sigma_{ri}^{-1})p_r - \frac{1}{\rho}\Sigma_{rp}^{-1}B_r^{-1}A_r \tag{57}$$

Substituting out for μ_{ri}, Σ_{ri} using equations (48) and (49) and aggregating across investors, market clearing becomes:

$$\frac{1}{\rho}(\Sigma_{rf}^{-1}\bar{f}_r - \Sigma_{rp}^{-1}B_r^{-1}A_r) + \frac{1}{\rho}\bar{\Sigma}_{r\epsilon}^{-1}f_r + \frac{1}{\rho}(\Sigma_{rp}^{-1}(B_r^{-1} - rI_r) - r\Sigma_{rf}^{-1} - r\bar{\Sigma}_{r\epsilon}^{-1})p + x_r = \bar{x}_r \tag{58}$$

where $\bar{\Sigma}_{r\epsilon}^{-1} = \int_0^1 \Sigma_{r\epsilon i}^{-1} di$ is the average precision of investor signals. This rearranges to the form in equation (50), confirming our guess. Matching coefficients yields solutions for A, B, C.

B.3. Information choice

Having solved the later stage, we now go back a step and solve for investor information choices, taking media reporting as given.

Indirect expected utility In equation (42), we found an expression for expected utility conditional on observing $p, \mathcal{I}$. Substituting out for the expectation using equation (44), and for q_i using asset demand (45), this becomes

$$\mathbb{E}_i[U_i|p,\mathcal{I}_i] = -\exp(-\rho r W_0)\exp(\rho c L_i)\left[\exp\left(-\frac{1}{2}(\mathbb{E}_i[f|p,\mathcal{I}_i] - pr)'\mathbb{V}_i[f|p,\mathcal{I}_i]^{-1}(\mathbb{E}_i[f|p,\mathcal{I}_i] - pr)\right)\right] \tag{59}$$

When the investor makes their information choice, they have not yet observed $p, \mathcal{I}$. We therefore need to take the expectation of equation (59) over these objects, or equivalently over the posterior expectation $\mathbb{E}_i[f|p,\mathcal{I}_i]$.[29] This is an expectation of an exponential of a squared Gaussian distribution, which is given by (see Veldkamp, 2023, ch. 7.3):

$$\mathbb{E}_i[U_i] = -\exp(-\rho r W_0)\exp(\rho c L_i)\left(\frac{|\mathbb{V}_i[f|p,\mathcal{I}_i]|}{|\Sigma_f|}\right)^{\frac{1}{2}} \cdot \left[\exp\left(-\frac{1}{2}\,\mathbb{E}_i[\mathbb{E}_i[f|p,\mathcal{I}_i]-pr]'\Sigma_f^{-1}\,\mathbb{E}_i[\mathbb{E}_i[f|p,\mathcal{I}_i]-pr]\right)\right] \quad (60)$$

The final bracketed term of this expression consists of expectations of posterior 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 they purchase information or not, 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 information choice.

Expected utility for an uninformed investor, who does not purchase information, is therefore proportional to:

$$\mathbb{E}_U[U_U] \propto -\left(\frac{|\mathbb{V}[f|p]|}{|\Sigma_f|}\right)^{\frac{1}{2}} \quad (61)$$

For an informed investor, who does purchase information, expected utility is proportional to:

$$\mathbb{E}_i[U_i] \propto -e^{\rho c}\left(\frac{|\mathbb{V}_i[f|p,\mathcal{I}_i]|}{|\Sigma_f|}\right)^{\frac{1}{2}} \quad (62)$$

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

Information capacity allocation An investor who purchases the media publication chooses how to allocate their limited capacity for processing information. As in the rational inattention literature (Maćkowiak et al., 2023), investors choose the properties of their noisy signals (46) to maximize their expected utility (60) subject to their capacity constraint (38). Since priors are Gaussian, equation (46) is the optimal signal structure, and the investors

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

only have to choose the noise variance matrix $\Sigma_{\varepsilon i}$.

The important step here is to note, as shown in e.g. **?**, 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.

The investor's signal is therefore 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:

$$\sigma_{\varepsilon i n^*}^{-2} = (e^{2K} - 1)\sigma_{fn^*}^{-2} \tag{63}$$

where $\sigma_{\varepsilon in^*}^2, \sigma_{fn^*}^2$ 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, equation (62) can be written:

$$\begin{aligned}
\mathbb{E}_i[U_i] &\propto -e^{\rho c} \prod_{n=1}^{N} \left(\frac{\mathbb{V}_i[f_n|p_n, \mathcal{I}_i]}{\sigma_{fn}^2} \right)^{\frac{1}{2}} && (64) \\
&= -e^{\rho c} \prod_{n=1}^{N_r} \left(\frac{\sigma_{fn}^{-2} + \sigma_{\varepsilon in}^{-2} + \sigma_{pn}^{-2}}{\sigma_{fn}^{-2}} \right)^{-\frac{1}{2}} && (65) \\
&= -e^{\rho c} \left(\frac{|\mathbb{V}[f|p]|}{|\Sigma_f|} \right)^{\frac{1}{2}} \left(\frac{\sigma_{fn^*}^{-2} e^{2K} + \sigma_{pn^*}^{-2}}{\sigma_{fn^*}^{-2} + \sigma_{pn^*}^{-2}} \right)^{-\frac{1}{2}} && (66)
\end{aligned}$$

The first of these equalities uses the observation that for all unreported firms, $\mathbb{V}_i[f_n|p_n, \mathcal{I}_i] = \sigma_{fn}^2$. The second uses the fact that investor i uses all of their information capacity to learn about a single firm, denoted n^*, with information precision given in equation (63).

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

$$\mathcal{L}_n \equiv \frac{\sigma_{fn}^{-2} e^{2K} + \sigma_{pn}^{-2}}{\sigma_{fn}^{-2} + \sigma_{pn}^{-2}} \tag{67}$$

This is strictly increasing in σ_{fn}^{-2}, and strictly decreasing in the precision of information contained in prices σ_{pn}^{-2}. Investors prefer to learn about assets where prices do not contain much information, as then the value-added of learning is greater.

We will show below that if more investors learn about asset n, its price will contain more information, and σ_{pn}^{-2} falls. All else equal, investors therefore prefer to learn about 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 assets which other investors are not learning about, ex-ante identical investors specialize by randomizing the use of their information capacity.

Suppose that conditional on paying c and buying news, investors devote their information processing capacity to learning about asset n with probability π_n. For such a mixed strategy to be optimal, it must be the case that investors are indifferent between any of the strategies in the mix. That is, the expected utility from learning about firm n must be equal to the expected utility from learning about n', given all other investors are playing the same mixed strategy. From equation (66), this implies that the learning indices must be equal for all assets which investors learn about with positive probability:

$$\mathcal{L}_n = \mathcal{L}_{n'} \quad \text{for all} \quad (n, n') \, \text{such that} \quad \pi_n, \pi_{n'} > 0 \tag{68}$$

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

Learning indices in equilibrium To make further progress on the factors required for condition (68) to hold, we return to equilibrium prices to solve for σ_{pn}^{-2}. Equation (54) shows that the precision of information in prices depends on the coefficient matrices B_r, C_r.

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 investor signals about firm n is then:

$$\bar{\sigma}_{n\epsilon}^{-2} = \lambda_n (e^{2K} - 1) \sigma_{fn}^{-2} \tag{69}$$

Substituting this into row n of equation (58) and rearranging, we obtain:

$$p_n = (\sigma_{pn}^{-2}(b_n^{-1} - r) - r\sigma_{fn}^{-2}(1 + \lambda_n(e^{2K} - 1)))^{-1}\Big[(\rho\bar{x}_n + \sigma_{pn}^{-2}b_n^{-1}a_n - \sigma_{fn}^{-2}\bar{f}_n) \\ - \lambda_n\sigma_{fn}^{-2}(e^{2K} - 1)f_n - \rho x_n\Big] \quad (70)$$

Matching coefficients between equations (50) and (70), we obtain:

$$b_n = -\frac{\lambda_n\sigma_{fn}^{-2}(e^{2K} - 1)}{\sigma_{pn}^{-2}(b_n^{-1} - r) - r\sigma_{fn}^{-2}(1 + \lambda_n(e^{2K} - 1))} \quad (71)$$

$$c_n = b_n \cdot \frac{\rho}{\lambda_n\sigma_{fn}^{-2}(e^{2K} - 1)} \quad (72)$$

Using equation (54) (and the fact that all matrices here are diagonal), the variance of noise in the price of asset n is:

$$\sigma_{pn}^2 = \sigma_x^2(b_n^{-1}c_n)^2 = \frac{\rho^2\sigma_x^2\sigma_{fn}^4}{\lambda_n^2(e^{2K} - 1)^2} \quad (73)$$

This clearly showcases the earlier point that σ_{pn}^2 is smaller (and so σ_{pn}^{-2} is larger) when λ_n rises. When more investors are informed about an asset, its price is a more precise signal of its returns. Substituting this into equation (67) and simplifying, the learning index is given by

$$\mathcal{L}_n = 1 + \frac{e^{2K} - 1}{1 + \lambda_n^2\sigma_{fn}^{-2}\sigma_x^{-2}\rho^{-2}(e^{2K} - 1)^2} \quad (74)$$

Many of the elements of this formula for the learning index are common across assets. Condition (68) is therefore satisfied if and only if:

$$\frac{\lambda_n^2}{\sigma_{fn}^2} = \frac{\lambda_{n'}^2}{\sigma_{fn'}^2} \quad \text{for all } \ (n, n') \, \text{such that } \ \lambda_n, \lambda_{n'} > 0 \quad (75)$$

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

A final implication of these results is that investors learn about all firms included in the media publication with positive probability. To see this, suppose no investor learns about firm $n0$, so $\lambda_{n0} = 0$. In equation (74), that firm's learning index would be $\mathcal{L}_{n0} = \exp(2K)$. This is strictly greater than the learning index for any firm with positive λ_n. As a result, if $\lambda_{n0} = 0$, an investor could always increase expected utility by deviating from the mixed strategy of other investors, and learning about $n0$ with probability 1. It is therefore not possible for a mixed strategy equilibrium to exclude some reported firms entirely.

Media purchase Using equations (61) and (66), the expected utility gain from purchasing the media publication is:

$$\mathbb{E}_i[U_i] - \mathbb{E}_U[U_U] = \left(\frac{|\mathbb{V}[f|p]|}{|\Sigma_f|}\right)^{\frac{1}{2}} (1 - e^{\rho c}\mathcal{L}_{n^*}^{-\frac{1}{2}}) \tag{76}$$

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

Investors purchase information if this is positive. The proportion of investors who purchase the publication is therefore such that investors are indifferent between purchasing information and not doing so. This occurs at

$$\mathcal{L}_{n^*} = e^{2\rho c} \tag{77}$$

A given value of c therefore pins down a unique learning index.

B.3.1. Media reporting decision

The media outlet chooses which firms to report on to maximize profits. Let q be the proportion of investors who purchase the outlet's publication, so profits are revenues cq minus costs, which we assume are independent of which firms the outlet chooses to report. Since c is taken as given, the outlet chooses reporting decisions to maximize their readership q.

To find the optimal reporting strategy, it is helpful to note that condition (75) implies that λ_n can be expressed as:

$$\lambda_n = \lambda_0 \sigma_{fn} \tag{78}$$

where λ_0 is identical for all firms n. Substituting this into equation (74), we find that λ_0 is uniquely determined by parameters common to all n and the learning index $\mathcal{L}_n$, which in turn is fixed by c (equation (77)). 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:

$$\lambda_n \equiv q\pi_n \tag{79}$$

Summing over all reported firms, and using the fact that $\sum_{n=1}^{N_r} \pi_n = 1$, we have:

$$q\sum_{n=1}^{N_r} \pi_n = \sum_{n=1}^{N_r} \lambda_n \tag{80}$$

$$\implies q = \lambda_0 \sum_{n=1}^{N_r} \sigma_{fn} \tag{81}$$

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

B.3.2. Relationship to the quantitative model

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

The appropriate analogue to the reporting policy derived here is that media outlets report on firms with large payoff variances *conditional* on being reported. To see why, consider an outlet choosing between reporting firms j and j'. If the outlet reports firm j, investors observe that, and evaluate the benefits of purchasing the outlet publication based on the resulting variance of asset j's payoff. If the outlet does not report j, but instead reports 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 payoffs conditional on the firm being reported. This is exactly the reporting policy derived in Section 3.2.2 in the quantitative model.

Since the model is static, we also do not consider the business cycle in this model. However, note that Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2018) and many others have shown that the variance of idiosyncratic shocks to firms rises in recessions.

In this model, assuming c is fixed, a rise in firm-level volatility implies greater demand for news: equations (78) and (81) show that more investors purchase the media publication, and the proportion of investors who are informed rises for every asset. We have taken N_r here as given, but in a dynamic setting it is plausible that outlets would respond to this greater demand for firm-level news by providing more of it, as we observe in the data.

C. Additional Details of Theoretical Analysis

C.1. Proofs

C.1.1. Proof of Theorem 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 $\boldsymbol{m}_t = \{m_{j,t}\}_{j=0}^{1}$, which satisfies the space constraint (19). Without loss of generality, assume that $\boldsymbol{m}_t$ involves all outlets reporting on firm j, and not reporting on firm j'.

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

$$\mathcal{P}_t(k_{j,t}, z_{j,t}, 1, \mathcal{I}_{i,t}^{\text{news}} | m_{i,j,t}^o = 1) = \text{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1). \tag{82}$$

Substituting this forecast into equation (25) reveals that when $m_{i,j,t}^o = 1$, forecaster i makes no forecast errors.

For a firm that is un-reported by outlet i, the optimal forecast by forecaster i is given by

$$\mathcal{P}_t(k_{j,t}, z_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}} | m_{i,j,t}^o = 0) = \mathbb{E}\left[(\text{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}) | k_{j,t}, z_{j,t}, m_{j,t}\right]. \tag{83}$$

The forecast in (83) is uncertain because the forecaster is uncertain about $a_{j,t}$. In general, this will lead forecaster i to make non-zero forecast errors when $m_{i,j,t}^o = 0$.[30]

[30] If $m_{j,t} = 1$, forecaster i is aware that investors know $a_{j,t}$, but they do not themselves observe it as their outlet did not report it. If instead $m_{j,t} = 0$, forecaster i knows that no outlet reported $a_{j,t}$, and so it is not part of investors' information set. However, there is still uncertainty in that case, because realized $a_{j,t}$ can still affect realized market value indirectly, through firm j's equity issuance (see Section 3.2.1). Since forecasters make predictions before the equity markets open, they cannot observe equity issuance. They do not therefore know what investor posteriors $g(a_{j,t})$ will be, and so cannot be certain about the realization of 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

$$\mathrm{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t}) = \overline{\mathrm{FE}}_{-i,t}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{-i,t}), \tag{84}$$

and thus $U_{i,t} = 0$.

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 $U_{i,t} = 0$ with certainty, a sufficient condition for $\boldsymbol{m}_t$ to be an equilibrium is that

$$\mathbb{E}\,\hat{U}_{i,t}(j, j') + \kappa_{j,t} - \kappa_{j',t} \leq 0, \tag{85}$$

where $\hat{U}_{i,t}(j, j')$ is the utility of forecaster i if outlet i deviates. If this condition holds for all pairs of reported and unreported firms j, j', outlets never deviate, and $\boldsymbol{m}_t$ is an equilibrium.

We now proceed to find an expression for $\mathbb{E}\,\hat{U}_{i,t}(j, j')$. First, notice that the deviation would have no effect on firms other than j and j'. From the definition of forecaster utility (equation (24)), we therefore have

$$\begin{aligned}\mathbb{E}\,\hat{U}_{i,t}(j, j') = &- \mathbb{E}\left[\mathrm{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t}) - \overline{\mathrm{FE}}_{-i,t}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{-i,t})\right] \\ &- \mathbb{E}\left[\mathrm{FE}_t(k_{j',t}, z_{j',t}, a_{j',t}, m_{j',t}, \mathcal{I}^{\text{news}}_{i,t}) - \overline{\mathrm{FE}}_{-i,t}(k_{j',t}, z_{j',t}, a_{j',t}, m_{j',t}, \mathcal{I}^{\text{news}}_{-i,t})\right]\end{aligned} \tag{86}$$

The first two terms give the utility change due to no longer reporting on firm j. Other forecasters are still reporting on j, and so it remains the case that $m_{j,t} = 1$, and the realized market value of firm j is unchanged. The average forecast error of other forecasters $\mathrm{F\bar{E}}_{t-i}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{-i,t})$ therefore remains unchanged at 0. However, the forecast of forecaster i does change, as their information set no longer contains $a_{j,t}$. Specifically,

$$\text{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}}) = \left[\mathcal{P}_t(k_{j,t}, z_{j,t}, 1, \mathcal{I}_{i,t}^{\text{news}} | m_{i,j,t}^o = 0) - \text{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\right]^2. \tag{87}$$

Substituting out for the optimal forecast using equation (27), and taking expectations, we obtain

$$\begin{aligned} \mathbb{E}[\text{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}_{i,t}^{\text{news}})] &= \mathbb{E}\left[\mathbb{E}(\text{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1) | k_{j,t}, z_{j,t}, m_{j,t} = 1)\right. \\ &\qquad \left. - \text{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\right]^2, \qquad (88) \\ &= \mathbb{V}[\text{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1) | k_{j,t}, z_{j,t}]. \qquad (89) \end{aligned}$$

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

The second two terms of equation (86) give the utility change due to reporting firm j'. Recall that investors observe a firm's asset quality if at least one outlet reports it (equation (23)). 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 (82)). Forecaster i therefore makes a zero forecast error about firm j'.

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

$$\overline{\text{FE}}_{-i,t}(k_{j',t}, z_{j',t}, a_{j't}, 1, \mathcal{I}_{-i,t}^{\text{news}}) = \int_{i' \neq i} \left[\mathcal{P}_t(k_{j',t}, z_{j',t}, \mathcal{I}_{i',t}^{\text{news}} | m_{i',j,t}^o = 0) - \text{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1)\right]^2 di' \tag{90}$$

All outlets i' are identical, so using the same steps as those used to derive equation (89) the expectation of this average forecast error becomes:

$$\mathbb{E}\left[\overline{\text{FE}}_{-i,t}(k_{j',t}, z_{j',t}, a_{j't}, 1, \mathcal{I}_{-i,t}^{\text{news}})\right] = \mathbb{V}[\text{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1) | k_{j',t}, z_{j',t}] \tag{91}$$

Substituting these results into equation (86), the utility of deviating in this way is

$$\mathbb{E}\,\hat{U}_{i,t}(j,j') = \mathbb{V}[\mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1)|k_{j',t}, z_{j',t}] - \mathbb{V}[\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)|k_{j,t}, z_{j,t}]. \quad (92)$$

Condition (85) is therefore satisfied, and the candidate $\boldsymbol{m}_t$ can be sustained as a symmetric equilibrium, if and only if

$$\mathbb{V}[\mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1)|k_{j',t}, z_{j',t}] - \kappa_{j',t} \leq \mathbb{V}[\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)|k_{j,t}, z_{j,t}] - \kappa_{j,t} \quad (93)$$

for all pairs of reported and unreported firms j, j'. The reporting policy for which this condition holds is the one described by equations 29-31.

□

C.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.

C.2. Alternative assumptions on outlets and forecasters

Here we consider two plausible alternative assumptions in the derivation of the media reporting policy in Section 3.2.2. The resulting newsworthiness function changes slightly from equation (30), but the qualitative properties remain unchanged.

C.2.1. Outlet objective function

In Section 3, we assumed that media outlets maximize the expected utility of their forecaster. However, media outlets observe all realizations of $a_{j,t}$, and observe the reporting decisions of other outlets. Outlets are therefore able to predict the *realized* utility of their forecaster 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:

$$\max_{m^o_{i,j,t}} - \int_0^1 \left[\mathrm{FE}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{i,t}) - \overline{\mathrm{FE}}_{-i,t}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}, \mathcal{I}^{\text{news}}_{-i,t})\right] dj - \int_0^1 \kappa_{j,t} m^o_{i,j,t} dj \tag{94}$$

subject to equations (21)-(22) and optimal predictions (27).

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

$$\hat{U}_{i,t}(j, j') + \kappa_{j,t} - \kappa_{j',t} \leq 0 \tag{95}$$

for all pairs of reported and unreported firms j, j'. This differs from equation (85) in that there is no longer an expectation operator present.

The results on realized forecast errors derived in Section 3.2.2 continue to hold, as nothing has changed in the forecaster problem. $\hat{U}_{i,t}(j, j')$ is therefore given by:

$$\begin{aligned} \hat{U}_{i,t}(j, j') = &\left[\mathbb{E}(\mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1) | k_{j',t}, z_{j',t}, m_{j',t} = 1) - \mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1)\right]^2 \\ &- \left[\mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1) | k_{j,t}, z_{j,t}, m_{j,t} = 1) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\right]^2 \end{aligned} \tag{96}$$

The unique symmetric pure strategy reporting equilibrium is therefore as in Section 3.2.2, except that the newsworthiness function is modified to:

$$\mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) = \left[\mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1) | k_{j,t}, z_{j,t}, m_{j,t} = 1) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\right]^2 \tag{97}$$

Like the form in equation (30), this is increasing in firm size. The key difference is that the newsworthiness function now also depends on realized $a_{j,t}$.

C.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. Here we derive the equilibrium reporting policy under the alternative assumption that forecaster i does not observe the reporting decisions of other outlets, as in e.g. 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 (94), and the constraints are as in equations (21)-(22). A vector $\boldsymbol{m}_t$ can be sustained as a symmetric pure strategy equilibrium if and only if condition (95) holds for all pairs of reported and unreported firm j, j'. The key way this alternative assumption changes the model is that forecasters no longer necessarily observe the aggregate media indicator $m_{j,t}$.

As in Section 3.1, if outlet i reports on a firm j, then $m_{j,t} = 1$. Moreover, forecaster i can infer that $m_{j,t} = 1$ for certain: they see that their outlet has reported on firm j, which is sufficient to imply $m_{j,t} = 1$ (equation (23)). As in Appendix C.1.1, if an outlet deviates to report on firm j', while other outlets report j, we therefore have:

$$\mathrm{FE}_t(k_{j',t}, z_{j',t}, a_{j',t}, m_{j',t} = 1, \mathcal{I}_{i,t}^{\mathrm{news}}) = \bar{\mathrm{FE}}_{t-i}(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t} = 1, \mathcal{I}_{-i,t}^{\mathrm{news}}) = 0 \tag{98}$$

The utility change from deviating therefore reduces to:

$$\begin{aligned}\hat{U}_{i,t}(j, j') =& \left[\mathbb{E}(\mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, m_{j',t}) | k_{j',t}, z_{j',t}, m^o_{i',j',t} = 0) - \mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1)\right]^2 \\ &- \left[\mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t}) | k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\right]^2\end{aligned} \tag{99}$$

This differs from equation (96), because the expectations are formed without the knowledge of the true $m_{j,t}, m_{j',t}$. In both cases, all the forecasters know is what their own outlets have printed. In the first of the expectations, this is the expected market value of firm j' formed by forecasters other than forecaster i, whose outlets did not report on j' ($m^o_{i',j',t} = 0$). In the second expectation, it is the expected market value of firm j formed by forecaster i, whose outlet has deviated and is not reporting firm j ($m^o_{i,j,t} = 0$). In both cases, the true aggregate reporting indicator is $m_{j,t} = m_{j',t} = 1$: outlet i reports firm j', and all other outlets report firm j. As the outlets can still observe each others' reporting choices, each outlet is aware of this fact. It is only the forecasters who are not.

Using the law of iterated expectations we have:

$$\begin{aligned}
&\mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, m_{j,t})|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0) \\
&\quad = \Pr(m_{j,t} = 1|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0)\, \mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0, m_{j,t} = 1) \\
&+ (1 - \Pr(m_{j,t} = 1|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0))\, \mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 0)|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0, m_{j,t} = 0)
\end{aligned} \tag{100}$$

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

Intuitively, $\Pr(m_{j,t} = 1|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0)$ denotes: from the point of view of a forecaster observing that their outlet *did not* report on a firm, what is the probability that some other outlet *did* report on that firm this period? The forecasters have rational expectations, so this probability is formed using their restricted information set, and a full knowledge of the equilibrium data generating process behind $m_{j,t}$. That is, 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 driving that other outlet's decisions, and thus the process for determining $m_{j,t}$.

At this point, the fact we focus on symmetric equilibria becomes critical. Under rational expectations, forecasters understand that they are in a symmetric media equilibrium. Therefore, when they observe that their own outlet has not reported on a particular firm, they infer that no outlet has done so. Formally, we have

$$\Pr(m_{j,t} = 1|k_{j,t}, z_{j,t}, m^o_{i,j,t} = 0) = 0 \tag{101}$$

There is one nuance here that is worth noting. Forecasters infer that $m_{j,t} = m^o_{i,j,t}$ because they have rational expectations, so they have full knowledge of the equilibrium. In equilibrium, their inference on $m_{j,t}$ is therefore correct. However, in equation (99) we are considering a deviation from that equilibrium. The implicit assumption here is that if such a deviation were to happen, forecasters would not be able to identify that it had happened. In other words, they continue to forecast $m_{j,t} = m^o_{i,j,t}$ with certainty, even though this will be incorrect under the deviation. This is in line with rational expectations: in any equilibrium, such a deviation is a probability-zero event, and so it is rational to attach no weight to it. All the forecaster observes is $k_{j,t}$, $z_{j,t}$, and $m^o_{i,j,t}$, 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 $m_{j,t}$.

Applying this to equation (99), the utility change from deviating becomes

$$\begin{aligned}\hat{U}_{i,t}(j,j') =& \big[\mathbb{E}(\mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 0)|k_{j',t}, z_{j',t}) - \mathrm{MV}_t(k_{j',t}, z_{j',t}, a_{j',t}, 1)\big]^2 \\ &- \big[\mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 0)|k_{j,t}, z_{j,t}) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\big]^2 \end{aligned} \tag{102}$$

The unique symmetric pure strategy reporting equilibrium is therefore as in Section 3.2.2, except that the newsworthiness function is modified to:

$$\mathrm{N}_t(k_{j,t}, z_{j,t}, a_{j,t}) = \big[\mathbb{E}(\mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 0)|k_{j,t}, z_{j,t}) - \mathrm{MV}_t(k_{j,t}, z_{j,t}, a_{j,t}, 1)\big]^2 \tag{103}$$

A firm is more newsworthy if news coverage would substantially alter the beliefs of forecasters and investors, and so would lead to a large change in market values.

Like the form in equation (30), this is increasing in firm size. As in equation (97), the newsworthiness function now also depends on realized $a_{j,t}$.

C.3. Equity market equilibrium under asymmetric information

Given the equity issuance price specified by (17), the optimal equity issuance decision problem for firms being reported by media is specified by

$$\mathrm{V}_t(k, z, a, 1) = \max_{e \geq 0} \mathrm{W}_t(k, z, a, e) - e, \tag{104}$$

The equity issuance price of an unreported firm is not determined by its asset quality but rather 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 prior on firms' asset quality $\mathcal{G}(a) : \{a_1 < a_2 < \cdots < a_N\} \rightarrow$

$(0,1)$, the equilibrium is defined as a collection of equity issuance policy function $\mathbf{e}_t(k,z,a)$, equity issuance price function $\mathrm{P}_t(k,z,e)$, investors' belief $\mathcal{B}_t(a|k,z,e)$ 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:

$$\mathrm{V}_t(k,z,a) = \max_{e\geq 0} \frac{\mathrm{P}_t(k,z,e)}{\mathrm{P}_t(k,z,e)+e} \cdot \mathrm{W}_t(k,z,a,e); \tag{105}$$

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

$$\mathcal{B}_t(a|k,z,e) = \frac{\mathcal{G}(a)\mathbf{1}_{\mathbf{e}_t(k,z,a)=e}}{\int \mathcal{G}(\tilde{a})\mathbf{1}_{\mathbf{e}_t(k,z,\tilde{a})=e} d\tilde{a}} \tag{106}$$

for equity issuances e on equilibrium paths and Divinity criteria as specified in Banks and Sobel (1987);

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

$$\int \frac{e}{e+\mathrm{P}_t(k,z,e)} \mathrm{W}_t(k,z,a,e)\mathcal{B}_t(a|k,z,e)da = e, \;\; \forall e>0. \tag{107}$$

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 $\frac{\partial^2 \mathrm{W}_t(k,z,a,e)}{\partial e \partial a} \leq 0$, there does not exist a pooling equilibrium. The following theorem characterizes a separating equilibrium through a sequential algorithm. For notation simplicity, we abstract from the time subscript t in the equations below.

Theorem 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 $\mathbf{e}^*(k,z,a)$, i.e.,*

$$\mathbf{e}^*(k,z,a) \equiv \arg\max_{e\geq 0} W(k,z,a,e) - e,$$

1. *The optimal equity issuance of firms with lowest asset quality is*

$$\mathbf{e}(k,z,a_1) = \mathbf{e}^*(k,z,a_1),$$

and the associate equity issuance price is

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

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 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:*

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

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

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

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

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

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

The belief to support this equilibrium outcome is

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

and the associated equity issuance price is

$$P(k,z,e) = \begin{cases} W(k,z,a_1,e) - e & \text{if } e > \mathbf{e}(k,z,a_2) \\ W(k,z,a_{\iota-1},e) - e & \text{if } e \in (\mathbf{e}(k,z,a_\iota), \mathbf{e}(k,z,a_{\iota-1})] \\ \frac{\int_{\tilde{a}:\{\mathbf{e}(k,z,\tilde{a})=0\}} W(k,z,\tilde{a},e)\mathcal{G}(\tilde{a})d\tilde{a}}{\int_{\tilde{a}:\{\mathbf{e}(k,z,\tilde{a})=0\}} \mathcal{G}(\tilde{a})d\tilde{a}} - e & \text{if } e \leq \mathbf{e}(k,a,a_{\bar{\iota}}), \end{cases}, \tag{108}$$

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

Proof. See Guo et al. (2024) for the detailed proof. □

D. Additional Details of Quantitative Analysis

D.1. Measurement of target moments

The firm-level variables used in constructing the target moments are measured in following way:

1. *Cash flow*: defined as net cash flow from operating activities (`oancfy` in the first fiscal quarter and changes in `oancfy` for the second to fourth fiscal quarters).

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

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

4. *Growth*: defined as the log-difference of total asset (`atq`).

5. *Revenue*: defined as the total sales (`saleq`)

6. *Age*: number of years since CRSP listing.

When we construct the cross-sectional dispersion of investment rate, we first run a regression

$$y_{j,t} = \gamma_j + \gamma_{s,t} + \epsilon_{j,t}, \tag{109}$$

where γ_j denotes the firm fixed effects and $\gamma_{s,t}$ denotes the interacted fixed effects between sectors (4-digit sic code) and time (calendar quarter). Then we compute the standard deviation of $\epsilon_{j,t}$ as the dispersion of investment rate.

When we construct the life-cycle differences, we run a regression

$$y_{j,t} = \gamma_j + \gamma_{s,t} + \sum_{\iota=1}^{4} \beta_\iota \cdot \mathbf{1}[Age_{j,t} \in (\iota \times 5, (\iota+1) \times 5]] + \beta_5 \cdot \mathbf{1}[Age_{j,t} > 25] + \epsilon_{j,t} \tag{110}$$

and use the estimate for β_5 as the target moment in our calibration.

D.2. Setup for the counterfactual studies

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

$$\mathrm{V}_t(k, z, a, 1) = \max_{e \geq 0} \mathrm{W}_t(k, z, a, e) - e, \tag{111}$$

and when it is not chosen, its value function is

$$\begin{aligned} &\mathrm{V}_t(k, z, a, 0) \\ = &\max_{b \in \{0,1\}} \; b \cdot \left(\max_{e \geq 0} \mathrm{W}_t(k, z, a, e - \phi^m) - e \right) \\ &+ (1-b) \cdot \left(\max_{e \geq 0} \frac{\mathrm{P}_t(k, z, a, 0, e)}{\mathrm{P}_t(k, z, a, 0, e) + e} \cdot \mathrm{W}_t(k, z, a, e) \right), \end{aligned} \tag{112}$$

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

$$\underbrace{\int \mathrm{R}_t^{\text{baseline}}(k,z)\mathcal{G}(a)\mathcal{F}_t^{\text{baseline}}(k,z)dkdzda}_{\text{Total capacity of media coverage}} \tag{113}$$

$$= \underbrace{\int \mathbf{b}_t(k,z,a)\cdot\left(1-(1-\alpha_m)\mathrm{R}_t(k,z,a)\right)\mathcal{G}(a)\mathcal{F}_t(k,z)dadkdz}_{\text{Total media coverage purchased by firms}}$$

$$+ \quad \underbrace{(1-\alpha_m)\cdot\int \mathrm{R}_t(k,z,a)\mathcal{G}(a)\mathcal{F}_t(k,z)dkdzda}_{\text{Total media coverage allocated based on the baseline news reporting policy}}$$

This market clearing condition will determine the price of media report ϕ^m.

D.3. Additional quantitative results

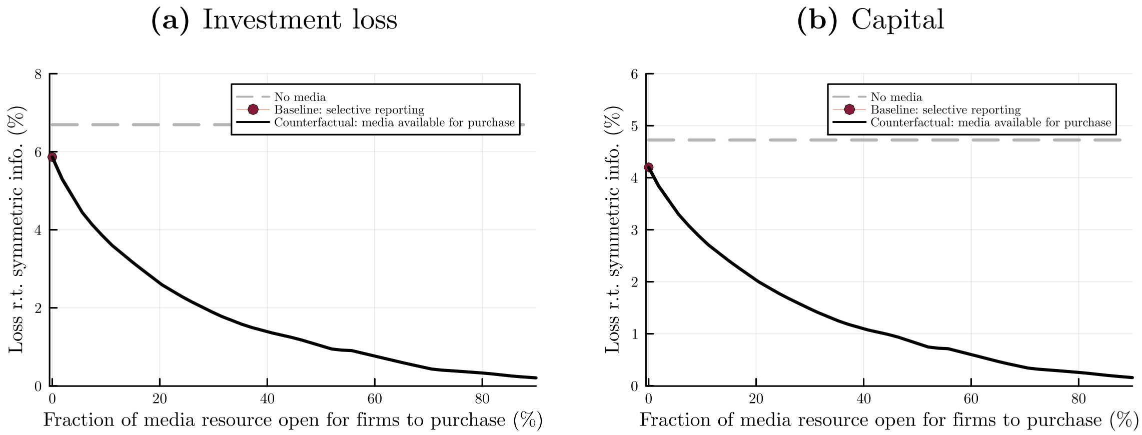
Uniform reporting We evaluate the role of media within a counterfactual economy with uniform-reporting media, i.e., the media allocate the total media coverage equally and report every firm with the same probability. As summarized in Table D.1, compared with the selective-reporting baseline economy, equally allocating the media coverage resource across firms can further alleviate the loss from asymmetric information. The main reason for this improvement is that more firms who can actually benefit from being reported do get reported under this new allocation. But the magnitude of this improvement is relatively minor, because there is still a large fraction of the media coverage resource allocated to the unconstrained firms that are not influenced by being reported at all.

Table D.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 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 various aggregate quantities between each economy and the symmetric-information economy.

Figure D.1: Aggregate Relevance of Media Allocation



Notes: Panel (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 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.

Additional results for the aggregate relevance of media coverage allocation In Section 4.4, we report the aggregate relevance of media coverage allocation measured by how much of the aggregate output loss from asymmetry information is alleviated. In Figure D.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.