Financial News Production

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Abstract

I establish that financial news production can be strongly influenced by factors unrelated to the arrival of, and demand for, information. Fluctuations in real economic activity, such as advertising, generate cash-flow shocks to the media sector, which reacts by changing news quantity and quality. Such endogenous dynamics in news production then shift the levels of uncertainty and information asymmetry about firms, affecting real and financial outcomes. Implementing a within-firm estimator on a comprehensive data set of media advertising revenue, news, and job postings, I compare news production about the same firm by different news media whose advertising revenues are differentially exposed to industry-level advertisement shocks. Financial news production is procyclical at the aggregate level and serves as a channel for economic shock transmission and amplification.

Keywords: Information Production, Uncertainty, Asymmetric Information, Financial Constraints, Real Effect, Shock Transmission

JEL Classification: D25, D80, E32, F36, G12, G30, L86

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1 Introduction

Financial news produced by media outlets can impact the real economy by shaping the information sets of investors and corporate managers. In the finance literature, it is often assumed that media-produced news is a simple reflection of the actual state of the economy. Yet, little is known about the actual process of financial news *production*, especially regarding the economic resources required to produce news.

In this paper, I establish that the production of financial news can be strongly influenced by factors unrelated to the arrival of, and demand for, information. The specific factor that I focus on is a financial shock to news media. I find that plausibly exogenous variation in advertising revenue, the largest source of revenue for news media, has a large effect on financial news production, in terms of both quantity and quality, in a way that is divorced from the actual underlying economic information. Second, I show that these fluctuations in financial news production shift the levels of uncertainty and information asymmetry, affect the cost of capital, and thus impact a wide range of real and financial outcomes. Third, I document that in aggregate, the procyclicality of advertising and news media revenue and employment can help explain why the quantity and quality of financial news are procyclical, even though the quantity of corporate-produced news, measured by the number of press releases, shows weak countercyclicality.

The above empirical findings delineate a novel and important *news production channel* of shock transmission. In an economic downturn, firms cut their advertising expenditure, the media sector's largest source of cash flow. This shock to advertising negatively affects news media, who respond by reducing news production and downsizing newsrooms. As a result, the information environment of the economy deteriorates, increasing the level of uncertainty and the degree of asymmetric information. High uncertainty leads firms to postpone their economic activity. Increased information asymmetry raises the cost of capital, hindering corporate financing. As such, the news production channel functions as a pathway of shock propagation and amplification, in which news media play a central role.

To make the case for the above economic mechanism, I first investigate how news media react to shocks to advertising revenue. To motivate my empirical design, I start by presenting two empirical facts. First, using three commonly adopted indices of financial constraints (i.e., Kaplan-Zingales, Whited-Wu, and size-age) along with a text-based measure on financial constraints, I show that media firms are financially constrained relative to non-media firms, especially after the year 2000. Second, I show that advertising revenue is the largest source of cash flow for news media. Therefore, news media and their news production are subject to shocks from the advertising market.

My empirical strategy relies on three approaches to establish the causal relationship between news production and advertising revenue. First, I construct a "leave-one-out" measure of advertising revenue. Specifically, when studying media m's news production on firm i, I exclude all advertising revenue coming from firm i's industry $g(i)$. As such, the advertising measure is at arm's length and hence addresses the endogeneity induced by firm i paying the media outlet to increase its media coverage. This construction also partly mitigates the concern that industry common shocks will simultaneously affect advertisers and news-covered firms in the same industry. Second, I implement a within-firm estimator (Khwaja and Mian, 2008) to avoid potential bias due to non-random matching between media outlets and firms. Specifically, I include media-by-firm fixed effects to account for unobserved heterogeneity such as cost of inputs to produce news, productivity, and potential specialization of a media outlet on a firm's news. I also include firm-by-time fixed effects to capture time-varying actual financial information of a firm, fluctuations in the demand for news on a firm, and cost of producing news on a firm. Finally, I instrument for the demand for advertising on media using advertising shocks at the level of the advertiser's industry. As such, my identification strategy compares news production on the same firm by media outlets that are differentially affected by industry-level advertising shocks.

To estimate the causal effect of advertising revenue on news quantity, news quality, and job postings, I implement the empirical design described above on a media-by-firm monthly panel. To do so, I build a novel media data set, compiling the most comprehensive data sources on advertising (Nielsen Ad Intel), financial news (RavenPack), and job postings by media companies (Burning Glass). The news production is measured along the dimension of quantity (e.g., extensive and intensive margins of the number of news articles), quality (e.g., percentage of novel and firm-specific news), and sentiment (used as controls in later analysis). The effect of advertising revenue on news quantity is significant—a one-standard-deviation (i.e., $6.2 million dollars) increase in quarterly advertising revenue leads to a 10.3 (10.49) percent rise in the extensive margin (i.e., whether there is any news produced on a firm) and an 8.3 (18.18) percent increase in the total number of news produced by a media outlet on a firm, in the following month (year). There is also a significant impact on news quality—a one-SD shock to advertising revenue leads the proportions of novel and firm-specific news to rise by 25 and 28 percent, respectively. I also estimate the effect of advertising revenue on media job postings. A one-SD rise in advertising revenue significantly increases the probability of a media outlet having a journalism job posting by 4.2 percent and the number of job postings by 2.5 percent. The media outlet also increases the salary it offers and lowers the required years of experience in hiring, indicating a strong desire to expand its newsroom. There is no significant effect on the required years of education, which is rigid with a college degree.

Media firms with different levels of financial constraints respond differently to advertising revenue shocks, highlighting the important role of financial constraints in media's news production. The response to cash-flow shocks by standalone media is roughly two times larger than that by media outlets belonging to a media group. This pattern is consistent with the prediction of the literature on internal capital markets (Matvos and Seru, 2014; Giroud and Mueller, 2015) in that conglomerates provide a cushion for cash-flow shocks, which can partly relax the financial constraints each subsidiary faces. Media firms also react asymmetrically to positive and negative advertising revenue shocks in that news production is particularly sensitive to negative shocks, which emphasizes the role of the news production channel in propagating and amplifying adverse shocks during an economic downturn.

The second part of the paper investigates the causal relationship between news production and corporate real and financial outcomes. There are several channels that could create such a linkage. First, financial news is mainly public information closely followed by investors. As a result, an increase in media news production lowers information asymmetry and thus also lowers the cost of capital by providing and disseminating more public information (Fang and Peress, 2009). Consequently, the firm expands its investment, employment, and output to seize the enhanced investment opportunity. The relative cost of external financing also declines (Myers and Majluf, 1984), resulting in a larger share of external financing as well. Such effects are observed in studies on bank loan ratings (Sufi, 2009) and analyst coverage loss (Kelly and Ljungqvist, 2012; Derrien and Kecskés, 2013). Additionally, increased news production influences corporate outcomes by reducing uncertainty: new information about firm stocks from news articles directly reduces investors' uncertainty about asset payoffs (Veldkamp, 2006). In addition, news about government policy, the macroeconomy, upstream and downstream industries, and competitors can lower the uncertainty faced by corporate managers when making real and financial decisions, which in turn leads firms to invest, hire, produce, and finance more (Bloom et al., 2007; Alfaro et al., 2023).

I find a significant effect of news production on the measures of uncertainty (e.g., realized and implied stock market volatility), asymmetric information (e.g., bid-ask spread), and cost of capital (e.g., implied and perceived cost of capital and discount rate). I document that an 8.30 percent increase in the number of news (corresponding to the one-month percentage effect on news from a one-SD shock to advertising revenue) leads to a 1.54 and 0.29 percentage decline in monthly realized and implied volatility. The same shock also induces a 0.39 percent drop in the bid-ask spread. These effects are equivalent to a 1.3-2.2 analyst coverage loss in a year, according to the estimated effects in Kelly and Ljungqvist (2012). Over a one-year horizon, an 18.18 percent increase in the number of news (corresponding to the one-year percentage effect on news from a one-SD shock to advertising revenue) leads to a

0.08 percentage point decline (i.e., a 1 percent effect) in implied cost of capital and a 0.07 percentage point drop (i.e., a 0.5 percent effect) in discount rate.

I then show that news production significantly affects firm real activities, including investment in both physical and intangible capital, employment, and output (e.g., sales and cost of goods sold). I document that an 18.18 percent increase in the number of news leads to a 0.5 percentage-point change in the physical investment rate, a 1.6 percentage-point change in intangible investment growth, a 0.4 and 1.1 percentage-point change in employment and output growth, respectively. These effects are equivalent to a 0.23 to 1 standard-deviation volatility shock (of size 0.308), as documented in Alfaro et al. (2023).

I find that a rise in news production increases cash holdings and financing, especially equity financing. The same 18.18 percent shock to the number of news increases equity issuance most (by 0.9% of the total assets), long-term debt issuance second (by 0.4% of the total assets), and short-term debt issuance least (with a almost zero effect). This finding is consistent with the prediction of asymmetric information and the pecking-order theory—when the degree of asymmetric information is lower, firms should change the composition of their financing to use more of the financing options that were previously too costly: equity first, then higher risk long-term debt, then lower risk short-term debt. In terms of effect size, I find that the effects induced by a one-SD shock from advertising revenue are equivalent to a 0.3 to 1.0 analyst coverage loss in a year, using the estimates in Derrien and Kecskés (2013).

At the aggregate level, I document the procyclicality of media news production, echoing the empirical findings from the micro samples. Specifically, I show that advertising expenditure of the real economy, media revenue and employment, and news quantity and quality are all procyclical. However, the number of corporate press releases, a proxy for actual economic information, reveals weak countercyclicality. This provides evidence for the key premise of this paper that there is a conceptual and empirical difference between media-produced news and actual underlying economic information.

To better quantify the impact of news production shocks on real and financial outcomes, I estimate a vector autoregression (VAR) model using monthly U.S. aggregate time series data. I find that a one percent decline in news production leads to a 1.5 percentage point increase in the level of uncertainty, 0.1 percent increase in the degree of asymmetric information. These impacts then transmit to a 0.25 percentage point rise in cost of capital, a 0.007 percent decline in monthly non-media employment, and a 0.005 percent decline in monthly industrial production. In terms of the forecast error variance decomposition, shocks to news production can explain 7 percent and 3 percent of the variance for non-media employment and industrial production over the short run and 4 percent and 1 percent of the same variance over the long run. Such a time series analysis provides supporting evidence for the micro-estimated effects and complements the cross-sectional analysis.

The news production channel sheds new light on how informational and financial frictions interact. Extensive work shows how informational frictions generate financial frictions (Myers and Majluf, 1984) and amplify economic fluctuations (Bernanke and Gertler, 1989; Bernanke et al., 1999). By contrast, this paper highlights how financial constraints in the media sector alter the information environment and induce informational frictions in the real economy. The news production channel offers a novel explanation for countercyclical uncertainty (Bloom et al., 2007; Benhabib et al., 2016) by building a pathway from first-moment cash-flow shocks to second-moment uncertainty shocks. In light of the recent decline in news media revenues and employment (Angelucci and Cagé, 2019), such a news production channel may be very relevant.

Literature review. First, this paper is closely related to the literature on how the news media sector generates and amplifies economic fluctuations. Nimark (2014) highlights the newsworthiness of unusual events and how news media's reporting of these signals generate excess aggregate fluctuations in a simple business cycle model. Chahrour et al. (2021) study the editorial role of news media and show that the time-varying media focus on different industries can be an independent source of business cycle fluctuations. Such a conceptual framework coincides with the one in this paper, both of which highlight the discrepancy between actual underlying economic information and news produced by the media sector. Our difference lies in the source of informational fluctuations: Nimark (2014) focuses on news media's preference for unusual events; Chahrour et al. (2021) focus on the editorial selection of news topics. In this paper, I highlight the role of cash-flow shocks that originate from real economic activity such as advertising.

Second, the findings in this paper are consistent with research in the field of industrial organization on newspapers, which focuses on a different set of political outcomes. Petrova (2011) highlights the important role of advertising income on media independence, another dimension of news quality. The paper finds that places with higher advertising revenues are likelier to have newspapers that are independent of political parties. Gentzkow et al. (2011) find that US daily newspapers have a robust positive effect on political participation. Angelucci and Cagé (2019) show that a reduction in advertising revenues lowers newspapers' incentives to produce journalistic-intensive content. Angelucci et al. (2020) find that the rollout of television was a negative shock in both the readership and advertising markets for newspapers. Newspapers responded by providing less content, particularly local news. Ewens et al. (2022) discover that private equity (PE) ownership has a mixed impact on local newspapers in that it increases digital circulation and survival but reduces journalist employment and local news coverage.

Third, this paper echoes the literature on the real effects of financial information production. Sufi (2009) finds that the introduction of bank loan ratings leads to an increase in the use of debt by firms that obtain a rating, and also to increases in firms' asset growth, cash acquisitions, and investment in working capital. Cornaggia et al. (2018, 2020, 2023) study the information production by credit rating agencies in the municipal bond market. Using the setting of analyst coverage termination induced by broker closures and mergers, Kelly and Ljungqvist (2012) and Derrien and Kecskés (2013) document that a loss in analyst coverage increases the degree of asymmetric information and thus affects asset prices and corporate policies. Gao et al. (2020) study how local newspaper closures affect public finance outcomes for local governments and find a increase in municipal borrowing costs. Heese et al. (2022) show that after a local newspaper closure, local facilities of publicly listed firms increase violations and penalties, indicating that the closures reduce firm monitoring by the press. Cao et al. (2023) document that information production by expert networks is associated with more efficient price response to negative news. Tetlock (2010) tests whether public financial news resolve asymmetric information and documents several return predictability and trading volume patterns that are consistent with the asymmetric information model's predictions. My work adds to this line of research by focusing on the financial cost of information production and highlighting the role of financial constraints in the dynamics of news production.

This paper complements the literature on financial media (Ahern and Peress, 2023). Previous papers focus on the role of financial media in its complementarity with asset markets (Veldkamp, 2006), shifting market sentiment (Tetlock, 2007), home bias (Engelberg and Parsons, 2011), amplification or attenuation of prevailing sentiment (Dougal et al., 2012), information dissemination (Fang and Peress, 2009; Peress, 2014), sensationalism (Ahern and Sosyura, 2015), political polarization (Goldman et al., 2024), affecting fund flows (Solomon et al., 2014), corporate strategic communication (Ahern and Sosyura, 2014; Goldman et al., 2022), market reacting to stale information (Tetlock, 2011; Fedyk and Hodson, 2023), news selection (Martineau and Mondria, 2023), and positioning effect (Fedyk, 2024). This paper highlights another important aspect of financial media, namely their financial constraints. This paper is also related to the literature on advertising-induced media bias (Reuter and Zitzewitz, 2006; Gurun and Butler, 2012) but complements it by focusing on the first-order effects of financial constraints on news quantity and quality, instead of bias.

This paper also adds to the literature on the cyclicality of information production and endogenous uncertainty. Closely related to my aggregate level empirical analysis, Benhabib et al. (2016) document the two-way feedback between information production and the real economy using an otherwise standard business cycle model with endogenous information acquisition. They show that information acquisition is endogenously procyclical, and therefore economic uncertainty faced by the firms is countercyclical. Benhabib et al. (2019) extend the Grossman-Stiglitz model with a real sector and highlight how the mutual learning between financial markets and the real economy leads to self-fulfilling surges in economic uncertainties. Veldkamp (2005) and Van Nieuwerburgh and Veldkamp (2006) use endogenous information flow and precision to explain the growth rate asymmetry (e.g., sudden crash and slow recovery) in business cycles. My empirical findings are consistent with the predictions of these models.

This paper also complements the literature on the real effects of financial constraints (Kashyap et al., 1993; Khwaja and Mian, 2008; Paravisini, 2008; Paravisini et al., 2015) by showing that economic shocks can not only be transmitted and amplified through financially constrained financial intermediaries such as banks, but also through financially constrained information intermediaries.

2 Data and Measurement

This section describes data sources and variable construction. I construct four data sets: a media-by-firm monthly panel of financial news production records, a monthly panel of media job postings, and a monthly and a yearly panel of U.S. public firms. My data come from several sources. I use Ad Intel, RavenPack, and Burning Glass for information on advertisement revenue, news production, and job postings of financial media outlets. I use Compustat, CRSP, IBES, and OptionMetrics for information on real and financial outcomes of U.S. public firms. The data and matching procedure are described in more detail below.

2.1 Media Advertising Revenues

The advertising data come from Nielsen Ad Intel provided by the Kilts-Nielsen Data Center. Nielsen Ad Intel is a comprehensive source of advertisement data in the United States covering an estimated $150 billion worth of advertising and nearly 400 million observations per year (Argente et al., 2021). The data source monitors advertising activity across various types of media, spanning TV, audio, digital, print, outdoor, and cinema. The database is widely used in the fields of marketing and industrial organization to study the effectiveness and profitability of TV advertising (Shapiro et al., 2021) and how entrants build market share (Argente et al., 2021). It provides weekly occurrence-level advertising information such as timestamp, advertising firm and brand, distributor (media outlet), duration, format, product type, and estimated dollar spending.

The data are available for the period of 2010-2020. I focus on the advertisement revenue of online media outlets since my data source of news production collects online news records. Specifically, I use Ad Intel's categories of internet (2010-2017), digital (2017-2020), and newspaper (2010-2020) advertising revenues.[1] Using the weekly occurrence data, I calculate the sum of all occurrence-level advertisement revenues for a media outlet in a given month. Such an aggregation yields a media-month panel of advertisement revenue, which is later merged with data sets of news production and job posting.

2.2 Financial News Production

The data on news production come from RavenPack News Analytics. RavenPack has three editions: Dow Jones edition for premium newswires (e.g., Dow Jones Financial Wire, Barron's, and WSJ), PR edition for corporate press releases, and Web edition for financial sites, blogs, and online news media. I use the combination of DJ and Web editions as the sample of media-produced news for the main analysis and the PR edition as the sample of

[1] According to the media type categorization by Ad Intel, I use advertising information of national digital, national internet, local internet, local newspaper, and national newspaper. The change in categorization terminology from "internet" to "digital" is induced by Ad Intel due to a change of data vendors in 2017.

corporate-produced information for construction of control variables. I focus on the sample from 2010 to 2020 to align with the coverage of media advertising data. The observation is at the level of news articles, indicating which media outlet produces a given article and which public firm is covered in the article. Each entry also contains timestamp, and scores for relevance, novelty and sentiment.

Measures of news quantity and quality. News quantity is measured by the total number of news produced by a media outlet on a public firm in a given month. I impute the number of news as zero if a media-firm pair appears in the RavenPack database but misses some months in the middle of coverage.

News quality is captured by percentage of novel news, percentage of firm-specific news, and news sentiment. According to RavenPack's user guide, the first article reporting a categorized event about one or more firms is considered to be the most novel and receives a novelty score of 100. Subsequent stories about the same event for the same firms receive scores following a decay function based on the number of stories in the past 24-hour window. Therefore, I label a news article as being novel if its novelty score assigned by RavenPack equals 100. The number of novel news is normalized by total number of news to compute the proportion of novel news produced by a media on a firm in a given month. RavenPack also provides the relevance score for each news article, which indicates how closely the news article is related to a given firm. I follow Boudoukh et al. (2019) and identify articles with a relevance score of 100 as being firm-specific. Similarly to the novelty measure, I calculate the monthly proportion of firm-specific news for a given media-firm pair.

I use RavenPack's Event Sentiment Score (ESS) as the measure of news sentiment, following Gao et al. (2018). ESS is a score generated by RavenPack's proprietary algorithm, which ranges from 0 to 100, which indicates neutral sentiment by a score of 50 and positive (negative) sentiment by a score above (below) 50. I take the average of all news on firm i produced by media m as the monthly news sentiment measure. I control for news sentiment when examining the effect of news quantity on real and financial outcomes. I also view sentiment as one aspect of news quality since negative news is usually considered to be more newsworthy (Tetlock, 2007; Solomon, 2012; Niessner and So, 2018; Chahrour et al., 2021).

Proxies for actual information and events. One of the main empirical challenges when studying financial news is that the actual full information set is unobserved. To partly resolve this issue, I use two additional data sources to proxy for actual corporate information and events. The first is Capital IQ Key Developments, a comprehensive database that tracks actual major corporate events (Kwon and Tang, 2020). The data source monitors over one hundred types of events including executive changes, mergers and acquisitions, changes in corporate guidance, and lawsuits/legal issues, and many more. I further complement the proxy for the actual information set with corporate press releases, which can be viewed as the corporate-produced information. The data set I use is RavenPack PR edition, which contains corporate press releases of public firms published on press release wires. For each firm in each month, I count the total number of corporate events recorded in Key Developments and the total number of corporate press releases in RavenPack PR edition. I control for these actual information measures when studying the impact of media-produced news.

2.3 Journalism Job Postings

To capture the labor market dynamics of the news industry, I obtain job posting data from Burning Glass Technologies Company. Burning Glass Technologies Company (BGT) is an analytics software company that provides real-time data on vacancy postings. The database screens more than 40,000 online job boards and company websites to capture the near-universe of online job postings at a daily frequency (Hershbein and Kahn, 2018). For each posting record, the data contain detailed information on firm name, standard occupation code, occupation description, and skill requirements.

The sample in this paper spans from 2010 to 2019. For my analysis, I restrict the sample to the postings of "News Analysts, Reporters and Correspondents" with six-digit Standard Occupation Classification (SOC) of 27-30xx. The empirical results are quantitatively similar if I include broadly-defined jobs in newsrooms such as photographers (27-4020) or writers and editors (27-3040).

Burning Glass uses a proprietary algorithm to standardize firm names, which in my sample are names of media firms. I conduct additional cleaning on media name, removing punctuation, spaces, and suffixes such as "Incorporated". I drop the observations without a media name. The standardized media names are then used in the matching with Ad Intel and RavenPack data sets. I aggregate the job postings to the media-month level. I impute the number of postings as zero if a company appears in the Burning Glass database but misses some months. The media-month panel contains the total number of job postings (extensive margin), whether a firm has any job posting in a given month (intensive margin), salary (i.e., the midpoint of minimum and maximum salary or the minimum salary if only minimum is available), and required minimum years of experience and education.

2.4 Real and Financial Outcomes

To study the real impact of financial news production, I collect data on publicly-traded U.S. firms along three dimensions: uncertainty and information asymmetry, real outcomes, and financial outcomes. Specifically, I obtain stock returns from CRSP, firm accounting information from Compustat, analyst forecasts from the Institutional Brokers' Estimate System (I/B/E/S), and option-implied volatility from OptionMetrics. The measures of uncertainty and information asymmetry are constructed at the monthly frequency and are merged with monthly news production records to compile a monthly panel of public firms. The yearly corporate real and financial outcome variables are matched with yearly news production records to compile a yearly panel of public firms. The merged sample spans from January 2010 to December 2020. Financial, utilities and public sector firms are excluded from the sample (i.e., SIC between 6000 and 6999, 4950 and 4999, and equal to or greater than 9000).

All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions can be found on page 47. Below I list the details of the measure construction.

Uncertainty and information asymmetry. I consider four measures of uncertainty used in the literature: realized stock market total and idiosyncratic volatility (Leahy and Whited, 1996; Bloom et al., 2007), option-implied volatility (Dew-Becker and Giglio, 2023; Alfaro et al., 2023), and analyst earnings forecast dispersion (Bloom, 2009; Bond et al., 2005). For each stock in a given month, I calculate realized volatility as the standard deviation of cum-dividend daily stock returns from CRSP, annualized by multiplying by $\sqrt{252}$. The idiosyncratic volatility is constructed as the standard deviation of residuals in a regression of weekly returns on weekly equal-weighted market returns for three years prior to month end (Ali et al., 2003). Following Dew-Becker and Giglio (2023) and Alfaro et al. (2023), option-implied volatility is the annualized monthly average of daily option-implied volatility from OptionMetrics, where the daily observations are the simple average of forward 30-day maturity at-the-money (ATM) call and put options.[2] Analyst earnings forecast dispersion is the cross-sectional standard deviation of analyst forecasts on earnings per share in a given month.

Following Kelly and Ljungqvist (2012), who study the effect of analyst coverage termination on asymmetric information, I construct two empirical proxies for information asymmetry: bid-ask spread and illiquidity. For each stock in a given month, I compute the bid-ask spread as the monthly average of daily bid-ask spread normalized by average of daily spread, multiplying by one hundred (Amihud and Mendelson, 1986). As in Amihud (2002), I measure illiquidity as the average daily ratio of absolute return to dollar volume in millions. Such an empirical proxy builds on the theoretical prediction by Wang (1993) that the correlation between absolute return and dollar volume increases with information asymmetry.

[2] I use the average of call and put options to reduce the influence of smirks or other asymmetries in implied volatility. The use of ATM options has the benefit of having the highest Black-Scholes Vega. I focus on the 30 day maturity options because these options are the most liquid and correspond to the monthly time horizon of my empirical design.

I also construct a list of monthly controls, including the number of corporate events documented in the Key Developments data set; the number of corporate press releases recorded in RavenPack PR edition; news sentiment defined by RavenPack; stock returns; absolute value of stock return; book-to-market ratio; and firm size measured by the log of lagged end-of-month market capitalization.

Cost of capital. I examine two types of measures for corporate cost of capital used in the literature: implied cost of capital (Gebhardt et al., 2001; Lee et al., 2021; Hartzmark and Shue, 2023) and perceived cost of capital (Gormsen and Huber, 2022, 2023). I obtain the data covering annual firm implied cost of capital from Lee et al. (2021).[3] Following the best practices described in Lee et al. (2021), I use the mechanical implied cost of capital by Gebhardt et al. (2001) (GLS), which is based on a residual income model. The inputs for future cash flows consist of mechanical forecasts from the cross-sectional forecast model of Hou et al. (2012). As documented in Lee et al. (2021), the estimation of firm-level implied cost of capital can be noisy due to the necessity of making assumptions about expected future cash flows and nonunique numerical solutions. To mitigate the problems of noise, I also use the composite implied cost of capital in Lee et al. (2021), which is a equal-weighted average of four commonly used implied cost of capital variants: the residual income based measures proposed by Gebhardt et al. (2001) (GLS) and Claus and Thomas (2001) (CAT) and the abnormal earnings based measures proposed by Easton (2004) (PEG) and Ohlson and Juettner-Nauroth (2005) (AGR).

The measures for percevied cost of capital and corporte discount rate are hand-collected by Gormsen and Huber (2022) and Gormsen and Huber (2023) from corporate conference calls.[4] For percevied cost of capital, Gormsen and Huber (2022) collect the text where firms state the "cost of capital," the "weighted average cost of capital," or the "WACC" for the whole firm. Such a measure can be viewed as firm's internal estimate of its weighted average cost

[3]The data set is downloaded from https://leesowang2021.github.io/data/.
[4]The data set is downloaded from https://costofcapital.org.

of capital. To measure discount rates, Gormsen and Huber (2023) rely on explicit manager statements about the minimum required IRR that they want to earn on new investment projects, which is firm's required return to capital.

Corporate real outcomes. I focus on three sets of corporate real outcome variables: investment (i.e., physical and intangible), employment, and output (i.e., sales and cost of goods sold), following Alfaro et al. (2023). Following Belo et al. (2014), investment rate in year t is defined as $\frac{CAPX_t}{\frac{1}{2}(PPENT_{t-1}+PPENT_t)}$. The investment rate is bounded between -0.5 and 0.5 to reduce influence of outliers. The empirical results are robust to different variable construction, such as $\frac{CAPX_t}{PPENT_{t-1}}$, $\frac{CAPX_t}{AT_{t-1}}$, or $\frac{\Delta AT_t}{AT_{t-1}}$. I follow Peters and Taylor (2017) to measure intangible investment as $R\&D + 0.3 \times XSGA$. Employment, sales, cost of goods sold are EMP, $SALE$, and $COGS$, respectively. To align with the investment rate, I focus on the growth rate of other variables by using the difference in logs such as $\Delta \ln(EMP)$. A array of control variables are constructed following Leary and Roberts (2014) and Alfaro et al. (2023).[5] I also include control variables on information, including the number of corporate events documented in the Key Developments data set, number of corporate press releases recorded in RavenPack PR edition, and news sentiment defined by RavenPack.

Corporate financial outcomes. Similarly to the design to examine the real impact of analyst coverage termination (Derrien and Kecskés, 2013), I capture corporate financial policies along the dimensions of financing (i.e., issuance of short-term debt, long-term debt, and equity), payouts, and the change in cash holdings. The changes in short-term and long-term debt are defined as $DLCCH$ and $DLTIS - DLTR$, respectively. The equity issuance is $SSTK$. Together, the total financing is $DLCCH + (DLTIS - DLTR) + SSTK$. I construct total payouts as the sum of dividends (DV) and share repurchases ($PRSTKC$).

[5]Control variables include stock return (CRSP 12-month compounded return including dividends and adjusted for delisting), tangibility ($\frac{PPEGT_t}{AT_{t-1}}$), book leverage ($\frac{DLC_t+DLTT_t}{DLC_t+DLTT_t+CEQ_t}$), Tobin's Q, return on asset ($\frac{EBIT_t}{AT_{t-1}}$), and firm size (measured as $\ln(SALE)$). Tobin's Q is constructed as $Q =$ (market value of assets)/(0.9 $\times$ book assets + 0.1 $\times$ market value of assets), where book assets $= AT$, market value of assets $= AT + ME - CEQ - TXDB$ (Duchin et al., 2010).

Finally, the change in cash holdings is $CHECH$. All corporate financial policy variables are scaled by total assets.

2.5 Data Merging and Summary Statistics

I construct four data sets for my main analysis, all spanning from January 2010 to December 2020. First, I build a media-by-firm monthly panel, which merges Ad Intel advertisement data and RavenPack firm-level news records by the names of media outlets. The panel covers more than one thousand media outlets which produce news on around six thousand U.S. public firms, through about three hundred thousand media-by-firm pairs. Second, I construct a media-by-month panel, assembling Burning Glass job postings and RavenPack Ad Intel advertisement data for the media outlets in the RavenPack sample. Such a merging is also by the names of media outlets.

Third, I merge standard financial databases, including CRSP, Compustat, I/B/E/S, and OptionMetrics with RavenPack news via CUSIP codes. This merged data set is then linked to Ad Intel advertisement data to construct the instrument variables for identifying the casual effect of news production on real and financial outcomes. After that, I resample the data set to monthly and yearly based on the frequency of outcome variables. As a result, I obtain a firm-by-month panel for measures of uncertainty and degree of asymmetric information and a firm-by-year panel for corporate policy variables such as investment and debt financing. Both panels include around four thousand U.S. public firms. The summary statistics of these four data sets are presented in Table 1.

[Insert Table 1 here]

Finally, I also construct two additional data sets to document stylized empirical facts. The first is a U.S. public firm sample from Compustat, which spans from 1970 to 2022. I use the sample to construct several financial constraint indices and to plot procyclicality of advertisement, revenue and employment of news media. The second is a international news sample from RavenPack, which I use to establish the procyclicality of aggregate news quantity and quality at the country level.

3 Research Design

This section describes the approach to identifying the causal effect of advertisement shocks on news production. Consider the following general representation of the news production by media m on firm i at time t:

$$News_{m,i,t} = News_{m,i,t}\left(W_{m,i,t}, Ad_{m,t}\right). \tag{1}$$

The first argument, $W_{m,i,t}$, represents factors that affect news production other than advertising revenue—i.e., demand for news on firm i; actual financial information of firm i; the cost of inputs for media m to produce news; the productivity of news production by media m, etc. The second argument, $Ad_{m,t}$, represents the amount of advertising revenue received by the media outlet m at time t.

My main goal is to estimate the effect of advertising revenue on news production: $\beta = \frac{\partial News_{m,i,t}}{\partial Ad_{m,t}}$. The identification problem is that the amount of advertising revenue, $Ad_{m,t}$, is an equilibrium outcome in the advertisement market that depends on the demand for advertising in media m, $D_{m,t}$, and media m's supply of advertising space, $S_{m,t}$, which may be given by the same factors, $W_{m,i,t}$, affecting news production:

$$Ad_{m,t} = Ad_{m,t}\left(S_{m,t}\left(W_{m,i,t}, ...\right), D_{m,t}\left(W_{m,i,t}, ...\right)\right). \tag{2}$$

My empirical strategy to address this problem is based on three elements. First, I directly resolve the endogeneity concerns induced by "sponsored news" (e.g., a firm paying the media outlet to increase its media coverage) and common industry shocks by the "leave-out" design in the measure construction. For example, firm i can sponsor media m to produce slanted news on itself by running advertisement $Ad_{i,m,t}$, which immediately alters the quantity and quality of $News_{m,i,t}$. Besides, there can be common shocks from firm i's industry $g(i)$ to $W_{m,i,t}$, which affects $News_{m,i,t}$ and $Ad_{m,t}$ simultaneously. I confront these endogeneity concerns directly and exclude media m's advertising revenue from firm i's industry $g(i)$ (i.e., $Ad_{g(i),m,t}$) from media m's total advertising revenue $Ad_{m,t}$. This construction gives a leave-out advertising measure $Ad_{-g(i),m,t}$, which mitigates the endogeneity concerns from sponsored news and industry common shock channels. As a result, the general representation now reads

$$News_{m,i,t} = News_{m,i,t}\left(W_{m,i,t}, Ad_{-g(i),m,t}\right). \tag{3}$$

Second, I instrument for the demand for advertising in media m, $D_{m,t}$, using advertisement shocks at the level of the advertiser's industry. This empirical approach obtains unbiased parameters if media outlets and firms are randomly matched. However, if media outlets specialize in the news market, the instrument may be correlated with factors that affect news production through channels other than advertising revenue. For example, suppose that media that specialize at producing news on manufacturing firms suffer a negative advertising revenue shock during the Covid period. If the productivity to generate news on manufacturing firms drops disproportionately during the Covid period, we would erroneously attribute this decline in news production to the advertising revenue shock.

To avoid potential bias due to non-random matching between media outlets and firms, the third element of my empirical strategy involves controlling for all unobserved heterogeneity (e.g., media specialization, proximity, and slants) in the cross-section with media-by-firm fixed effects, and for the time-varying cost of inputs to produce news on a firm, actual financial information of a firm, and demand for news on a firm with firm-time fixed effects. As a result, my estimation compares variation in news production within news-covered firms instead of comparing variation in total news produced across media outlets. In the example above, my estimation procedure compares the change in news produced on a manufacturing firm by a media that is negatively shocked in the advertisement market with the corresponding change in a media outlet that is not affected. Such an empirical strategy leverages the within-firm estimator in Khwaja and Mian (2008) and is widely used in the literature to study the effects of credit shocks on employment (Chodorow-Reich, 2014) and international trade (Paravisini et al., 2015).

The identification assumption is that (unobserved) factors other than advertising revenue that may affect the news production on manufacturing firms differently across these two media outlets are not related to the advertising composition of advertisers from which the two media outlets receive advertising revenue. Note that this assumption is much weaker than the one required for estimation using total news production at the media level, which does not control for cost to produce news, actual information arrival, and information demand. The identification assumption is violated if a media outlet's advertiser affiliation is correlated with other non-advertising media-level shocks (e.g., shocks to media's other sources of revenues such as subscription).

3.1 Main Specification

Formally, I estimate β, the effect of advertising revenue on financial news production, using the following empirical specification, on a media (m)-firm (i)-month (t) panel data set:

$$News_{m,i,t+1} = \beta \ln\left(Ad_{-g(i),m,[t-2,t]}\right) + \alpha_{m,i} + \eta_{i,t} + \gamma X_{m,i,t} + \varepsilon_{m,i,t}, \tag{4}$$

where, as in equation (3) above, $News_{m,i,t+1}$ represents the news produced by media m in month $t+1$, which I measure along the dimensions of news quantity and news quality. Specifically, I focus on an extensive margin variable of whether there is any news produced by media m on firm i, $\mathbb{1}\left(News_{m,i,t+1}\right)$ and the intensive margin of the log number of news produced by media m on firm i, $\ln\left(\#\ News_{m,i,t+1}\right)$. I gauge the quality of financial news along the dimensions of proportion of novel news $Novel_{m,i,t+1}$ (%), proportion of firm-specific news $\textit{Firm-Specific}_{m,i,t+1}$ (%), and news sentiment.

The variable of interest is $\ln\left(Ad_{-g(i),m,[t-2,t]}\right)$, the log of leave-$g(i)$-industry-out advertising revenue of media m in the three-month period from month $t-2$ to month t. I aggregate the advertising revenues over three months to smooth the measure given the seasonal and volatile nature of advertisement. A three-month time window also better synchronizes with the timing of news media transmitting cash-flow shocks to news production and hiring dynamics. My results are insensitive to the choice of time window.

I include $\alpha_{m,i}$, the unobserved heterogeneity of firm i's news produced by media m, accounting for cost of inputs to produce news, productivity, and potential specialization of media m on firm i's news. I also include $\eta_{i,t}$, the firm-month fixed effects, which capture time-varying actual financial information of firm i, fluctuations in the demand for news on firm i, and cost of producing news about firm i in month t. The time-varying controls $X_{m,i,t}$ include a full set of distributed lags of dependent variables from t to $t-5$ and non-overlapping lagged independent variables from $t-3$ to $t-5$.

The estimated β can be interpreted as a media-level elasticity: it measures the percentage change in the number of news that a media outlet produces on a public firm that is induced by a one-percent change in advertising revenue. The estimated β can also be interpreted as a media-level semi-elasticity: it measures the changes in the probability that a media outlet covers a public firm and the probability that a media outlet produces a novel or firm-specific piece of news that are induced by a one-percent change in advertising revenue.

To provide the labor market foundation of financial news production, I also examine the effect of advertising revenue on media job postings on a media (m)-by-month (t) panel, using the specification below:

$$Posting_{m,t+1} = \beta \ln\left(Ad_{m,[t-2,t]}\right) + \alpha_m + \eta_t + \gamma X_{m,t} + \varepsilon_{m,t}, \tag{5}$$

where $Posting_{m,t+1}$ is measured by extensive margin $\mathbb{1}\left(Posting_{m,t+1}\right)$ of having a posting or not and intensive margin of log number of postings $\ln\left(\#\ Posting_{m,t+1}\right)$. Since the job postings are at the level of media outlets instead of at the media-by-firm level, the within-firm estimator is infeasible. Nevertheless, I include media fixed effects α_m to absorb all unobserved time-invariant media heterogeneity. I also include month fixed effects η_t to account for aggregate shocks. The time-varying controls $X_{m,i,t}$ include a full set of distributed lags of dependent variables from t to $t-5$ and non-overlapping lagged independent variables from $t-3$ to $t-5$.

Dynamic specifications. To trace the dynamic response of news production and job postings to advertising revenues, I also estimate the following local projection specifications in levels for the news production:

$$News_{m,i,t+1+h} = \beta^h \ln\left(Ad_{-g(i),m,[t-2,t]}\right) + \alpha^h_{m,i} + \eta^h_{i,t} + \gamma^h X_{m,i,t} + \varepsilon^h_{m,i,t} \tag{6}$$

and for job postings:

$$Posting_{m,t+1+h} = \beta^h \ln\left(Ad_{m,[t-2,t]}\right) + \alpha^h_{m} + \eta^h_{t} + \gamma^h X_{m,t} + \varepsilon^h_{m,t}, \tag{7}$$

where $h = 0, 1, 2, 3, ...$ The construction of dependent, independent, and control variables are identical to what I have in the one-period static specifications (4) and (5).

3.2 The Instrumental Variable

In addition to the within-firm estimator illustrated above, I estimate all specifications using a leave-out version of shift-share style instrumental variable. Below I detail the construction procedure. To fix ideas, denote the advertising expense by advertiser a on media outlet m in month t as $Ad_{a,m,t}$.

First, I aggregate the dollar amount of advertising expenses to the industry level: $Ad_{g,t} = \sum_{a\in g}\sum_m Ad_{a,m,t}$, where $Ad_{g,t}$ is the total advertising expenditure of industry g in month

t. I measure the industry-level growth rate of advertisement as $\Delta \ln(Ad_{g,t}) = \ln(Ad_{g,t}) - \ln(Ad_{g,t-1})$. Second, I construct the lagged industry share as $s_{g,m,t-1} = \frac{Ad_{g,m,t-1}}{Ad_{m,t-1}}$ where $Ad_{g,m,t-1} = \sum_{a \in g} Ad_{a,m,t-1}$ is the total advertising revenue of media outlet m from industry g in month $t-1$. Third, I construct the shift-share style instruments $IV_{m,t} = \sum_{g} (s_{g,m,t-1} \times \Delta \ln(Ad_{g,t}))$ as the lagged share-weighted average of industry advertisement growth rates.

Fourth, I adjust the instrument variables to be the "leave-out" version. When studying media m's news production on firm i, I drop $Ad_{g(i),m,t-1}$, the advertising revenue from firm i's industry, $g(i)$. I implement such a leave-out adjustment to the lagged industry shares in the second step by excluding $Ad_{g(i),m,t-1}$ and re-normalize the shares of other industries for the shares to add up to one. For the aggregation in the third step, I also exclude $\Delta \ln\left(Ad_{g(i),t}\right)$, the growth rate of firm i's industry $g(i)$. Finally, I obtain the leave-out version of the shift-share style instruments as $IV_{-g(i),m,t} = \sum_{g \neq g(i)} (s_{g,m,t-1} \times \Delta \ln(Ad_{g,t}))$. The level specification requires to add the lagged base level back to the instruments. Operationally, I use six-month smoothed lagged industry shares and three-month industry-level growth rates of advertisement.

4 Financial Shocks and News Production

In this section, I present three sets of empirical results on the relationship between financial shocks to advertising revenues and news production. First, to motivate my main empirical analysis, I document two stylized facts: first, news media are fairly constrained relative to non-media; second, advertising revenue is the largest source of cash flow for news media. As a result, news media and their outputs are subject to shocks from advertisement market. Second, using the empirical design described in Section 3, I estimate the effects of advertising revenue on news quantity and quality. Third, to provide the labor market foundation for time-varying news production, I estimate the effect of advertising revenue on media job postings.

4.1 News Media Are Financially Constrained

I document two stylized empirical facts to motivate my empirical design, which ties shocks in the advertisement market to variation in news production through financially constrained news media.

Fact 1: News media are financially more constrained than other firms since 2000.

I first confirm the premise that news media are financially constrained, using an annual sample of U.S. public firms from Compustat with financial, utilities and public sector firms excluded. I categorize a public firm as a news media firm if its NAICS code is in 513110 (newspaper publishers), 519130 (internet publishing and broadcasting and web search portals), 511110 (news syndicates), 515112 (radio stations), or 515120 (television broadcasting). I measure the degree of financial constraint by the Kaplan-Zingales (KZ), Whited-Wu (WW), and size-age (SA) indices and the Bodnaruk-Loughran-McDonald (BLM) text-based measure.[6] Since only the relative value matters for the first three indices, I standardize them by subtracting the sample median and normalizing by the sample interquartile range.

I document the empirical fact that news media are financially more constrained than other firms since 2000. I compare the distributions of news media's financial indices to the distributions of non-media's financial indices. To do so, I plot the annual time series

[6] Using Lamont et al. (2001)'s estimated coefficients for Kaplan and Zingales (1997), the KZ index is calculated as $\mathit{KZ\ Index} = -1.002 \times \mathit{CF} + 3.1392 \times \mathit{TLTD} - 39.3678 \times \mathit{TDIV} - 1.3148 \times \mathit{CASH} + 0.2826 \times Q$, where CF is the ratio of cash flow to total assets; $TLTD$ is the ratio of long-term debt to total assets; $TDIV$ is the ratio of total dividends to assets and Q is Tobin's Q; $CASH$ is the ratio of liquid assets to total assets. According to Whited and Wu (2006), the WW index is calculated as $\mathit{WW\ Index} = -0.091 \times CF - 0.062 \times DIVPOS + 0.021 \times TLTD - 0.044 \times LNTA + 0.102 \times ISG - 0.035 \times SG$, where $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends; $LNTA$ is the natural log of total assets; ISG is the firm's three-digit industry sales growth; SG is firm sales growth. Following Hadlock and Pierce (2010), the SA index is calculated as: $\mathit{SA\ Index} = -0.737 \times \mathit{Size} + 0.043 \times \mathit{Size}^2 - 0.040 \times \mathit{Age}$, where Size is the log of inflation-adjusted book assets, and Age is the number of years the firm has been on Compustat with a non-missing stock price. Following Bodnaruk et al. (2015), the BLM text-based index is the percentage frequency of constraining words in firms' 10-K text, where constraining words are defined by the Loughran-McDonald Master dictionary. The word frequency measures and dictionary are downloaded from `https://sraf.nd.edu`.

of medians, 25-75 percentile ranges, and 10-90 percentile ranges for non-media firms and medians and 25-75 percentile ranges for media firms. The time series of distributions is presented in Figure 1.

[Insert Figure 1 here]

The patterns of four financial indices are consistent. Before 2000, news media are in general less constrained than other firms with lower median index values and the 25-75 percentile ranges are consistently below the ranges for non-media firms. However, starting from around 2000, the financial constraints of news media rise steeply and exceed those of non-media firms. In the time period of my main analysis sample (2010-2020), the distribution of financial constraints for news media is steadily above that of non-media.

Fact 2: Advertisement is the largest source of revenue for news media.

I then demonstrate the importance of advertising revenue as the largest source of revenue for news media; its share is persistently higher than 50% for both print and online news media. The revenue composition data is obtained from Census Service Annual Survey, which contains a table of estimated sources of revenue for employer firms. Figure 2 decomposes the revenues of print media (newspapers and periodical publishers) and online media (internet publishing and broadcasting and web search portals) from 2010 to 2021.

[Insert Figure 2 here]

The dominant role that advertising revenue plays in the cash flow of news media as shown in Figure 2 validates my empirical strategy to use advertising revenue as a proxy for the financial constraints faced by news media.

4.2 Effect of Advertising Revenue on News Production

This section analyzes the effect of advertising revenue on news quantity and quality. I first estimate the main specification (4) on the media-firm-month panel. The estimated coefficient β can be interpreted as the one-month effect of advertising revenue in the previous quarter on news production. Table 2 presents the results. Besides the estimated coefficients, I also report the percentage effects on news production for a one-standard-deviation shock to advertising revenue with a size of 6.25 million.

[Insert Table 2 here]

The effect of advertising revenue on news quantity is significant. In terms of magnitude, a one-standard-deviation (i.e., \$6.2 million dollars) increase in quarterly advertising revenue leads to a 10.3 percent rise in the extensive margin of whether there is any news produced on a firm. A one-SD increase in advertising revenue also leads the total number of news produced by a media outlet to increase by 8.3 percent in the following month. There is also a significant impact on news quality—a one-SD increase in advertising revenue leads the proportions of novel and firm-specific news to rise by 25 and 28 percent, respectively. Such a large magnitude indicates that media outlets allocate more resources to produce high-quality news after a positive cash-flow shock. There is also a significant drop in the news sentiment. This negative relationship between advertising revenue and news sentiment is direct evidence against the "sponsored news" channel through which firms advertise on news media to sponsor favorably slanted news.

To continuously track the impact of advertising revenue on news production, I also estimate the dynamic local projection specification (6) with a twelve-month horizon. In Figure 3, I visually present the cumulative percentage effects to examine how the impact of advertising revenue accumulates.

[Insert Figure 3 here]

The effect on the extensive margin is stable at around 11 percent, which indicates a quick expansion in news coverage on previously uncovered firms. The effect on the intensive margin gradually builds up, starting from 8.3 percent in a month to around 18 percent six months later and ending with 18.18 percent over a one-year horizon. These estimates will be used in the later sections to quantify the real effect of time-varying news production.

4.3 Effect of Advertising Revenue on Journalism Job Postings

To provide the labor market foundation for the effects presented above, I analyze how media job postings respond to advertising revenue. I start by estimating the static specification (5) on the media-month panel. The results are shown in Table 3. In addition to the estimated coefficients, I also report the percentage effects on job postings and job characteristics for a one-standard-deviation shock to advertising revenue with a size of 6.25 million.

[Insert Table 3 here]

A one-SD rise in advertising revenue significantly increases the probability of a media outlet having a journalism job posting by 4.2 percent and the number of job postings by 2.5 percent. The media outlet also increases the salary and lowers the required years of experience in hiring, indicating a strong desire to expand its newsroom. There is no significant effect on the required years of education, which is rigid with a college degree.

I also estimate the dynamic specification (7) to obtain estimates for month-by-month cumulative effects on job postings. Figure 4 shows the results.

[Insert Figure 4 here]

It takes around eleven months for the effect on the extensive margin of job posting to peak at around 12 percent. Such a pattern indicates a slow response by media outlets in creating new openings. The effect on the intensive margin is stable at around 2 to 4 percent.

4.4 Heterogeneous Effects

To better study the role of financial constraints in media news production, I examine whether news media facing different degrees of financial constraints react distinctly to cash-flow shocks from advertisement. Using the sample cut of more and less constrained media as an example, I estimate the following specification, which is the baseline specification (4) with the independent variable interacted with the variable capturing the financial constraints.

$$
\begin{aligned}
News_{m,i,t+1} = & \beta_1 \ln\left(Ad_{-g(i),m,[t-2,t]}\right) \times \mathbb{1}\left(\text{More Constrained}\right)_{m,t} \\
& + \beta_2 \ln\left(Ad_{-g(i),m,[t-2,t]}\right) \times \mathbb{1}\left(\text{Less Constrained}\right)_{m,t} + \alpha_{m,i} + \eta_{i,t} + \varepsilon_{m,i,t},
\end{aligned} \tag{8}
$$

I consider three types of heterogeneity—Table 4 presents the heterogeneous effects of more versus less constrained media (Panel a), standalone versus media group (Panel b), and small versus large media outlets (Panel c).

[Insert Table 4 here]

Heterogeneous effects of more and less constrained media. First, I cut the sample according to whether a media outlet experiences a positive or negative cash-flow shock from advertisement. The rationale behind this exercise is that a positive (negative) cash-flow shock can temporarily relax (strengthen) the financial constraint. I define a media outlet to be more constrained if its annual growth rate of advertising revenue is negative and less constrained if the growth rate is positive.

The results in Table 4 Panel (a) indicate significantly larger effects for more constrained media on all dimensions of news quantity and quality. For example, the effect size on the extensive and intensive margin is one to two times larger. The pattern also exists for the percentages of novel and firm-specific news. These results validate advertising revenue as a good proxy for media's financial constraints. The large difference in the effect sizes can also be interpreted as the asymmetric response by news production to positive and negative cash-flow shocks. As shown in Table 4 Panel (a), news production are particularly sensitive to negative shocks, which strengthens the role of the *news production channel* in propagating and amplifying adverse shocks during an economic downturn.

Heterogeneous effects of standalone and media group. Second, I split the sample by whether a media outlet is a standalone or belongs to a media group. I define a media outlet as a standalone if in RavenPack its parent source name coincides with its source name. Otherwise, I categorize the media outlet as a part of a media group. The literature on internal capital markets (Matvos and Seru, 2014; Giroud and Mueller, 2015) argues that conglomerates provide a cushion for cash-flow shocks, which can partly relax the financial constraints each subsidiary faces. The results are shown in Table 4 Panel (b).

Consistent with the prediction of the internal capital markets view, I find smaller and even insignificant effects for media outlets that belong to a media group. The effect sizes for the standalone media outlets are roughly two times those for the media group. This result again provides direct and strong evidence that it is through the channel of financial constraints that advertising revenue affects news production.

Heterogeneous effects of small and large media. Third, I cut the sample by the median size of media outlets, where the size is measured by the total advertising revenue they receive. Table 4 Panel (c) presents the results.

The first empirical pattern to notice is that advertising revenue has considerable impact on new quantity, even for the relatively large media outlets. This pattern is consistent with the stylized Fact 1 in Figure (1) that almost all news media are fairly financially constrained.

The second finding is that the effect sizes on news quality are much larger for the large media than those for the small media. Such a discrepancy suggests that media outlets of different sizes may have distinct product market strategies—small media produce less journalistic-intensive news potentially by appropriating and copying and large media tend to invest in producing high-quality content (Angelucci et al., 2020; Cagé et al., 2020).

To strengthen such an argument, I further cut the sample by whether a media outlet is among the top ten largest media outlets or not, where the size is measured by the total advertising revenue they receive. The top ten largest media outlets in the sample are the

Wall Strett Journal (WSJ), The New York Times (NYT), Yahoo!Finance, MarketWatch, Benzinga, Reuters, Business Insider, Seeking Alpha, Bloomberg, and Associated Press. Table 4 Panel (d) reports the results.

The findings in Panel (d) are consistent with those in Panel (c). Advertising revenue has an significant effect on new quantity, even for the top ten largest media outlets. Again, the effect sizes on news quality are much larger for the top ten largest media outlets. than those for other media.

Heterogeneous effects of S&P 500 and non-S&P 500 firms. Finally, I cut the sample by whether the public firms covered by financial media oulets are in S&P 500 or not. Table 4 Panel (e) presents the results.

The coefficients in Panel (e) are significant for both S&P 500 and non-S&P 500 firms, indicating that it is not the media coverage on micro-cap firms that drives the main empirical findings. Notably, for S&P 500 firms, the effect sizes on news quality are much larger. Such an empirical finding suggests that, after receiving more resources from advertising, media focus on increasing news quality when covering large public firms.

5 The Real and Financial Impact of News Production

The previous section presents empirical evidence on how real economic activity, such as advertising, affects news production. In this section, I dissect how news production impacts real economic outcomes and corporate financial policies. A number of channels may link time-varying news production to firm real and financial outcomes.

First, financial media produce public news that is mainly consumed by investors. As a result, an increase in media news production has a first-order effect in lowering information asymmetry and thus lowering the cost of capital by providing and disseminating more public information (Fang and Peress, 2009).[7] Consequently, the firm expands in investment,

[7] This connection can be established via the composition of information, where different compositions

employment, and output to seize the enhanced set of investment opportunities. Along with the decrease in degree of information asymmetry, the cost of external financing declines in both absolute and relative terms compared to the cost of internal financing, which leads the optimal level of external financing to rise as well. As the cost of external financing drops, the firm uses more equity and debt instead of internal cash to finance projects, which leads to an increase in the cash holdings. Such an economic mechanism is similar to the one in previous studies on the introduction of bank loan ratings (Sufi, 2009) and loss of analyst coverage (Kelly and Ljungqvist, 2012; Derrien and Kecskés, 2013).

Another channel for news production to affect outcomes is through its effect on uncertainty. This pathway can be established through investors, who read news about a firm and learn new information about the payoff of the firm's stock, which directly reduces the associated risk and uncertainty (Veldkamp, 2006). In accordance with this channel, Kwan et al. (2022) find that institutional investors' consumption of media news on public firms is positively related to their stock holdings of those firms. Besides, the consumption of a firm's media news increases the value-add of that position to the fund's performance. The second way to tie media-produced news to uncertainty is through corporate managers who make real and financial corporate decisions. News about the policy, macroeconomy, upstream and downstream industries, and competitors can all affect the uncertainty faced by the firm. This is particularly relevant since in my sample, many news articles contain information on several firms. Corporate managers can learn useful information even about their own firms from these non-firm-specific news. As a result, higher news production by the news media sector lowers the uncertainty embedded in corporate real and financial decisions, which in

of public and private information influence the cost of capital. This is because investors require a higher return to hold stocks with greater private information, as shown in Easley and O'hara (2004). Alternatively, the revealing of public information attracts greater investor demand due to improved asset liquidity, as demonstrated by Diamond and Verrecchia (1991). Media coverage can also attract investor attention and induce trading especially by retail investors (Barber and Odean, 2008). Such an attention channel is also related to the literature on advertisement and investor attention (Lou, 2014; Madsen and Niessner, 2019; Focke et al., 2020; Liaukonytė and Žaldokas, 2022). The resulting increase in asset demand and liquidity lowers the cost of capital. Importantly, the conceptual framework and empirical results of this paper do not rely on which of these channels is at work.

turn leads firms to invest, hire, produce, and finance more (Bloom et al., 2007; Alfaro et al., 2023).

If we deviate from the premise of firm value maximization and account for agency problems, financial media can play a monitoring role in corporate governance. Dyck et al. (2008) study the effect of media coverage on corporate governance using data from Russia. They document a positive relationship between coverage in the Anglo-American press and the probability that a corporate governance violation is reversed. Without such case-by-case data of corporate governance violations, whether news coverage affects corporate governance can be hard to test empirically. The empirical difficulty is that improved corporate governance by media news production can have both positive and negative effects on corporate investment, output, and financing since the managers can "enjoy a quiet life" or "build an empire" (Bertrand and Mullainathan, 2003). The former leads to a downward deviation from firm's optimal level of activity, such as investment, while the latter leads to an upward deviation. As a result, previous studies usually focus on measures of efficiency such as ROA (Giroud and Mueller, 2010), instead of the level of activity. I follow the literature and use ROA as the outcome variable in the main specification (9). I find that news production has a positive but insignificant effect on firm ROA.

5.1 Empirical Design

In order to study the effects of news production on corporate real and financial outcomes, I use two data sets: a monthly firm panel which merges data on news production with measures of uncertainty (e.g., stock market volatility and analyst earnings forecast dispersion) and measures of asymmetric information (e.g., bid-ask spread and illiquidity) and a yearly firm panel which compiles news production records, firm real outcomes (e.g., investment, employment, and output), firm cost of capital (e.g., implied and perceived cost of capital), and firm financial outcomes (e.g, debt financing, equity financing, and cash holdings).

Main specification. I estimate the following specification, after taking the first difference to eliminate the time-invariant firm fixed effects:

$$\Delta y_{i,t} = \beta \Delta \ln \left(\#\ News_{i,t-1} \right) + \tau_{g(i),t} + \gamma X_{i,t-1} + \varepsilon_{i,t}. \tag{9}$$

The main variable of interest is the news quantity measured by the log of number of news $\ln \left(\#\ News_{i,t-1} \right)$ although the analysis can be applied to all other measures of news quantity and quality. Outcome variables include measures of uncertainty and asymmetric information for monthly analysis. For analysis on the annual panel, I include corporate real outcomes variables such as investment (i.e., physical and intangible), employment, and output (i.e., sales and cost of goods sold) and corporate financial outcomes such as firm cost of capital, financing (i.e., issuance of short-term debt, long-term debt, and equity), payouts, and the change in cash holdings.

The independent variable is lagged by one period relative to the outcome variables to resolve the obvious simultaneity that corporate outcomes can be the content of news themselves. I add industry-time fixed effects to control for time-varying industry shocks such as dynamics in the media sectoral focus (Chahrour et al., 2021).

The specifications include three important and extensive sets of controls. First, to account for the actual financial information, I include the number of corporate events recorded in the Key Developments data set, the number of corporate press releases recorded in RavenPack PR edition, and news sentiment calculated by RavenPack. Second, I include a set of standard financial controls. For the monthly specification that studies uncertainty and asymmetric information, I control for stock return, absolute value of stock return, book-to-market ratio, and firm size measured by the log of lagged end-of-month market capitalization. For the annual specification that studies corporate real and financial outcomes, I follow Leary and Roberts (2014) to include stock return, tangibility, book leverage, Tobin's Q, return on asset, and firm size measured as the log of sales. See the table on page 47 for detailed definition and construction of variables. Third, to account for potential autocorrelation, I add a one-period lag of the dependent variable.

Predicted financial cost as the instrumental variable. I use a measure of the financial cost of news production as an instrumental variable for the actual news that is produced. The instrumental variable is constructed as below in four steps. To fix ideas, suppose at time t, media m receives total advertising revenue $Ad_{m,t}$ and produces news of the amount $News_{m,t}$. First, I calculate the average financial cost to produce one piece of news as $\frac{Ad_{m,t}}{News_{m,t}}$. Second, denote the number of news that media outlet m produces on firm i at time t as $News_{m,i,t}$. Then the total financial cost for media m's news on firm i is $C_{m,i,t} = Ad_{m,t} \times \frac{News_{m,i,t}}{News_{m,t}}$. Third, for firm i, I aggregate financial costs spent by all media on producing its news at time t as $C_{i,t} = \sum_m C_{m,i,t}$. $C_{i,t}$ can be interpreted as the total predicted financial cost spent on producing firm i's news at time t, which I use to instrument for the actual amount of news that is produced.

Finally, I modify the instrumental variable by excluding the effect of advertising shocks specific to firm i's industry, denoted as $g(i)$, in order to ensure that the instrumental variable maintains an arm's length construction. Since the empirical specification (9) is in first differences, I calculate the growth rate for the total financial cost of news production $\Delta \ln (C_{i,t})$ as the instrumental variable for the growth rate of actual number of news $\Delta \ln \left(\# \; News_{i,t}\right)$, which reads

$$IV_{i,t} = \Delta \ln \left(\sum_m \left(Ad_{-g(i),m,t} \times \frac{News_{m,i,t}}{News_{m,t}} \right) \right).$$

5.2 Uncertainty and Asymmetric Information

This subsection shows direct evidence for the effects of increased news production on lowering uncertainty and asymmetric information. I consider four dimensions of uncertainty from the literature: realized stock market total and idiosyncratic volatility (Leahy and Whited, 1996; Bloom et al., 2007), option-implied volatility (Dew-Becker and Giglio, 2023; Alfaro et al., 2023), and analyst earnings forecast dispersion (Bloom, 2009; Bond et al., 2005). I construct two measures of information asymmetry used in Kelly and Ljungqvist (2012): bid-ask spread and illiquidity. See Section 2 and the table on page 47 for detailed definition and construction of variables. These measures are merged with monthly news production records at the firm level. Table 5 presents the results estimated using specification (9). According to the estimated coefficients, I calculate the magnitude of the effect and percentage effect for an 8.30 percent increase in the number of news (i.e., # *News*). The 8.30 percent increase corresponds to the one-month percentage effect on news from a one-standard-deviation shock to advertising revenue, as reported in Column (2) Table 2.

[Insert Table 5 here]

From Column (1) to Column (6) in Table 5, a consistent pattern emerges: a rise in news production decreases all four measures of uncertainty and both measures of information asymmetry. An 8.30 percent rise in news quantity in this month leads to a 0.66 percentage point decline in realized volatility, which is a 1.54 percent drop relative to the mean value. To get a better sense of the magnitudes, I compare my estimated effects with those from Kelly and Ljungqvist (2012) who study the effect of a one analyst coverage loss induced by broker closure on information asymmetry. Take the effects on realized volatility as an example. To match the same percentage effect from a negative one-SD shock to advertising revenue, one would expect to see a 1.291 analyst coverage loss in a year, or equivalently 0.108 analyst coverage loss in a month. As for the effect on asymmetric information, a negative one-SD shock to advertising revenue is equivalent to 2.248 (0.187) analyst coverage loss in a year (month). The same calculation for the illiquidity measure would yield a relatively small number of analyst coverage loss to match the effect. The reason is mainly due to the relatively large percentage effect (i.e., 18%) documented in Kelly and Ljungqvist (2012). The comparison for other measures are infeasible since there are no comparable estimates available in the literature.

5.3 Cost of Capital and Discount Rate

In this subsection, I establish the financial pathway for media news production to impact real and financial outcomes through the cost of capital. Corporate cost of capital and discount rate directly determine firms' required returns to capital and thus affect corporate financing and real acativity such as investment, which transmits shocks from news production to the real economy.

To establish such a pathway, I directly measure the implied and perceived cost of capital and discount rate in each firm year. First, I examine the effect of media news production on firms' implied cost of capital, using data shared by Lee et al. (2021). Following the recommendations in Lee et al. (2021), I use the implied cost of capital by Gebhardt et al. (2001) (GLS) as my preferred measure. To ensure robustness, I also use a composite implied cost of capital constructed by Lee et al. (2021), which is a simple average of four implied cost of capital variants. Second, I document how firms' perceived cost of capital and discount rate respond to media news production. I use the data shared by Gormsen and Huber (2022) and Gormsen and Huber (2023), who hand-collected firms' percevied cost of capital and discount rate from corporate conference calls. See Section 2 and the table on page 47 for detailed definition and construction of variables.

Table 6 presents the results estimated using specification (9). According to the estimated coefficients, I calculate the magnitude of the effect and percentage effect for an 18.18 percent increase in the number of news (i.e., *# News*). The 18.18 percent increase corresponds to the one-year percentage effect on news from a one-standard-deviation shock to advertising revenue, as reported in Panel (b) Figure 3.

[Insert Table 6 here]

As shown in Table 6, media news production significantly decreases firms' cost of capital. This is true for GLS implied cost of capital, composite implied cost of capital, perceived cost of capital, and discount rate. For example, the coefficient in Column (1) indicates that an

18.18 percent increase in news production leads to a 0.08 percentage point decline in implied cost of capital, which is a 1 percent effect relative to the mean value of 8.75 percent. For the discount rate, as shown in Column (4), the same news production shock transmits to a 0.07 percentage point drop, which is a 0.5 percent effect relative to the mean value of 14.79 percent.

5.4 Corporate Real Outcomes

I now turn to corporate real outcomes by focusing on three sets of measures: investment (i.e., physical and intangible), employment, and output (i.e., sales and cost of goods sold), following Alfaro et al. (2023). The investment rate is in percentage change by definition. For other outcomes, I calculate their growth rates by taking the log difference. See Section 2 and the table on page 47 for detailed definition and construction of variables. Table 7 shows the estimated effects of news quantity on corporate real outcomes. According to the estimated coefficients, I calculate the magnitude of the effect for an 18.18 percent increase in the number of news (i.e., *# News*). The 18.18 percent increase corresponds to the one-year percentage effect on news from a one-standard-deviation shock to advertising revenue, as reported in Panel (b) Figure 3.

[Insert Table 7 here]

The results in Table 7 indicate that a rise in news production from the previous year has a significant and expanding effect on corporate real activity in the current year. Such a pattern is consistent with the predictions of both uncertainty and asymmetric information channels. In terms of magnitude, I compare my estimated effects with those from Alfaro et al. (2023) who document the effects of a two-SD volatility shock on firm real outcomes. For the investment rate, to match the size of the effect from a one-SD shock to advertising revenue, one would expect to see a 13 percentage point drop in annual stock market volatility, which is a 0.42 SD volatility shock. The same comparison would obtain a 7.2 to 12.9 percentage point drop (i.e., a 0.23 to 0.42 SD volatility shock) in annual volatility for employment, sales, and cost of goods sold to have the same effect sizes. The exception is the investment in intangible capital (e.g., R&D, intellectual property, etc.,), which responds more to news production due to its high sensitivity to information and reliance on equity financing (Brown et al., 2009; Kerr and Nanda, 2015). Consistent with the prediction of the corporate governance channel (Bertrand and Mullainathan, 2003; Giroud and Mueller, 2010), in Column (6), I find that news production has a positive effect on firm *ROA*. Although the estimated effect is small and insignificant, such a result suggests that financial media's monitoring improve corporate efficiency.

5.5 Corporate Financial Outcomes

This subsection examines how news production affects corporate financial outcomes. I capture corporate financial policies along the dimensions of financing (i.e., issuance of short-term debt, long-term debt, and equity), payouts, and the change in cash holdings, following Derrien and Kecskés (2013) who examine the real impact of analyst coverage termination. The issuance of short-term and long-term debt are measured by changes in the level of debt. All corporate financial policy variables are scaled by total assets. See Section 2 and the table on page 47 for detailed definition and construction of variables. Table 8 presents the results on how news production affects corporate financial outcomes. According to the estimated coefficients, I calculate the magnitude of the effect for an 18.18 percent increase in the number of news (i.e., *# News*). The 18.18 percent increase corresponds to the one-year percentage effect on news from a one-standard-deviation shock to advertising revenue, as reported in Panel (b) Figure 3.

[Insert Table 8 here]

The results in Table 8 reveal three main findings. First, the results are consistent with the predictions of asymmetric information and the pecking-order theory (Myers and Majluf, 1984). Following an increase in news production, firms face a lower degree of information asymmetry and should change the composition of their financing to use more of those which were previously too costly: equity first, then higher risk long-term debt, then lower risk short-term debt. This prediction matches the empirical results in that a rise in news production increases equity issuance most (by 0.9% of the total assets), long-term debt issuance second (by 0.4% of the total assets), and short-term debt issuance least (with a almost zero effect). Moreover, firms increase their cash holdings after a positive shock to news production. This is because the lower degree of information asymmetry lowers the cost of external financing. Consequently, firms reduce their reliance on internal resources such as cash to finance their projects, leading the cash holdings to rise.

Second, the news production is significantly positively associated with the change in cash holdings. Such a result is inconsistent with the uncertainty channel. The rationale is that an increase in news production would lower uncertainty and thus mitigate firms' precautionary saving motive, which in turn lowers the cash holdings. Therefore, the empirical result is inconsistent with the uncertainty channel's prediction of a negative correlation between news production and cash holdings.

Finally, in terms of the magnitude, I compare the estimated effects with those from Derrien and Kecskés (2013) who document the effect of a one analyst coverage loss. To match the same effects induced by a one-SD shock from advertising revenue, one would expect to see a 0.3 to 1.0 analyst coverage loss in a year, except for the effect on the short-term debt issuance, whose effect size is too small to do such a calculation.

6 Procyclicality of News Production

The main goal of this work is to establish the news production channel of shock transmission and its relevance to the real economy. Section 4 uses media-by-firm data to identify the effect of financial shocks on news production. Section 5 exploits firm-level data to trace the impact of financial news production on corporate real and financial outcomes. Both of the micro sample analysis focus on cross-sectional variations to establish causality.

This section studies how financial news production fluctuates along with business cycles and transmits financial shocks to uncertainty, asymmetric information, cost of capital, and real outcomes. I start with presenting two stylized facts on the procyclicality of financial news production. First, using aggregate time series of more than fifty years, I document that aggregate avertising expenditure, media sector's revenue, and media sector's employment are all highly procyclical. Second, as a result of the previous empirical fact, financial news production, in terms of both news quantity and quality, is procyclical. This synchronicity is not a simple consequence of economic expansion and contraction. As a benchmark, the number of corporate press releases, a proxy for actual underlying economic information, shows weak countercyclicality. In terms of magnitudes, I show that one percent decline in aggregate advertising expense leads to 1.2 percent decrease in media revenue and 0.4 percent drop in media employment.

I then quantity the impact of news production shocks using vector autoregression (VAR) estimations on monthly U.S. aggregate time series. I include media employment as the measure for aggregate news production, the level of S&P 500 index, S&P 500 implied volatility as the measure for uncertainty, Amihud illiquidity and bid-ask spread as the measures for asymmetric information, cost of capital, federal funds rate, wage, consumer price index, and finally real activity such as average hours, non-media employment, and industrial production. I find that a one percent decline in news production leads to a 1.5 percentage point increase in the level of uncertainty, 0.1 percent increase in the degree of asymmetric information. These impacts then transmit to a 0.25 percentage point rise in cost of capital, a 0.007 percent decline in non-media employment, and a 0.005 percent decline in industrial production. In terms of the forecast error variance decomposition, shocks to news production can explain 7 percent and 3 percent of the variance for non-media employment and industrial production over the short run and 4 percent and 1 percent of the same variance over the long run. Such a time series analysis provides supporting evidence for the micro-estimated effects and complements the cross-sectional analysis.

Table 9 presents the summary statistics for annual aggregate time series (Panel a) from 1970 to 2022 and monthly aggregate time series (Panel b) from January 1970 to June 2022.

[Insert Table 9 here]

These empirical findings highlight the key economic mechanism of the *news production channel*. In an economic downturn, firms cut their advertising expenditure, which is the largest source of cash flow for news media. As a result, financially constrained news media experience a negative revenue shock. The news media respond by downsizing their newsrooms. Consequently, the information environment of the economy deteriorates—less news is produced and novel or firm-specific information is missed. Such declines in news quantity and quality then transmit to financial markets and the real economy and negatively impact a wide range of real and financial outcomes.

6.1 Stylized Empirical Facts

Fact 3: Advertisement, revenue and employment of news media are procyclical.

I document the procyclicality of advertisement, media revenue and employment at the aggregate level. I use an annual Compustat sample of U.S. public firms, which spans from 1970 to 2022, and then aggregate the firm-year panel to construct macro time series. As visual evidence, in Figure 5, I plot the macro time series of annual growth rates for the revenue and employment of the news media sector, the advertising expenditure of all sectors, and the real GDP. I also add the series of the number of news from a balanced sample. A strong pattern of procyclicality emerges—all time series comove with the GDP growth in a very responsive manner.

[Insert Figure 5 here]

To better quantify this procyclicality, I regress the annual growth rates of advertising expenditure, media sales, and media employment on the real growth rate of GDP and advertising expenditure. I implement these regressions on aggregate time series, which are value-weighted averages across the U.S. public firms from a Compustat firm-year panel. Table 10 presents the empirical results.

[Insert Table 10 here]

According to the estimate in Column (1), a one percent drop in GDP corresponds to a 1.7 percent drop in advertisement. And the estimates in Columns (2) and (3) indicate that a one percent drop in advertisement transmits to a 1.2 percent drop in media revenue and a 0.4 percent drop in media employment.

Fact 4: News production is procyclical.

As a consequence of the previous empirical fact, news production is procyclical. To make up for the short time period of RavenPack data coverage, I document the procyclicality of news production in an international RavenPack DJ-PR edition panel of 50 countries from 2000 to 2021. Figure 6 presents binned scatter plots of annual growth rates of the number of news, the number of corporate press releases, the percentages of novel and firm-specific news against the annual growth rate of real GDP. I include corporate press releases as a benchmark for actual underlying economic information. Table 11 reports the regression results with country fixed effects.

[Insert Figure 6 here]

[Insert Table 11 here]

According to the estimates, a one percent drop in GDP corresponds to a 2 percent drop in the number of news, which is quantitatively quite close to the response of media revenue and employment estimated in Fact 3. However, the number of corporate press releases loads insignificantly on GDP growth. If anything, the number of corporate press releases shows a weak countercyclicality. This contrast between media-produced news and corporate information provides confirming evidence to the *news production channel*, which formalizes the difference between media-produced news and actual economic information and highlights the effect of media revenue on media news production.

There is a noticeable nonlinearity in the relationship between the number of news (and also percentage of novel news) and GDP growth, where the highest GDP growth bins (e.g., greater than six percent) do not have the highest news production. This nonlinearity supports the premise of financially constrained news production—in a period of really good economic conditions, the financial constraints faced by news media are largely relaxed, which leads to a lower sensitivity of news production to revenue shocks.

6.2 VAR Estimations

To better quantify the impact of news production shocks on real and financial outcomes, I estimate a vector autoregression (VAR) model using monthly U.S. aggregate time series data.

Data and Specification. The VAR estimations use monthly data from January 1970 to June 2022, which consists of 630 monthly observations in total. I use monthly data to maximize statistical power as in other work in the literature (Bloom, 2009; Jurado et al., 2015; Berger et al., 2020; Ludvigson et al., 2021; Dew-Becker and Giglio, 2023).

I use seasonally-adjusted media sector's employment as the measure for aggregate news production since it is the only measure available at the monthly frequency and spans a relatively long time period. The media employment is obtained from BLS and is defined as the total employment for the information sector with the two-digit NAICS code as 51.[8] Follow-

[8]The information sector includes publishing industries (except Internet, NAICS 511), motion picture and sound recording industries (NAICS 512), broadcasting (except Internet, NAICS 515), telecommunications (NAICS 517), data processing, hosting, and related services (NAICS 518), and other information services (including Internet publishing and broadcasting, NAICS 519).

ing Bloom (2009), I include the level of stock market (e.g., S&P 500 index) to control for the effect of first-moment shocks when examining the impact of news production shocks. Relative to the setup in Bloom (2009) that focuses on uncertainty, I add measures of illiquidity, bid-ask spread, and cost of capital to better evaluate how news production shocks transmit through three conceptual channels studied in Section 5: uncertainty, asymmetric information, and cost of capital. Uncertainty is measured by S&P 500 option-implied volatility constructed by Dew-Becker and Giglio (2023). As shown in Dew-Becker and Giglio (2023), such a measure is highly correlated with the VIX and is available in a longer time period.[9] Illiquidity and bid-ask spread, as measures of asymmetric information, are the value-weighted averages across firms in S&P 500. Cost of capital is the value-weighted average of composite implied cost of capital constructed by Lee et al. (2021) across firms in S&P 500. I omit corporate perceived cost of capital and discount rate in this analysis since the data from Gormsen and Huber (2022) and Gormsen and Huber (2023) is available only since 2002. I trace prices using federal funds rate (effective rate, Federal Reserve Board of Governors), average hourly earnings for production workers in manufacturing, and consumer price index (all urban consumers, seasonally adjusted). I measure real activity using average hours in manufacturing for production workers (BLS, seasonally adjusted), non-media employment (BLS, seasonally adjusted), and industrial production in manufacturing (Federal Reserve Board of Governors, seasonally adjusted). The non-media employment is constructed by substracting media employment from total private non-farm employment. All variables used in the estimations are Hodrick-Prescott (HP) detrended with $\lambda = 129,600$. I multiply the measures of uncertainty, cost of capital, and federal funds rate by one hundred so they are in percentage.

The variables in the estimation order are ln(media employment), ln(S&P 500 index),

[9] Dew-Becker and Giglio (2023) use options price data from the Berkeley Options Database (BODB) and OptionMetrics. The VIX is measured using a so-called model-free implied volatility. Dew-Becker and Giglio (2023)'s measure is based on the at-the-money Black-Scholes implied volatility. The latter requires only observing a single option price and is 99.5 percent correlated with the VIX. See Dew-Becker and Giglio (2023) for details. For the periods when S&P 500 option-implied volatility is unavailable, I use S&P 500 realized volatility to impute missing values.

uncertainty, ln(Amihud illiquidity), ln(bid-ask spread), cost of capital, federal funds rate, ln(average hourly earnings), ln(consumer price index), average hours, ln(non-media employment), and ln(industrial production). This ordering follows Bloom (2009) and is based on the assumptions that financial news production shocks first influence measures of financial markets (level, volatility, liquidity, bid-ask spread, and cost of capital), then prices (wages, CPI, and interest rates), and finally quantities (hours, non-media employment, and output). I include twelve lags in VAR estimations. The results are robust to alternative choices of lags such as three, six, or nine.

Impulse responses to news production shock. Figure 7 plots the Cholesky orthogonalized cumulative impulse response functions to a one percent news production shock. I find that a one percent decline in news production leads to to a 1.5 percentage point increase in the level of uncertainty (Panel a), 0.1 percent increase in the degree of asymmetric information (Panels b and c). These impacts then transmit to a 0.25 percentage point rise in cost of capital (Panel d), a 0.007 percent decline in non-media employment (Panel e), and a 0.005 percent decline in industrial production (Panel f).

[Insert Figure 7 here]

Forecast error variance decomposition. Figure 8 plots the forecast error variance decomposition from VAR estimations. In the short run, news production shocks explain 1 percent of uncertainty and 7 percent and 3 percent of non-media employment and industrial production, respectively. Over a one-year horizon, news production shocks explain 1 percent of uncertainty, degree of asymmetric information, and cost of capital. These shocks also explain 4 percent and 1 percent of non-media employment and industrial production, respectively, over a one-year horizon.

[Insert Figure 8 here]

7 Conclusion

I document how news media shape the information environment of the economy by producing news under financial shocks. Fluctuations in real economic activity, such as advertising, generate cash-flow shocks to the financially constrained media sector, which endogenously reacts by changing news quantity and quality. Such dynamics in news production then shift the levels of uncertainty and information asymmetry, affecting real and financial outcomes. Linking comprehensive data on media advertising revenue, job postings, and news quantity and quality, I show that a one-standard-deviation increase in quarterly media advertising revenue leads to an 8.3 (18.18) percent rise in news quantity in the following month (year), along with a 25 percent increase in news novelty. This result holds when using a within-firm estimator on the same firm covered by news media whose advertising revenues are differentially exposed to industry-level advertising shocks. This effect on news production then transmits to 0.5 to 1.5 percent declines in uncertainty and asymmetric information and 0.4 to 1.6 percentage point expansions in real activity, and increases in corporate financing and cash holdings by 1 percent of total assets. These magnitudes are comparable to the effects documented in the literature of gaining coverage by one extra analyst. I document the procyclicality of news production at the aggregate level as evidence supporting such a channel. A VAR analysis is implemented to quantify the effect of news production shocks on uncertainty, asymmetric information, and real activity.

List of Variables

Measure	Definition and Construction
Ad	Total advertising revenue a media receives in a quarter
$\mathbb{1}$(News) (%)	Dummy variable of whether there is any news produced by a media outlet on a public firm in a given
# News	The total number of news produced by a media outlet on a public firm in a given month
Novel (%)	Percentage of novel news, where novel news has a 100 novelty score assigned by RavenPack
Firm-Specific (%)	Percentage of firm-specific news, where firm-specific news has a 100 relevance score assigned by RavenPack
Sentiment	News sentiment RavenPack's Event Sentiment Score (ESS), which ranges from 0 to 100, which indicates neutral sentiment by a score of 50 and positive (negative) sentiment by a score above (below) 50.
$\mathbb{1}$(Posting) (%)	Dummy variable of whether there is any journalism job posting by a media outlet in a given
# Postings	Total number of journalism job postings by a media outlet in a given month
Salary	Midpoint of minimum and maximum salary or the minimum salary if only minimum is available
Experience	Required minimum years of experience
Education	Required minimum years of education
Realized Volatility (%)	Standard deviation of firms' cum-dividend daily stock returns from CRSP, annualized by multiplying by $\sqrt{252}$
Implied Volatility (%)	Standard deviation of residuals of weekly returns on weekly equal weighted market returns for three years prior to month end
Idiosycratic Volatility (%)	Annualized monthly average of firms' daily option-implied volatility from OptionMetrics, where the daily observations are the simple average of forward 30-day maturity at-the-money (ATM) call and put options
Forecast Dispersion	Cross-sectional standard deviation of analyst forecasts on earnings per share in a given month
Bid-Ask Spread	Monthly average of daily bid-ask spread normalized by average of daily spread, multiplying by one hundred
Amihud Illiquidity	Average daily ratio of absolute return to dollar volume in million
Return (%)	CRSP stock return
abs(Return) (%)	Absolute value of CRSP stock return
B/M	Book-to-market ratio
Size	Log of end-of-month market capitalization in the monthly panel and log of $SALE$ in the annual panel

List of Variables (Continued)

Measure	Definition and Construction
Implied Cost of Capital (%)	Mechanical implied cost of capital by Gebhardt et al. (2001) (GLS), which is based on a residual income model. The inputs for future cash flows consist of mechanical forecasts from the cross-sectional forecast model of Hou et al. (2012). See Lee et al. (2021) for details.
Composite Implied Cost of Capital (%)	Equal-weighted average of four commonly used implied cost of capital variants: the residual income based measures proposed by Gebhardt et al. (2001) (GLS) and Claus and Thomas (2001) (CAT) and the abnormal earnings based measures proposed by Easton (2004) (PEG) and Ohlson and Juettner-Nauroth (2005) (AGR). See Lee et al. (2021) for details.
Perceived Cost of Capital (%)	Hand-collected by Gormsen and Huber (2022) from corporate conference calls. Gormsen and Huber (2022) for details
Discount Rate (%)	Hand-collected by Gormsen and Huber (2023) from corporate conference calls. See Gormsen and Huber (2023) for details
Investment Rate	$CAPX_t/\frac{1}{2}\left(PPENT_{t-1} + PPENT_t\right)$
Intangible Investment	$R\&D + 0.3 \times XSGA$
Employment	EMP
Sales	$SALE$
COGS	$COGS$
Short-Term Debt	$DLCCH/AT$
Long-Term Debt	$(DLTIS - DLTR)/AT$
Equity Issuance	$SSTK/AT$
Total Financing	$\left(DLCCH + (DLTIS - DLTR) + SSTK\right)/AT$
Payouts	$(DV + PRSTKC)/AT$
Cash Holdings	$CHECH/AT$
Tangibility	$PPEGT_t/AT_{t-1}$
Book Leverage	$(DLC + DLTT)\,/\,(DLC + DLTT + CEQ)$
Tobin's Q	$Q =$ (market value of assets)/(0.9$\times$book assets+0.1$\times$ market value of assets), where book assets $= AT$, market value of assets $= AT + ME - CEQ - TXDB$
ROA	$EBIT_t/AT_{t-1}$

List of Variables (Continued)

Measure	Definition and Construction
KZ Index	$KZ\ Index = -1.002 \times CF + 3.1392 \times TLTD - 39.3678 \times TDIV - 1.3148 \times CASH + 0.2826 \times Q$, where CF is the ratio of cash flow to total assets; $TLTD$ is the ratio of the long-term debt to total assets; $TDIV$ is the ratio of total dividends to assets and Q is Tobin's Q; $CASH$ is the ratio of liquid assets to total assets
WW Index	$WW\ Index = -0.091 \times CF - 0.062 \times DIVPOS + 0.021 \times TLTD - 0.044 \times LNTA + 0.102 \times ISG - 0.035 \times SG$, where $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends; $LNTA$ is the natural log of total assets; ISG is the firm's three-digit industry sales growth; SG is firm sales growth
SA Index	$SA\ Index = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$, where $Size$ is the log of inflation adjusted book assets, and Age is the number of years the firm has been on Compustat with a non-missing stock price
Text-Based Index	Percentage frequency of constraining words in firms' 10-K filing text, where constraining words are defined by the Loughran-McDonald finance dictionary
# KD Events	Number of corporate events in Capital IQ Key Developments
# Corporate Press Releases	Number of corporate press releases in RavenPack PR edition

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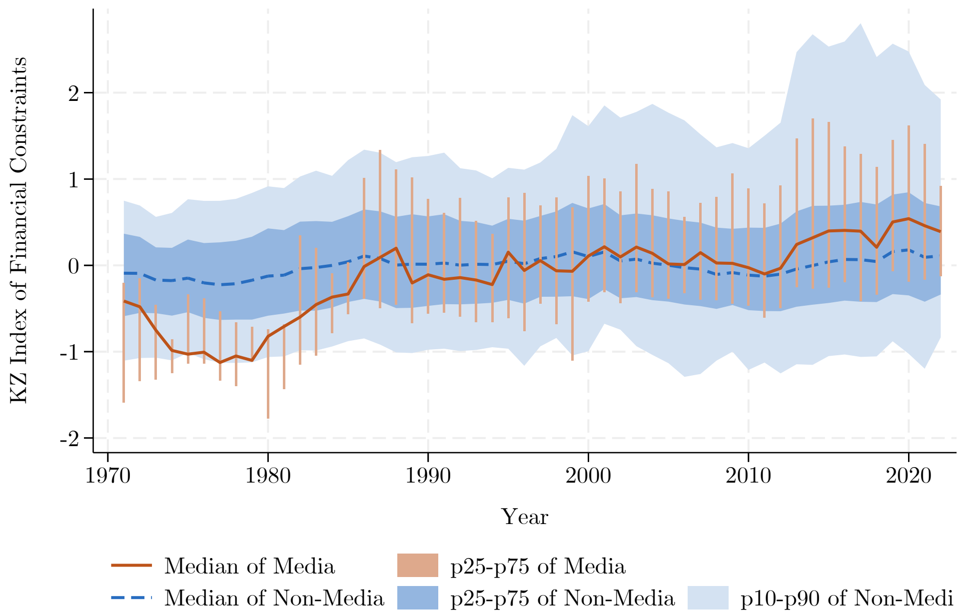
Figures

Figure 1. Financial Constraint Indices of Media and Non-Media Firms

(a) Kaplan-Zingales Index



(b) Whited-Wu Index

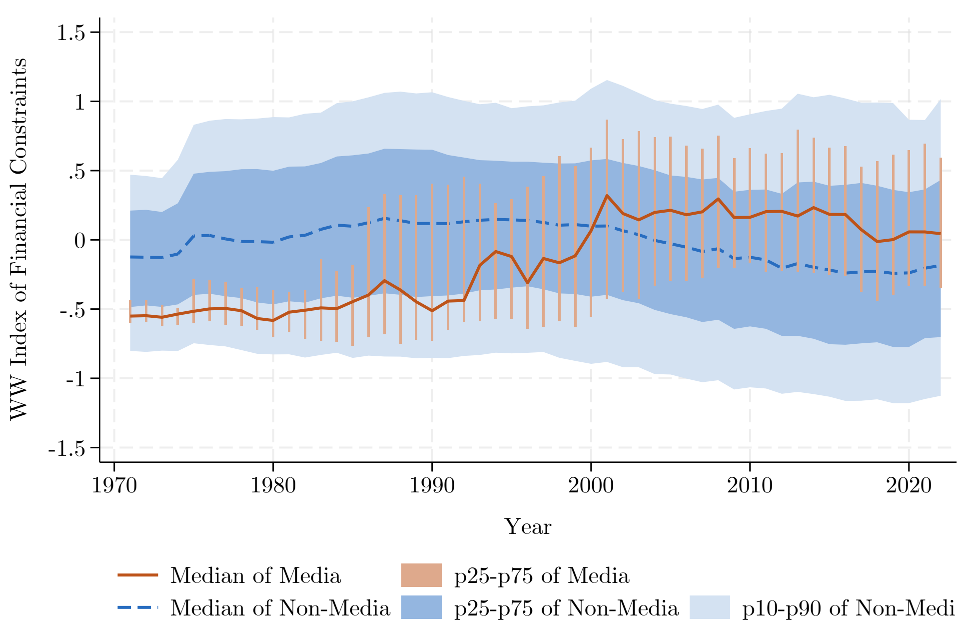
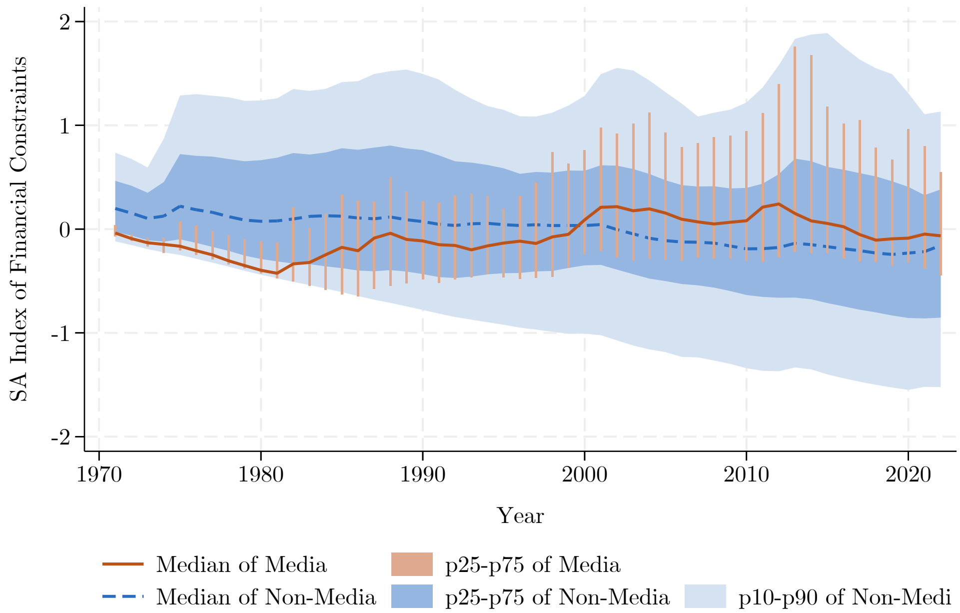
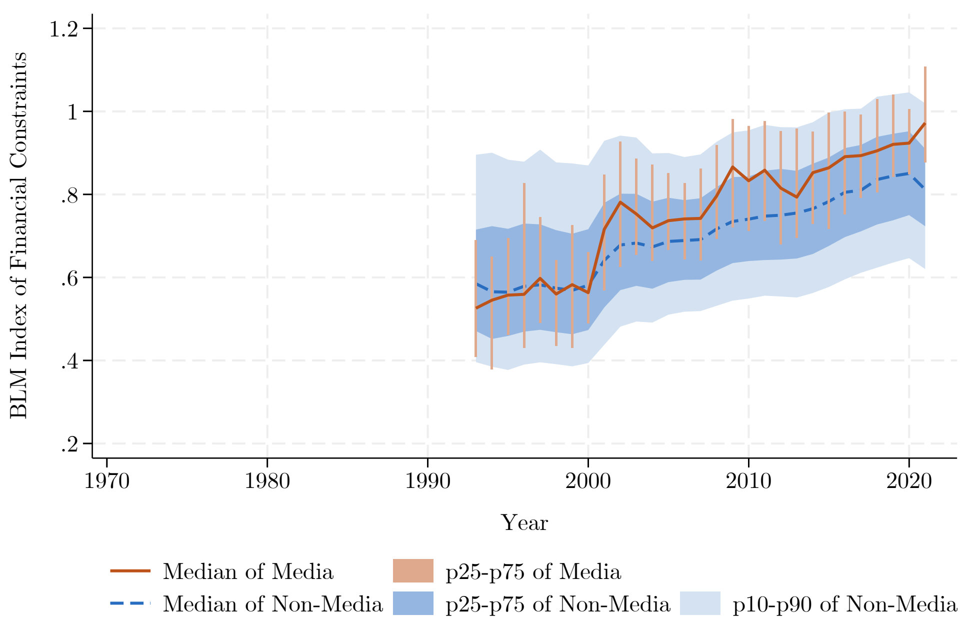


Figure 1. Financial Constraint Indices of Media and Non-Media Firms

(c) Size-Age Index



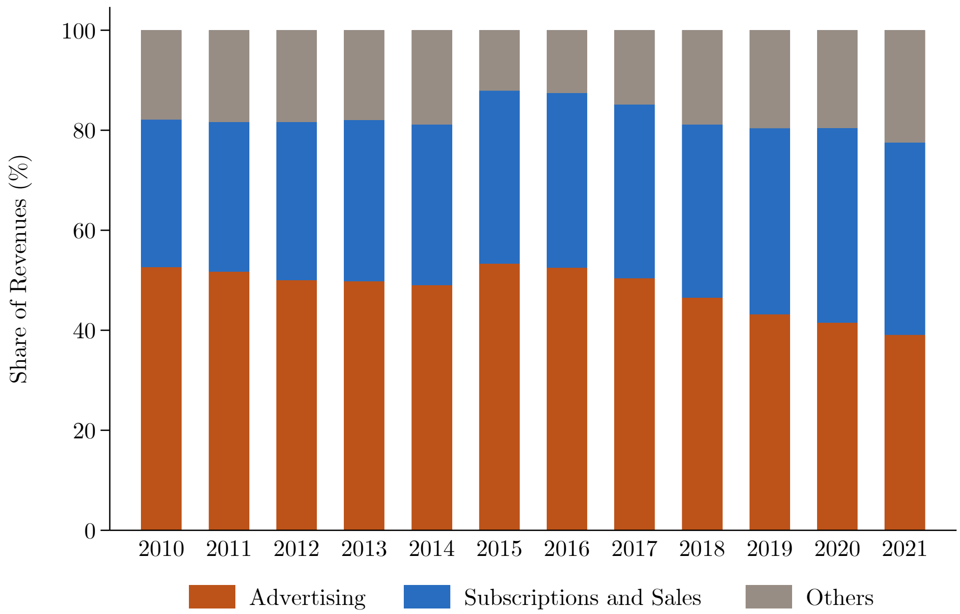
(d) Bodnaruk-Loughran-McDonald Text-Based Index



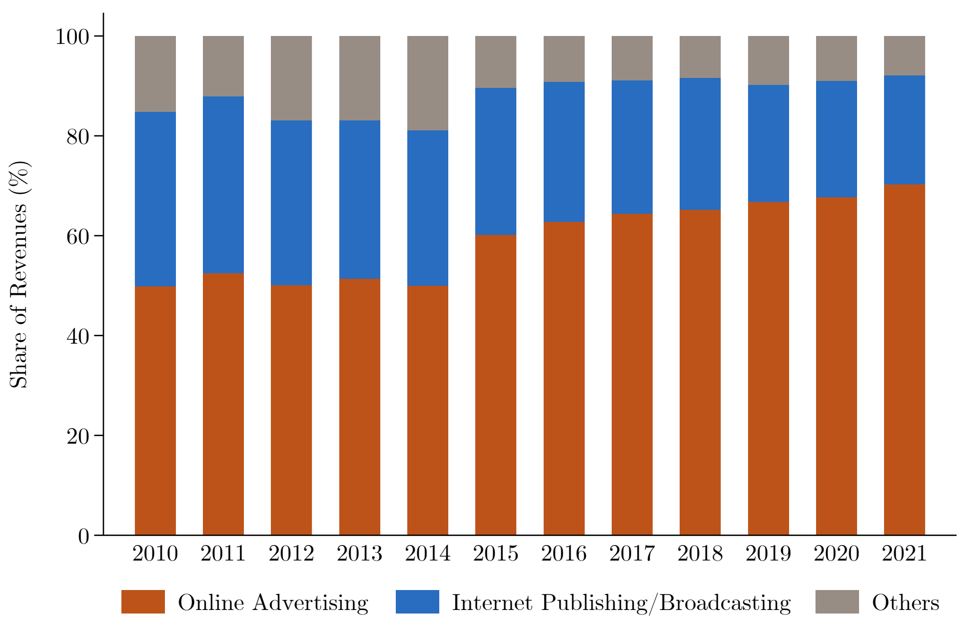
Notes. This figure plots the annual time series of medians, 25-75 percentile ranges, and 10-90 percentile ranges for Kaplan-Zingales (Panel a), Whited-Wu (Panel b), Size-Age (Panel c), and Bodnaruk-Loughran-McDonald text-based (Panel d) indices of financial constraints for media and non-media firms in the Compustat sample, respectively. See the table on page 47 for definition and construction of variables.

Figure 2. Advertisement As the Largest Source of News Media Revenues

(a) Print News Media



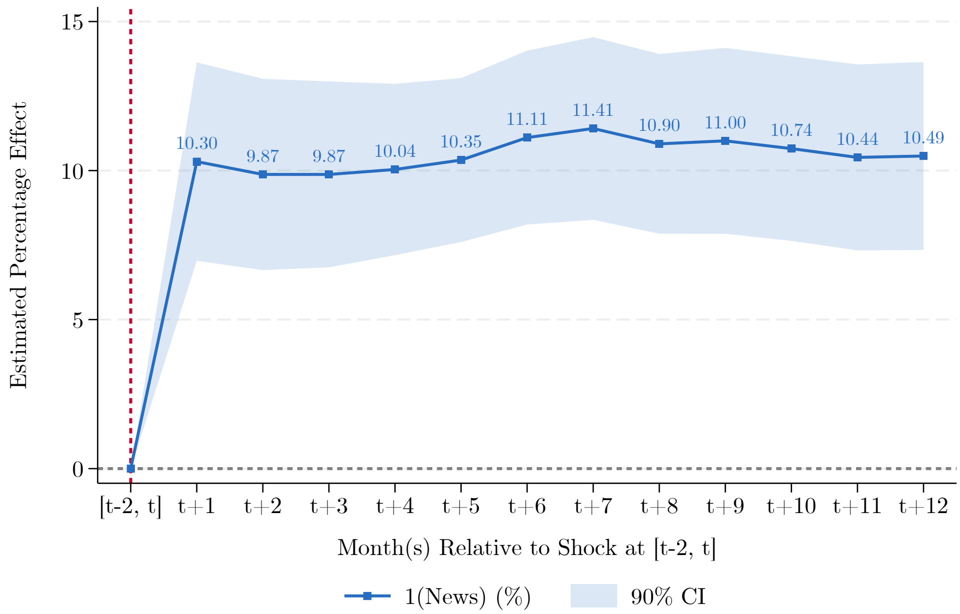
(b) Online News Media



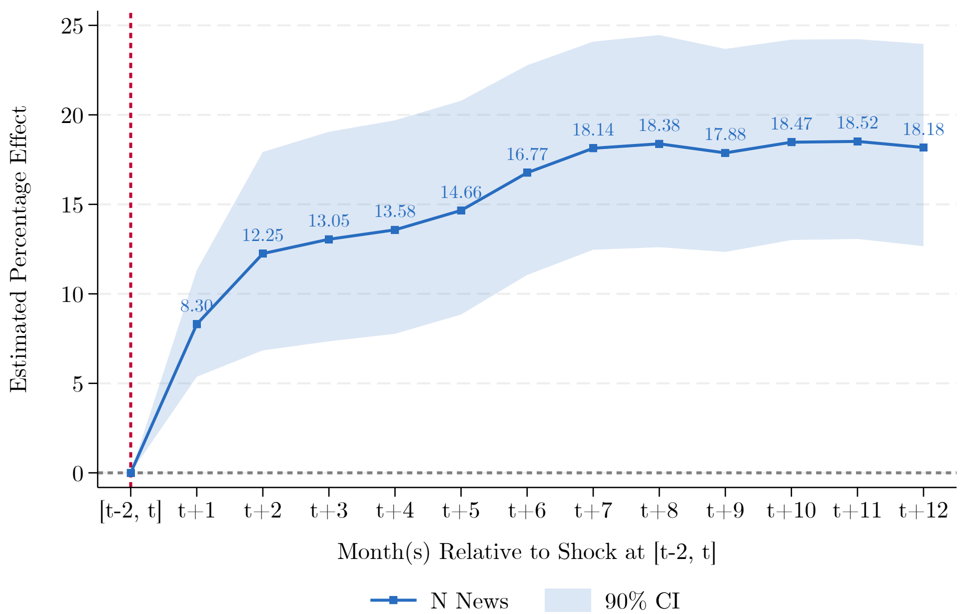
Notes. This figure plots the share for each source of revenue of print media (newspapers and periodical publishers, Panel a) and online media (internet publishing and broadcasting and web search portals, Panel b) from 2010 to 2021, respectively. The data source is Census Service Annual Survey (SAS).

Figure 3. Cumulative Effects of Advertising Revenues on News Production

(a) 𝟙(News) (%)



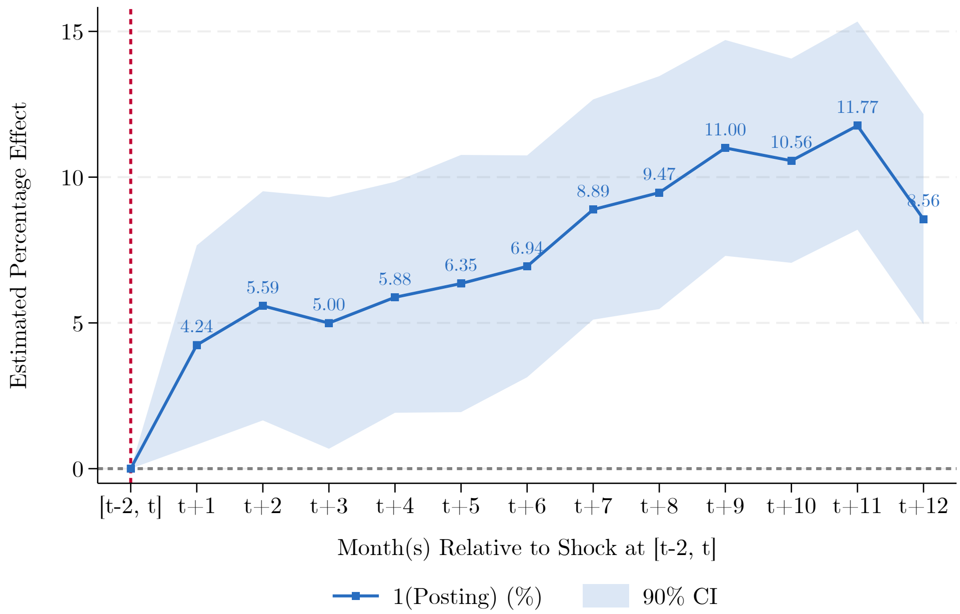
(b) Number of News



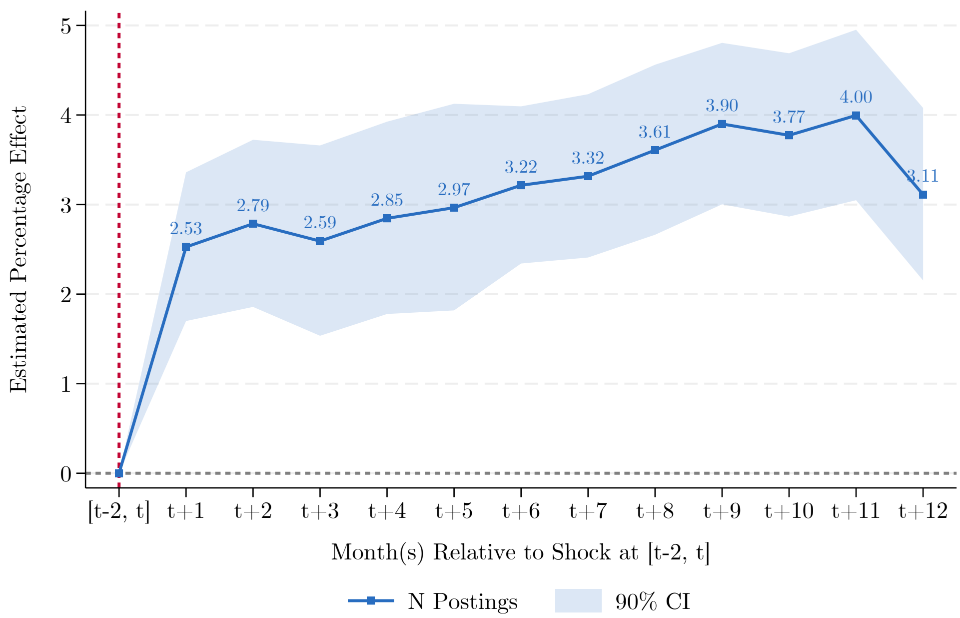
Notes. This figure plots twelve-month cumulative percentage effects of a one-SD shock to advertising revenues $Ad_{[t-2,t]}$ at time $[t-2,t]$ on media news production from time $t+1$ to $t+12$. The percentage effects are calculated from the estimated coefficients β^h in the specification (6). Panel (a) plots the cumulative effects on the extensive margin $\mathbb{1}$(News) (%). Panel (b) plots the cumulative effects on the intensive margin N News. See the table on page 47 for definition and construction of variables.

Figure 4. Cumulative Effects of Advertising Revenues on Journalism Job Postings

(a) 𝟙(Posting) (%)

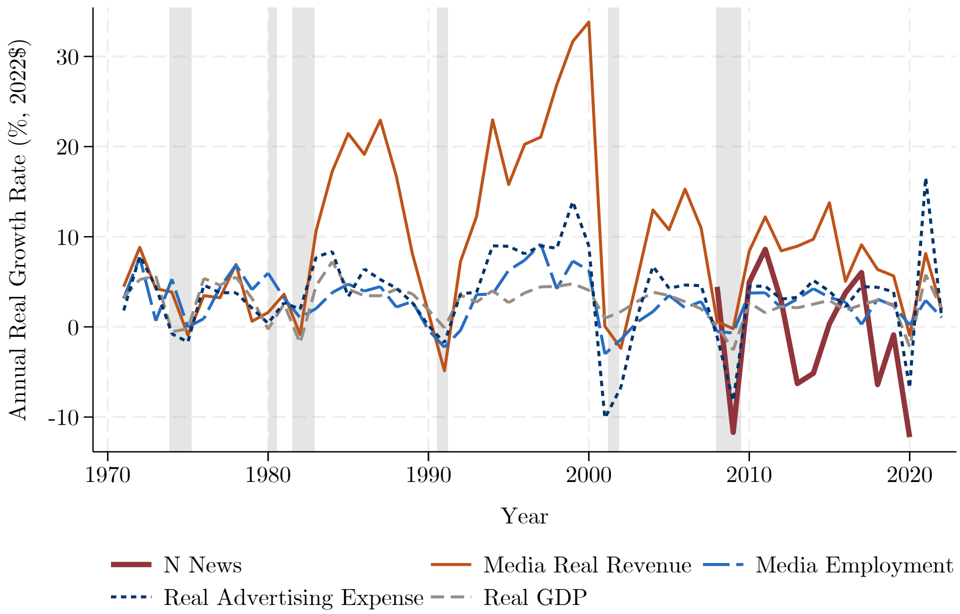


(b) Number of Postings



Notes. This figure plots twelve-month cumulative percentage effects of a one-SD shock to advertising revenues $Ad_{[t-2,t]}$ at time $[t-2, t]$ on journalism job postings from time $t+1$ to $t+12$. The percentage effects are calculated from the estimated coefficients β^h in the specification (7). Panel (a) plots the cumulative effects on the extensive margin $\mathbb{1}$(Posting) (%). Panel (b) plots the cumulative effects on the intensive margin N Postings. See the table on page 47 for definition and construction of variables.

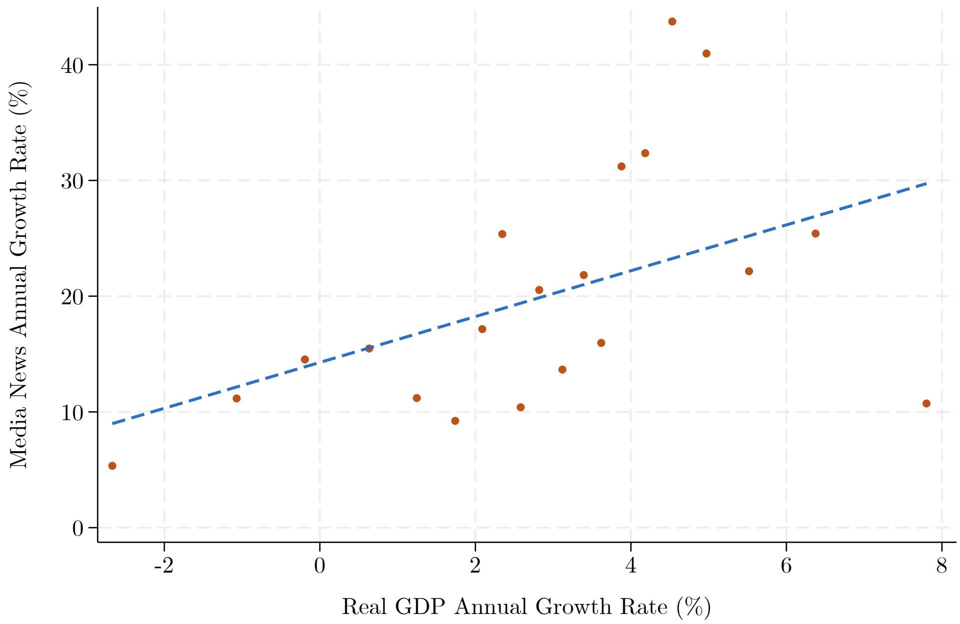
Figure 5. Procyclicality of News Production, Advertisement, and Media Revenue and Employment



Notes. This figure plots annual growth rates for the number of news, revenue and employment of media sector, advertising expenditure of all sectors, and real GDP, using the U.S. public firm sample from Compustat. The shaded bars indicate NBER recessions. See the table on page 47 for definition and construction of variables.

Figure 6. Procyclicality of Media News Production: International Sample

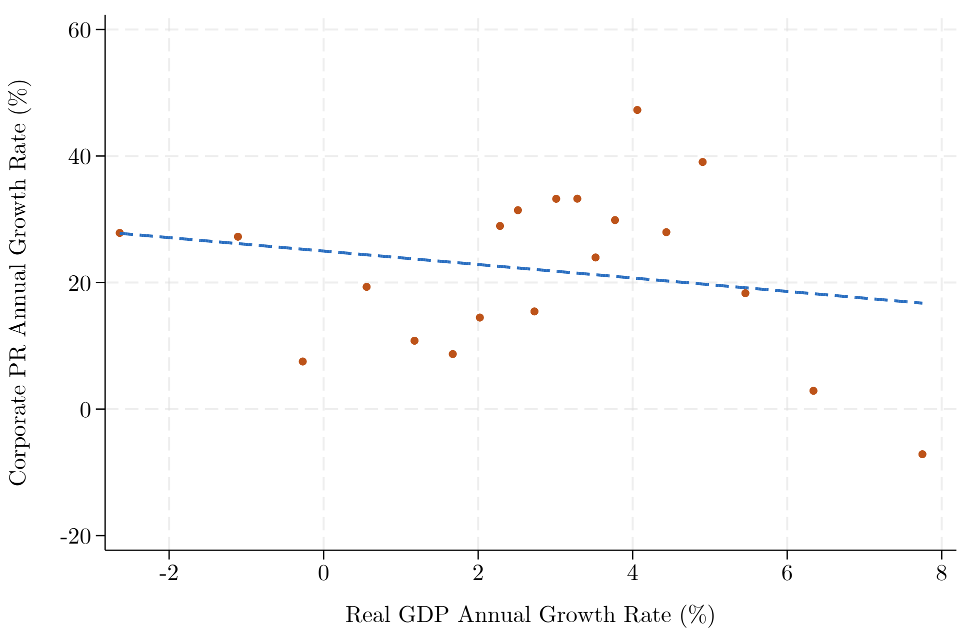
(a) Number of News



$$\Delta \ln\left(\#\ News_{c,t}\right) = \beta \times \Delta \ln\left(GDP_{c,t}\right) + \alpha_c + \epsilon_{c,t}$$

$$\hat{\beta} = 1.981^{***}(0.639)$$

(b) Number of Corporate Press Releases

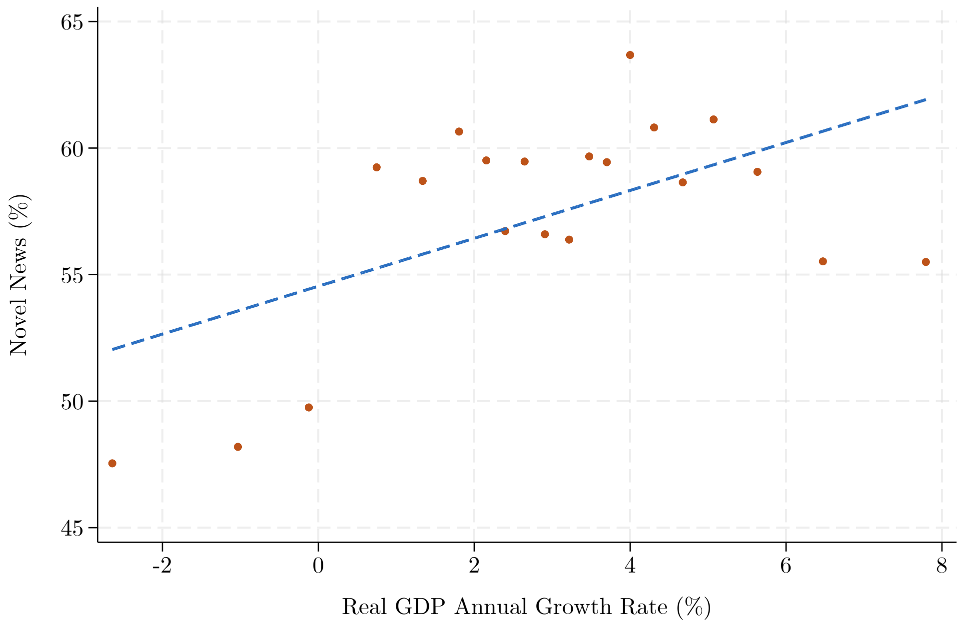


$$\Delta \ln\left(\#\ Corporate\ PR_{c,t}\right) = \beta \times \Delta \ln\left(GDP_{c,t}\right) + \alpha_c + \epsilon_{c,t}$$

$$\hat{\beta} = -1.063(0.822)$$

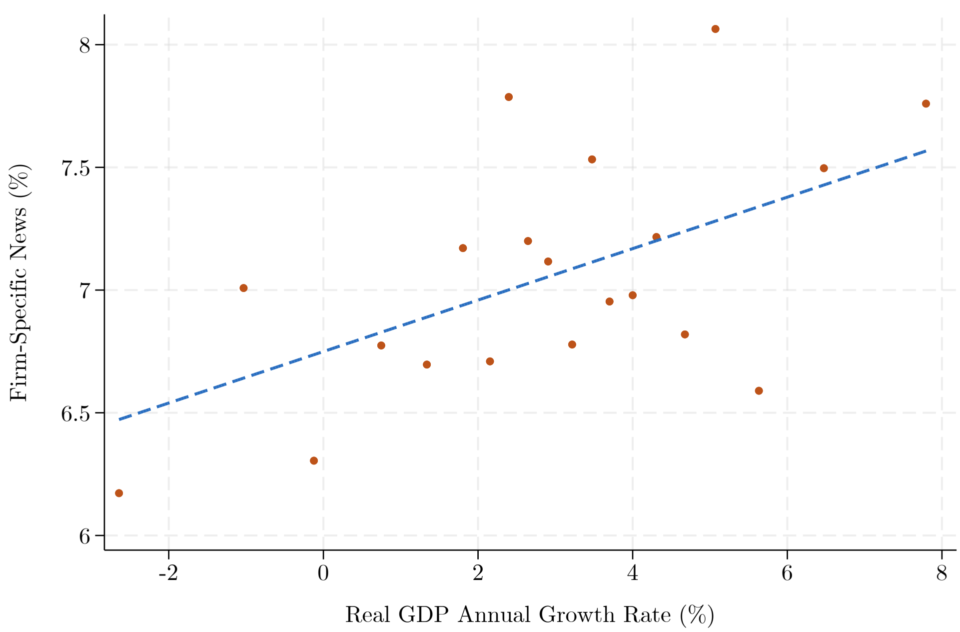
Figure 6. Procyclicality of Media News Production: International Sample

(c) Percentage of Novel News (%)



$$Novel_{c,t} = \beta \times \Delta \ln \left(GDP_{c,t}\right) + \alpha_c + \epsilon_{c,t}$$
$$\hat{\beta} = 0.946^{***}(0.225)$$

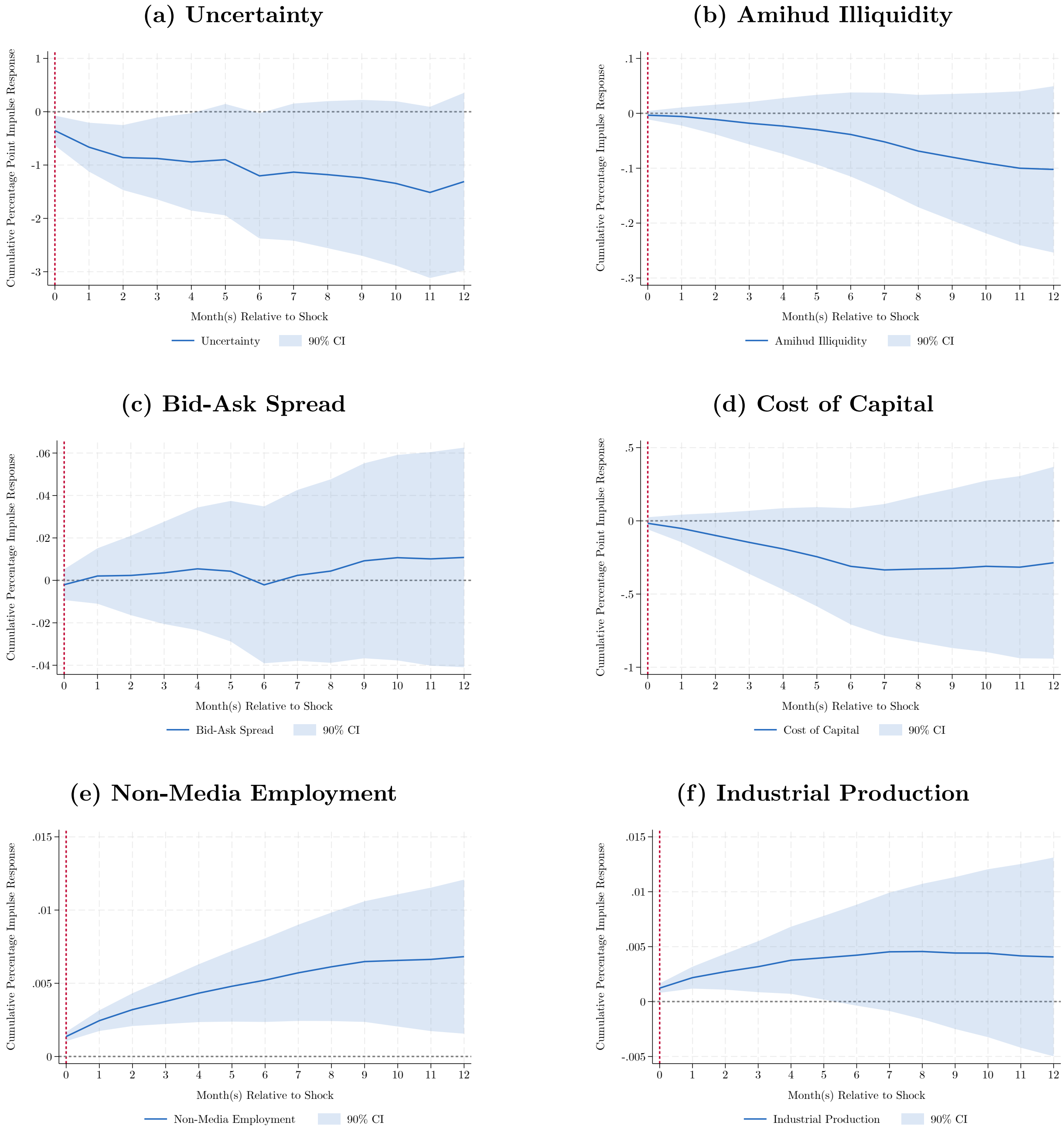
(d) Percentage of Firm-Specific News (%)



$$\textit{Firm-Specific}_{c,t} = \beta \times \Delta \ln \left(GDP_{c,t}\right) + \alpha_c + \epsilon_{c,t}$$
$$\hat{\beta} = 0.105^{**}(0.051)$$

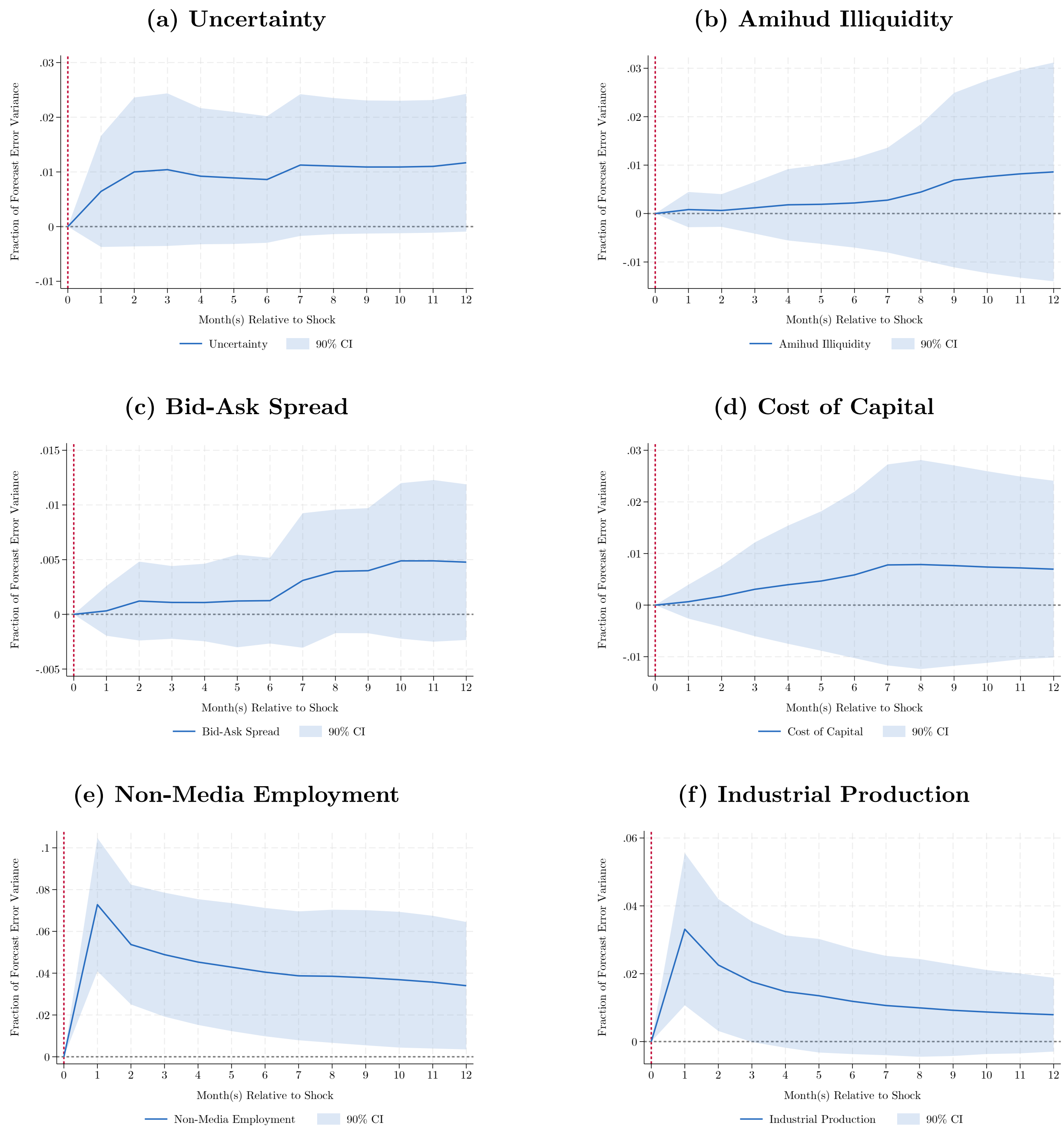
Notes. This figure includes binned scatter plots of annual growth rates of media-produced news (Panel a) and corporate press releases (Panel b), percentage of novel (Panel c) and firm-specific news (Panel d) over the annual growth rate of real GDP, using an international RavenPack sample of 50 countries from 2000 to 2021. Regression specifications, which include country fixed effects α_c, and estimated coefficients are presented below each plot. Standard errors double clustered at the level of country and year are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See the table on page 47 for definition and construction of variables.

Figure 7. VAR Cumulative Impulse Responses to News Production Shocks



Notes. This figure plots VAR Cholesky orthogonalized cumulative impulse response functions of uncertainty (Panel a), Amihud illiquidity (Panel b), bid-ask spread (Panel c), cost of capital (Panel d), non-media employment (Panel e), and industrial production (Panel f) to a one percent news production shock. See Subsection 6.2 for details on data and specification.

Figure 8. VAR Forecast Error Variance Decomposition to News Production Shocks



Notes. This figure plots fraction of the forecast error variance of uncertainty (Panel a), Amihud illiquidity (Panel b), bid-ask spread (Panel c), cost of capital (Panel d), non-media employment (Panel e), and industrial production (Panel f) to news production shock. See Subsection 6.2 for details on data and specification.

Tables

Table 1. Descriptive Statistics

(a) Descriptive Statistics for Monthly Media-Firm Panel

	N	Mean	SD	25%	50%	75%
Ad	9,973,799	4,879,694	11,800,479	129,979	821,951	3,674,564
$\mathbb{1}$(News) (%)	9,973,799	36.291	48.084	0.000	0.000	100.000
# News	9,973,799	7.006	115.596	0.000	0.000	2.000
Novel (%)	9,973,799	10.798	29.942	0.000	0.000	0.000
Firm-Specific (%)	9,973,799	5.335	18.720	0.000	0.000	0.000
Sentiment	1,210,072	54.107	12.127	50.000	51.000	61.500

(b) Descriptive Statistics for Monthly Media Panel

	N	Mean	SD	25%	50%	75%
Ad	57,139	1,522,424	6,244,971	18,322	137,681	736,464
# News	57,139	2,257	10,155	6	189	1,063
# Firms Covered	57,139	152	455	4	36	114
Novel (%)	57,139	41.142	42.711	0.000	31.250	86.364
Firm-Specific (%)	57,139	1.490	3.821	0.000	0.163	1.482
Sentiment	27,005	52.352	9.877	47.8	53.429	58.333
$\mathbb{1}$(Posting) (%)	14,814	23.93	42.67	0.00	0.00	0.00
# Postings	14,814	0.71	3.05	0.00	0.00	0.00
Salary	14,814	42,824	25,749	27,500	37,167	48,000
Experience	14,814	3.13	1.56	2.00	3.00	4.00
Education	14,814	15.80	0.87	16.00	16.00	16.00

Table 1. Descriptive Statistics

(c) Descriptive Statistics for Monthly Firm Panel

	N	Mean	SD	25%	50%	75%
# News	201,006	886	9,529	72	143	321
Δ ln(N News)	201,006	0.040	0.645	–0.359	0.028	0.427
Realized Volatility (%)	201,006	42.646	29.917	23.896	34.622	51.618
Implied Volatility (%)	201,006	46.283	27.032	28.733	39.240	55.533
Idiosycratic Volatility (%)	201,006	40.387	23.047	24.433	34.427	49.509
Forecast Dispersion	201,006	0.231	0.649	0.043	0.097	0.227
Bid-Ask Spread	201,006	3.819	2.316	2.293	3.202	4.637
Amihud Illiquidity	201,006	0.331	3.888	0.000	0.002	0.013
# KD Events	201,006	5.067	4.746	2.000	4.000	6.000
# Corporate Press Releases	201,006	5.851	9.912	2.000	4.000	8.000
Sentiment	201,006	53.355	6.043	49.880	53.091	56.977
Return (%)	201,006	1.713	16.814	–5.762	0.943	7.718
abs(Return) (%)	201,006	10.181	13.490	3.017	6.779	13.000
B/M	201,006	0.467	0.487	0.197	0.373	0.636
Size	201,006	13.932	1.978	12.584	13.938	15.247

Table 1. Descriptive Statistics

(d) Descriptive Statistics for Annual Firm Panel

	N	Mean	SD	25%	50%	75%
# News	23,353	7,515	101,436	526	1,138	2,558
Δ ln(# News)	23,353	0.051	0.468	–0.172	0.079	0.321
Implied Cost of Capital (%)	20,061	8.745	6.594	5.457	7.470	10.155
Composite Implied Cost of Capital (%)	20,061	4.021	10.692	–2.210	1.708	7.163
Perceived Cost of Capital (%)	19,449	9.730	1.083	8.983	9.737	10.507
Discount Rate (%)	9,087	14.786	2.424	13.217	14.659	16.286
Investment Rate	19,427	0.060	0.040	0.033	0.052	0.077
Δ ln(Intangible Investment)	23,353	0.060	0.195	–0.016	0.043	0.130
Δ ln(Employment)	23,353	0.024	0.098	–0.010	0.009	0.053
Δ ln(Sales)	23,353	0.070	0.287	–0.023	0.055	0.154
Δ ln(COGS)	23,353	0.065	0.298	–0.026	0.055	0.156
ROA	23,353	–0.022	0.221	–0.034	0.034	0.079
ΔShort-Term Debt	23,353	0.006	0.087	–0.001	0.000	0.007
ΔLong-Term Debt	23,353	0.020	0.111	–0.010	0.000	0.041
Equity Issuance	23,353	0.053	0.179	0.000	0.003	0.014
Total Financing	23,353	0.083	0.245	–0.004	0.016	0.085
Payouts	23,353	0.038	0.064	0.000	0.013	0.046
ΔCash Holdings	23,353	0.005	0.155	–0.024	0.002	0.040
# KD Events	23,353	44.753	39.592	24.000	40.000	57.000
# Corporate Press Releases	23,353	49.780	84.633	21.000	40.000	64.000
Sentiment	23,353	53.211	3.583	51.143	53.167	55.254
Return (%)	23,353	20.958	54.952	–13.067	10.530	40.661
Tangibility	23,353	0.544	3.861	0.168	0.372	0.776
Book Leverage	23,353	0.345	0.422	0.036	0.302	0.531
Tobin's Q	23,353	2.611	2.260	1.247	1.771	2.949
Size	23,353	6.229	2.416	4.812	6.495	7.868

Notes. This table reports descriptive statistics for monthly media-by-firm panel (Panel a), monthly media panel (Panel b), monthly public firm panel (Panel c), and annual public firm panel (Panel d). See the table on page 47 for variable definition and construction.

Table 2. Advertising Revenues Affect News Quantity and Quality

	(1) $\mathbb{1}(News_{t+1})$ (%)	(2) $\ln(\#\ News_{t+1})$	(3) $Novel_{t+1}$ (%)	(4) $Firm\text{-}Specific_{t+1}$ (%)	(5) $Sentiment_{t+1}$
OLS					
$\ln(Ad_{[t-2,t]})$	0.726***	0.014***	0.474***	0.275***	–0.099***
	(0.179)	(0.004)	(0.110)	(0.058)	(0.030)
IV					
$\ln(\widehat{Ad_{[t-2,t]}})$	2.294***	0.049***	1.654***	0.928***	–0.293***
	(0.447)	(0.010)	(0.287)	(0.146)	(0.088)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
OLS	3.26%	2.31%	7.15%	8.40%	–0.30%
IV	10.30%	8.30%	24.96%	28.35%	–0.88%
Mean of Dep. Var.	36.29	7.01	10.80	5.34	54.11
Controls	Y	Y	Y	Y	Y
Media-Firm FE	Y	Y	Y	Y	Y
Firm-Month FE	Y	Y	Y	Y	Y
N(Observations)	9,973,799	9,973,799	9,973,799	9,973,799	1,210,072
N(Media)	1,095	1,095	1,095	1,095	1,095
N(Firm)	5,689	5,689	5,689	5,689	5,689
N(Media-Firm)	286,772	286,772	286,772	286,772	286,772
N(Month)	132	132	132	132	132
KP F-stat	128.4	128.4	128.4	128.4	112.7

Notes. This table reports OLS and IV estimates for effects of advertising revenues on news quantity and quality, using the specification (4). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of media and month are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Advertising Revenues Affect Journalism Job Postings

	(1) $\mathbb{1}(Posting_{t+1})$ (%)	(2) $\ln(\#\ Postings_{t+1})$	(3) $\ln(Salary_{t+1})$	(4) $Experience_{t+1}$	(5) $Education_{t+1}$
OLS					
$\ln(Ad_{[t-2,t]})$	0.791***	0.015***	0.023**	–0.215***	0.037
	(0.252)	(0.003)	(0.009)	(0.080)	(0.029)
IV					
$\ln(\widehat{Ad}_{[t-2,t]})$	0.623**	0.015***	0.026**	–0.246***	0.032
	(0.303)	(0.003)	(0.010)	(0.092)	(0.025)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
OLS	5.39%	2.47%	3.82%	–11.19%	0.38%
IV	4.24%	2.53%	4.33%	–12.81%	0.33%
Mean of Dep. Var.	23.93	0.71	42,824	3.13	15.80
Controls	Y	Y	Y	Y	Y
Media FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
N(Observations)	14,814	14,814	14,814	14,814	14,814
N(Media)	492	492	492	492	492
N(Month)	132	132	132	132	132
KP F-stat	23.78	23.78	23.78	23.78	23.78

Notes. This table reports OLS and IV estimates for effects of advertising revenues on journalism job postings, using the specification (5). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of media and month are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Advertising Revenues Affect News Quantity and Quality: Heterogeneity

	(1) $\mathbb{1}(News_{t+1})$ (%)	(2) $\ln(\#\ News_{t+1})$	(3) $Novel_{t+1}$ (%)	(4) $Firm\text{-}Specific_{t+1}$ (%)	(5) $Sentiment_{t+1}$
Panel (a) More Constrained vs Less Constrained Media (IV estimates)					
$\ln(Ad_{[t-2,t]})$	2.426***	0.051***	1.730***	0.968***	–0.293***
$\times\mathbb{1}$ (More Constrained)	(0.461)	(0.011)	(0.299)	(0.152)	(0.088)
$\ln(Ad_{[t-2,t]})$	0.648	0.025**	0.590***	0.380***	–0.258
$\times\mathbb{1}$ (Less Constrained)	(0.527)	(0.011)	(0.201)	(0.089)	(0.238)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
More Constrained	10.89%	8.67%	26.10%	29.57%	–0.88%
Less Constrained	2.91%	4.16%	8.90%	11.61%	–0.78%
Panel (b) Standalone vs Group Media (IV estimates)					
$\ln(Ad_{[t-2,t]})$	2.414***	0.052***	1.769***	0.982***	–0.302***
$\times\mathbb{1}$ (Standalone)	(0.440)	(0.010)	(0.267)	(0.141)	(0.095)
$\ln(Ad_{[t-2,t]})$	1.403**	0.026	0.751	0.507**	–0.250***
$\times\mathbb{1}$ (Group)	(0.631)	(0.016)	(0.567)	(0.240)	(0.076)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
Standalone	10.84%	8.84%	26.69%	30.00%	–0.91%
Group	6.30%	4.33%	11.33%	15.49%	–0.75%
Panel (c) Small vs Large Media (IV estimates)					
$\ln(Ad_{[t-2,t]})$	2.094***	0.051***	0.863***	0.545***	0.252
$\times\mathbb{1}$ (Small)	(0.398)	(0.010)	(0.179)	(0.088)	(1.128)
$\ln(Ad_{[t-2,t]})$	2.297***	0.049***	1.665***	0.934***	–0.293***
$\times\mathbb{1}$ (Large)	(0.451)	(0.010)	(0.289)	(0.147)	(0.088)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
Small	9.40%	8.67%	13.02%	16.65%	0.76%
Large	10.31%	8.31%	25.12%	28.53%	–0.88%

Table 4. Advertising Revenues Affect News Quantity and Quality: Heterogeneity

	(1) $\mathbb{1}(News_{t+1})$ (%)	(2) $\ln(\# \, News_{t+1})$	(3) $Novel_{t+1}$ (%)	(4) $Firm\text{-}Specific_{t+1}$ (%)	(5) $Sentiment_{t+1}$
Panel (d) Top 10 Largest Media vs Others (IV estimates)					
$\ln(Ad_{[t-2,t]})$	1.544***	0.034***	2.009***	1.153***	–0.297***
$\times\mathbb{1}$ (Top10)	(0.270)	(0.007)	(0.365)	(0.185)	(0.089)
$\ln(Ad_{[t-2,t]})$	2.651***	0.056***	0.855***	0.423***	–0.197**
$\times\mathbb{1}$ (Others)	(0.558)	(0.013)	(0.172)	(0.080)	(0.089)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
Top10	6.93%	5.70%	30.31%	35.22%	–0.89%
Others	11.90%	9.56%	12.90%	12.92%	–0.59%
Panel (e) S&P500 vs Non-S&P500 Firms (IV estimates)					
$\ln(Ad_{[t-2,t]})$	1.872***	0.049***	2.361***	2.131***	–0.265*
$\times\mathbb{1}$ (S&P500)	(0.520)	(0.011)	(0.476)	(0.374)	(0.135)
$\ln(Ad_{[t-2,t]})$	2.378***	0.055***	1.528***	0.714***	–0.298***
$\times\mathbb{1}$ (Non-S&P500)	(0.436)	(0.010)	(0.261)	(0.110)	(0.086)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size \$6.245m)					
S&P500	8.41%	8.31%	35.63%	65.09%	–0.80%
Non-S&P500	10.68%	9.38%	23.06%	21.81%	–0.90%
Mean of Dep. Var.	36.29	7.01	10.80	5.34	54.11
Controls	Y	Y	Y	Y	Y
Media-Firm FE	Y	Y	Y	Y	Y
Firm-Month FE	Y	Y	Y	Y	Y
N(Observations)	9,973,799	9,973,799	9,973,799	9,973,799	1,210,072
N(Media)	1,095	1,095	1,095	1,095	1,095
N(Firm)	5,689	5,689	5,689	5,689	5,689
N(Media-Firm)	286,772	286,772	286,772	286,772	286,772
N(Month)	132	132	132	132	132
KP F-stat (Panel a)	73.33	73.33	73.33	73.33	56.88
KP F-stat (Panel b)	52.16	52.16	52.16	52.16	35.78
KP F-stat (Panel c)	76.20	76.20	76.20	76.20	56.43
KP F-stat (Panel d)	72.22	72.22	63.88	63.88	57.18
KP F-stat (Panel e)	73.31	73.31	61.67	61.67	46.46

Notes. This table reports OLS and IV estimates for effects of advertising revenues on news quantity and quality, using the specification (8). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of media and month are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5. News Production Affects Corporate Uncertainty and Information Asymmetry

	(1) Δ*Realized Volatility$_t$* (%)	(2) Δ*Implied Volatility$_t$* (%)	(3) Δ*Idiosyncratic Volatility$_t$* (%)	(4) Δ*Forecast Dispersion$_t$*	(5) Δ*Bid-Ask Spread$_t$*	(6) Δ*Amihud Illiquidity$_t$*
OLS						
$\Delta \ln(\#\ News_{t-1})$	–6.907***	–1.591***	–0.294***	–0.007***	–0.231***	–0.015*
	(0.228)	(0.098)	(0.010)	(0.001)	(0.010)	(0.009)
IV						
$\Delta \ln(\widehat{\#\ News_{t-1}})$	–7.906***	–1.616***	–0.273***	–0.006***	–0.181***	–0.021
	(0.364)	(0.169)	(0.013)	(0.001)	(0.016)	(0.018)
Magnitude of effect for an 8.30% shock to $\#$ *News$_{t-1}$*						
(the one-month effect of a one-SD advertising revenue shock to news production)						
OLS	–0.573	–0.132	–0.024	–0.001	–0.019	–0.001
IV	–0.656	–0.134	–0.023	0.000	–0.015	–0.002
Percentage effect for an 8.30% shock to $\#$ *News$_{t-1}$*						
(the one-month effect of a one-SD advertising revenue shock to news production)						
OLS	–1.34%	–0.29%	–0.06%	–0.25%	–0.50%	–0.38%
IV	–1.54%	–0.29%	–0.06%	–0.22%	–0.39%	–0.53%
Mean of Dep. Var.	42.646	46.283	40.387	0.231	3.819	0.331
Controls	Y	Y	Y	Y	Y	Y
Industry-Month FE	Y	Y	Y	Y	Y	Y
N(Observations)	201,006	201,006	201,006	201,006	201,006	201,006
N(Firm)	4,033	4,033	4,033	4,033	4,033	4,033
N(Month)	132	132	132	132	132	132
KP F-stat	138.9	138.9	138.9	138.9	138.9	138.9
Kelly and Ljungqvist (2012)'s estimated percentage effects of a one analyst coverage loss						
Percentage effect	14.30%	—	—	—	2.10%	18.00%
Number of analyst coverage gain to match the effect of a news shock (of size 8.30%)						
IV	1.291	—	—	—	2.248	0.351
Number of news shock (of size 8.30%) to match the estimated effects in Kelly and Ljungqvist (2012)						
IV	0.775	—	—	—	0.445	2.849

Notes. This table reports OLS and IV estimates for effects of media news production on firm uncertainty and information asymmetry, using the specification (9). Note that Kelly and Ljungqvist (2012) estimate the coverage termination's effects on annualized daily return volatility in a three-day window around quarterly earnings announcements instead of the usual daily return volatility. See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of firm and month are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6. News Production Affects Cost of Capital

	(1) Δ*Implied Cost of Capital$_t$* (%)	(2) Δ*Composite Implied Cost of Capital$_t$* (%)	(3) Δ*Perceived Cost of Capital$_t$* (%)	(4) Δ*Discount Rate$_t$* (%)
OLS				
$\Delta \ln(\# \; News_{t-1})$	–0.252	–1.314***	–0.029***	–0.221
	(0.329)	(0.188)	(0.005)	(0.332)
IV				
$\Delta \ln(\widehat{\# \; News_{t-1}})$	–0.462***	–2.154**	–0.070**	–0.398**
	(0.095)	(0.757)	(0.025)	(0.166)
Magnitude of effect for an 18.18% shock to # *News*$_{t-1}$				
(the one-year effect of a one-SD advertising revenue shock to news production)				
OLS	–0.046	–0.239	–0.005	–0.040
IV	–0.084	–0.392	–0.013	–0.072
Percentage effect for an 18.18% shock to # *News*$_{t-1}$				
(the one-year effect of a one-SD advertising revenue shock to news production)				
OLS	–0.52%	–5.94%	–0.05%	–0.27%
IV	–0.96%	–9.74%	–0.13%	–0.49%
Mean of Dep. Var.	8.745	4.021	9.730	14.786
Controls	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
N(Observations)	20,061	20,061	19,449	9,087
N(Firm)	3171	3171	2878	1283
N(Year)	12	12	12	12
KP F-stat	23.03	23.03	22.08	17.78

Notes. This table reports OLS and IV estimates for effects of media news production on measures of cost of capital, using the specification (9). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of firm and year are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7. News Production Affects Corporate Real Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Invest Rate$_t$	$\Delta\ln(Intangible\ Invest_t)$	$\Delta\ln(Emp_t)$	$\Delta\ln(Sales_t)$	$\Delta\ln(COGS_t)$	ΔROA_t
OLS						
$\Delta\ln(\#\ News_{t-1})$	0.014***	0.047***	0.019***	0.054***	0.047***	0.008**
	(0.002)	(0.005)	(0.003)	(0.009)	(0.007)	(0.003)
IV						
$\Delta\ln(\widehat{\#\ News_{t-1}})$	0.029***	0.088***	0.023***	0.086***	0.061**	0.014
	(0.009)	(0.015)	(0.005)	(0.025)	(0.021)	(0.009)
Magnitude of effect for an 18.18% shock to $\#$ *News*$_{t-1}$						
(the one-year effect of a one-SD advertising revenue shock to news production)						
OLS	0.003	0.009	0.003	0.010	0.009	0.001
IV	0.005	0.016	0.004	0.016	0.011	0.003
Mean of Dep. Var.	0.216	0.060	0.024	0.070	0.065	-0.022
Controls	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
N(Observations)	23,353	23,353	23,353	23,353	23,353	23,353
N(Firm)	3,803	3,803	3,803	3,803	3,803	3,803
N(Year)	12	12	12	12	12	12
KP F-stat	26.56	26.56	26.56	26.56	26.56	26.56
Alfaro et al. (2023)'s estimated effects of a two-SD volatility shock (of size 0.616)						
Magnitude of effect	–0.025	–0.032	–0.020	–0.134	–0.093	—
Change in volatility to match the effect of a news shock (of size 18.18%)						
IV	–0.130	–0.308	–0.129	–0.072	–0.073	—
Number of news shock (of size 18.18%) to match the estimated effects in Alfaro et al. (2023)						
IV	4.742	2.000	4.783	8.571	8.386	—

Notes. This table reports OLS and IV estimates for effects of media news production on corporate real outcomes, using the specification (9). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of firm and year are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. News Production Affects Corporate Financial Outcomes

	(1) $\Delta ST\ Debt_t$	(2) $\Delta LT\ Debt_t$	(3) $Equity\ Issuance_t$	(4) $Total\ Financing_t$	(5) $Payouts_t$	(6) $\Delta Cash\ Holdings_t$
OLS						
$\Delta\ln(\#\ News_{t-1})$	–0.001	0.009**	0.037***	0.040***	–0.003*	0.041***
	(0.002)	(0.004)	(0.005)	(0.004)	(0.001)	(0.005)
IV						
$\Delta\ln(\widehat{\#\ News}_{t-1})$	–0.008	0.020*	0.051***	0.056***	–0.003	0.062***
	(0.006)	(0.009)	(0.012)	(0.013)	(0.002)	(0.009)
Magnitude of effect for an 18.18% shock to $\#\ News_{t-1}$ (the one-year effect of a one-SD advertising revenue shock to news production)						
OLS	0.000	0.002	0.007	0.007	–0.001	0.007
IV	–0.001	0.004	0.009	0.010	–0.001	0.011
Mean of Dep. Var.	0.006	0.020	0.053	0.083	0.038	0.005
Controls	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
N(Observations)	23,353	23,353	23,353	23,353	23,353	23,353
N(Firm)	3,803	3,803	3,803	3,803	3,803	3,803
N(Year)	12	12	12	12	12	12
KP F-stat	26.56	26.56	26.56	26.56	26.56	26.56
Derrien and Kecskés (2013)'s estimated effects of a one analyst coverage loss						
Magnitude of effect	0.000	–0.011	–0.009	–0.020	0.001	–0.011
Number of analyst coverage gain to match the effect of a news shock (of size 18.18%)						
IV	—	0.340	1.030	0.504	0.496	1.006
Number of news shock (of size 18.18%) to match the estimated effects in Derrien and Kecskés (2013)						
IV	—	2.943	0.971	1.984	2.017	0.994

Notes. This table reports OLS and IV estimates for effects of media news production on corporate financial outcomes, using the specification (9). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of firm and year are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Descriptive Statistics for Aggregate Time Series

(a) Descriptive Statistics for Annual Aggregate Time Series

	N	Mean	SD	25%	50%	75%
Δln(GDP)	52	0.028	0.021	0.019	0.029	0.041
Δln(Advertising)	52	0.036	0.049	0.019	0.039	0.058
Δln(Media Emp)	52	0.095	0.088	0.033	0.083	0.145
Δln(Media Sales)	52	0.071	0.053	0.039	0.067	0.113
Δln(Non-Media Emp)	52	0.029	0.026	0.010	0.031	0.042
Δln(Non-Media Sales)	52	0.017	0.014	0.009	0.019	0.027

(b) Descriptive Statistics for Monthly Aggregate Time Series

	N	Mean	SD	25%	50%	75%
Δln(Media Emp)	630	0.001	0.017	–0.001	0.001	0.003
Δln(S&P 500)	630	0.005	0.044	–0.019	0.009	0.035
Uncertainty (%)	630	48.384	10.315	41.417	46.968	53.418
ΔUncertainty (%)	630	0.024	6.667	–3.717	0.133	3.526
Δln(Amihud Illiquidity)	630	–0.006	0.158	–0.061	0.001	0.058
Δln(Bid-Ask Spread)	630	0.001	0.151	–0.074	–0.007	0.067
Cost of Capital (%)	630	8.686	4.732	4.996	7.566	11.934
ΔCost of Capital (%)	630	–0.002	0.800	–0.383	–0.059	0.362
Federal Funds Rate (%)	630	4.986	3.851	1.690	5.070	6.920
ΔFederal Funds Rate (%)	630	–0.005	0.524	–0.080	0.010	0.120
Δln(Wage)	630	0.003	0.003	0.001	0.003	0.005
Δln(CPI)	630	0.003	0.003	0.002	0.003	0.005
Δln(Hours)	630	–0.000	0.007	–0.002	0.000	0.002
Δln(Non-Media Emp)	630	0.001	0.007	0.001	0.002	0.003
Δln(Industrial Production)	630	0.002	0.010	–0.002	0.002	0.006

Notes. This table reports descriptive statistics for annual aggregate time series (Panel a) from 1970 to 2022 and monthly aggregate time series (Panel b) from January 1970 to June 2022. See the table on page 47 for variable definition and construction.

Table 10. Procyclicality of Advertisement and Media Revenue and Employment

	(1) $\Delta \ln(Ad_t)$	(2) $\Delta \ln(Media\ Sales_t)$	(3) $\Delta \ln(Media\ Sales_t)$	(4) $\Delta \ln(Media\ Emp_t)$	(5) $\Delta \ln(Media\ Emp_t)$
$\Delta \ln(Ad_t)$		1.282***	1.203***	0.350***	0.374***
		(0.176)	(0.260)	(0.056)	(0.083)
$\Delta \ln(GDP_t)$	1.748***		0.255		-0.076
	(0.222)		(0.616)		(0.197)
Sample	U.S. Time Series				
Time Span	1970-2022				
N(Observations)	52	52	52	52	52
R^2	0.544	0.506	0.508	0.427	0.428

Notes. This table reports OLS estimates for regressing annual growth rates of aggregate advertising expenditure, media sector sales, and media sector employment on real growth rates of GDP and aggregate advertising expenditure, using the U.S. aggregate time series constructed from a Compustat panel of U.S. public firms. Newey-West standard errors with six lags are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Procyclicality of News Production: International Sample

	(1) $\Delta \ln(\#\ News_t)$	(2) $\Delta \ln(\#\ PR_t)$	(3) $Novel_t$ (%)	(4) $Firm\text{-}Specific_t$ (%)
$\Delta \ln(GDP_t)$	1.981***	–1.063	0.946***	0.105**
	(0.639)	(0.822)	(0.225)	(0.051)
Country FE	Y	Y	Y	Y
Sample	International Panel			
Time Span	2000-2021			
N(Observations)	1,100	1,100	1,100	1,100
N(Country)	50	50	50	50
R^2	0.053	0.013	0.144	0.409

Notes. This table reports OLS estimates for regressing annual growth rate of number of news and number of corporate press releases, percentage of novel news, and percentage of firm-specific news on real growth rate of GDP, using a international country-year panel. Standard errors double clustered at the level of country and year are in parentheses.

Internet Appendix

Financial News Production

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Table of Contents

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A Additional Empirical Results

A.1 Price Informativeness, Nonsynchronicity, and Delay

I study the effect of financial news production on price informativeness. Following Chen et al. (2007) and Bond et al. (2012), I focus on two measures of price informativeness. The first measure is probability of informed trading PIN, which was developed in Easley et al. (1996) and Easley et al. (2002). Based on a structural market microstructure model, this measure directly captures the probability of informed trading in a stock. I use the data from Trade and Quote (TAQ) Intraday Indicators by WRDS, which classify all trades as either a buyer-initiated trade or a seller-initiated trade using the Lee and Ready (1991) algorithm. I then estimate a firm-year PIN based on the number of buys and sells in each trading day of the year, using the R package `PINstimation`. I set a firm's PIN to be missing in a year if there are less than thirty trading days available for the estimation.

The second measure is price nonsynchronicity, which was first proposed by Roll (1988) and recently developed by Morck et al. (2000) and Durnev et al. (2003). The measure is defined as $1 - R^2$, where R^2 is the R-square from the following regression:

$$r_{i,t} = \alpha_i + \beta_i^{MKT} \cdot r_{m,t} + \beta_{g(i)}^{IND} \cdot r_{g(i),t} + \varepsilon_{i,t},$$

where $r_{i,t}$ is the return of firm i in industry $g(i)$ at time t, $r_{m,t}$ is the value-weighted market return of the CRSP universe at time t, and $r_{g(i),t}$ the return of industry $g(i)$ defined by three-digit SIC code at time t. For each firm in each year, I run such a regression on daily returns and obtain the measures of price nonsynchronicity (i.e., $1-R^2$) and market beta (i.e., β^{MKT}). I set the measure to be missing if it is estimated with less than 30 daily observations.

I also consider the firm-specific price informativeness, which was recently developed by Dávila and Parlatore (2023a) and Dávila and Parlatore (2023b).[2]

[2] The data and programs are downloaded from https://github.com/edavila/identifying_price_informativeness. I extend the sample to 2022 using the programs shared by the authors.

Finally, I consider the measure of price delay (Hou and Moskowitz, 2005) as a proxy for price efficiency. The measure of price delay captures how quickly market-wide information is incorporated into stock prices by examining the sensitivity of a firm's returns to contemporaneous and lagged market returns. For each firm in each year, I first estimate the following regression using daily returns:

$$r_{i,t} = \alpha_i + \beta_i^{MKT} \cdot r_{m,t} + \sum_{l=1}^{4} \beta_i^{MKT,l} \cdot r_{m,t-l} + \varepsilon_{i,t},$$

where $r_{i,t}$ is the return of firm i at time t, $r_{m,t}$ is the value-weighted market return of the CRSP universe at time t. I then estimate a second regression in which the coefficients on lagged market returns are constrained to be zero. The price delay measure is calculated as $1 - R^2(\text{restricted model})/R^2(\text{unrestricted model})$.

Table A3 presents the results estimated using the same specification (9) in my main analysis. According to the estimated coefficients, I calculate the magnitude of the effect and percentage effect for an 18.18 percent increase in the number of news (i.e., # *News*). The 18.18 percent increase corresponds to the one-year percentage effect on news from a one-standard-deviation shock to advertising revenue, as reported in Panel (b) Figure 3.

[Insert Table A3 here]

As shown in Table A3, media news production significantly increases firms' price informativeness and decreases firms' price delay and market betas. The is true for PIN, Dávila and Parlatore (2023b)'s measure of price informativeness, and price nonsynchronicity. In terms of the magnitudes, an 18.18 percent increase in news production leads to 1 percent rise in PIN, 3 percent rise in Dávila and Parlatore (2023b)'s price informativeness, 2 percent rise in price nonsynchronicity, and 7 percent decline in market beta.

A.2 Analyst Coverage and Forecast Error

I examine the complementarity between the information production by financial media and financial analysts. Specifically, I study the effects of media news production on the number of analyst coverage and absolute percentage analyst forecast error on one/two/three-year-ahead earnings per share (EPS).

Following Bouchaud et al. (2019), I obtain analyst-by-analyst EPS forecasts from the I/B/E/S Detail History File (unadjusted). I keep all forecasts that were issued 45 days after an announcement of total fiscal year earnings. If an analyst issues multiple forecasts for the same firm and the same fiscal year during this 45-day period, I keep only the first forecast. The firm-level consensus EPS forecast is calculated from detailed analyst-by-analyst forecasts. I then match actual reported EPS from the I/B/E/S unadjusted actuals file with the calculated consensus forecasts. My measure, absolute percentage analyst forecast error, is calculated as the absolute value of the difference between actual EPS and consensus EPS forecast, which is normalized by lagged price per share.

Table A4 shows the results estimated using the same specification (9) in my main analysis. According to the estimated coefficients, I calculate the magnitude of the effect and percentage effect for an 18.18 percent increase in the number of news (i.e., *# News*). The 18.18 percent increase corresponds to the one-year percentage effect on news from a one-standard-deviation shock to advertising revenue, as reported in Panel (b) Figure 3.

[Insert Table A4 here]

The coefficient in Column (1) indicates that media news production significantly increases analyst coverage. An 18.18 percent increase in news production leads to an increase of 0.07 analyst coverage, which is a 1 percent effect from the mean value 6.1. The coefficients in Columns (2)-(4) show that by consuming media-produced news, analysts make more accurate forecasts on future EPS. The absolute percentage forecast error drops by 0.13 percentage point (4 percent relative to the mean) over a one-year horizon and by 0.24 percentage point

(4-5 percent relative to the mean) over the two and three-year horizons.

A.3 Procyclicality of News Production

I also document the procyclicality of advertisement, media revenue and employment at the firm level and compare the procyclicality of media and non-media firms. I regress the annual growth rates of advertising expenditure, sales, and employment on the real growth rate of GDP. I implement this regression on the firm-year panel with firm fixed effects. I also compare media and non-media's degrees of procyclicality by interacting GDP growth with dummy variables. Table A5 presents the results. It reveals that news media revenue and employment are significantly more sensitive to aggregate fluctuations relative to those of non-media firms.

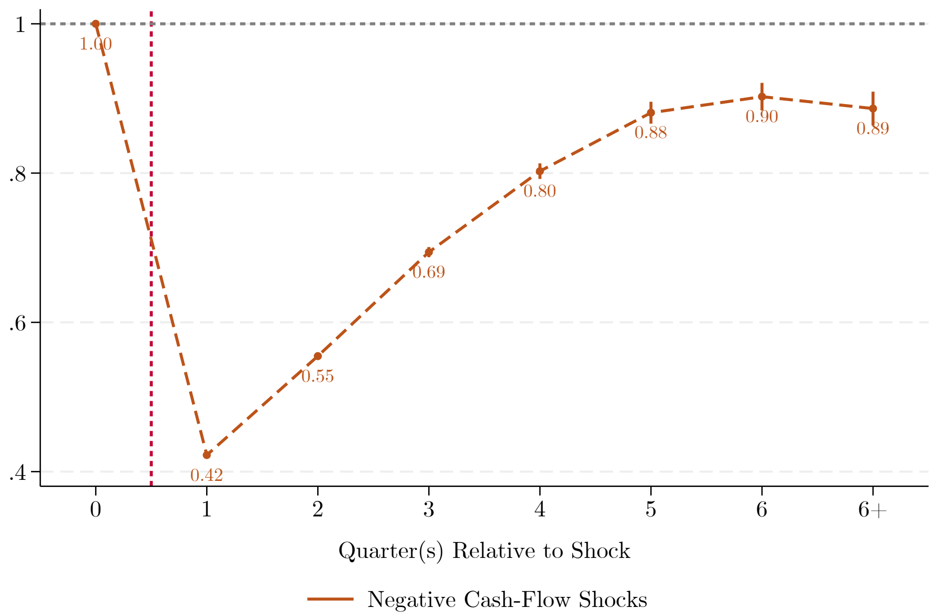
[Insert Table A5 here]

According to the estimates, a one percent drop in GDP corresponds to a 1.8 percent drop in advertisement, a 2.5-3.8 percent drop in media revenue, and a 0.7-0.9 percent drop in media employment. News media are significantly more sensitive to GDP growth relative to non-media, which comove with GDP growth by a 1.7-2.1 percent drop in revenue and a 0.4-0.6 percent drop in employment.

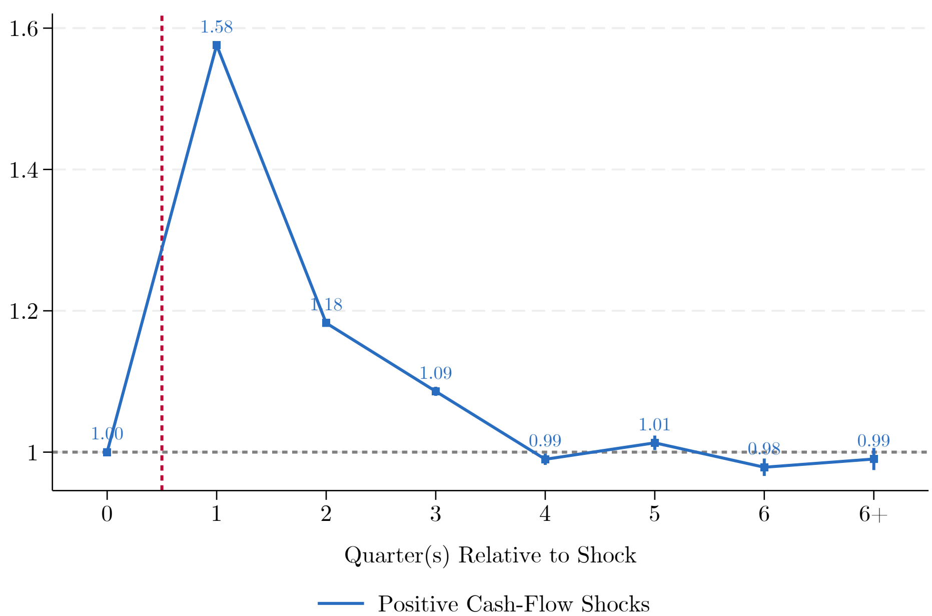
B Additional Figures

Figure A1. Cash-Flow Shock Persistence

(a) Level of Advertising Revenue After >20% Negative Shocks



(b) Level of Advertising Revenue After >20% Positive Shocks



Notes. This figure plots the level of quarterly advertising revenue for media outlets which experience cash-flow shocks that are greater than negative twenty percent (Panel a) or positive twenty percent (Panel b).

C Additional Tables

Table A1. Advertising Revenues Affect News Quantity and Quality (Media Panel)

	(1) $\ln(\#\ News_{t+1})$	(2) $\ln(\#\ Firms_{t+1})$	(3) $Novel_{t+1}$ (%)	(4) $Firm\text{-}Specific_{t+1}$ (%)	(5) $Sentiment_{t+1}$
OLS					
$\ln(Ad_{[t-2,t]})$	0.032***	0.017***	0.282**	0.027*	–0.093*
	(0.008)	(0.006)	(0.132)	(0.014)	(0.051)
IV					
$\ln(\widehat{Ad_{[t-2,t]}})$	0.034***	0.017***	0.324***	0.032***	–0.097**
	(0.009)	(0.006)	(0.121)	(0.012)	(0.045)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ (of size $6.245m)					
OLS	5.35%	2.81%	1.10%	2.91%	–0.29%
IV	5.70%	2.81%	1.26%	3.44%	–0.30%
Mean of Dep. Var.	2,257	151.93	41.81	1.51	52.22
Controls	Y	Y	Y	Y	Y
Media FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
N(Observations)	57,139	57,139	57,139	57,139	27,005
N(Media)	1,095	1,095	1,095	1,095	1,095
N(Month)	132	132	132	132	132
KP F-stat	201.8	201.8	201.8	201.8	141.2

Notes. This table reports OLS and IV estimates for effects of advertising revenues on news quantity and quality, using the specification (5). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of media and month are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Advertising Revenues Affect News Quantity and Quality: Robustness

	(1) $\mathbb{1}(News_{t+1})$ (%)	(2) $\ln(\# \ News_{t+1})$	(3) $Novel_{t+1}$ (%)	(4) $Firm\text{-}Specific_{t+1}$ (%)	(5) $Sentiment_{t+1}$
Panel (a) Excluding SIC1 Industries (IV estimates)					
$\ln(\widehat{Ad_{[t-2,t]}})$	1.347***	0.029***	0.863***	0.506***	–0.222***
	(0.268)	(0.006)	(0.154)	(0.080)	(0.048)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ **(of size $6.245m)**					
	6.05%	4.84%	13.02%	15.46%	–0.67%
Panel (b) Excluding Highly-Correlated Industries (IV estimates)					
$\ln(\widehat{Ad_{[t-2,t]}})$	0.786***	0.017***	0.490***	0.302***	–0.133***
	(0.165)	(0.004)	(0.098)	(0.053)	(0.034)
Percentage effect of a one-SD shock to $Ad_{[t-2,t]}$ **(of size $6.245m)**					
	3.53%	2.81%	7.39%	9.22%	–0.40%
Mean of Dep. Var.	36.29	7.01	10.80	5.34	54.11
Controls	Y	Y	Y	Y	Y
Media-Firm FE	Y	Y	Y	Y	Y
Firm-Month FE	Y	Y	Y	Y	Y
N(Observations)	9,973,799	9,973,799	9,973,799	9,973,799	1,210,072
N(Media)	1,095	1,095	1,095	1,095	1,095
N(Firm)	5,689	5,689	5,689	5,689	5,689
N(Media-Firm)	286,772	286,772	286,772	286,772	286,772
N(Month)	132	132	132	132	132
KP F-stat (Panel a)	131.9	131.9	131.9	131.9	126.4
KP F-stat (Panel b)	125.9	125.9	125.9	125.9	131.3

Notes. This table reports IV estimates for effects of advertising revenues on news quantity and quality, using the specification (8). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of media and month are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3. News Production Affects Price Informativeness, Nonsynchronicity, and Delay

	(1)	(2)	(3)	(4)	(5)
	ΔPIN_t	Δ*Price* *Informativeness*$_t$	Δ*Price* *Nonsynchronicity*$_t$	Δ*Price* *Delay*$_t$	$\Delta\beta_t^{MKT}$
OLS					
$\Delta\ln(\#\ News_{t-1})$	0.003*	0.003*	0.021***	–0.022***	–0.096***
	(0.001)	(0.001)	(0.004)	(0.006)	(0.027)
IV					
$\Delta\ln(\widehat{\#\ News}_{t-1})$	0.008***	0.007***	0.062***	–0.033**	–0.157**
	(0.002)	(0.002)	(0.018)	(0.015)	(0.069)
Magnitude of effect for an 18.18% shock to $\#$ *News*$_{t-1}$					
(the one-year effect of a one-SD advertising revenue shock to news production)					
OLS	0.001	0.001	0.004	–0.004	–0.017
IV	0.001	0.001	0.011	–0.006	–0.029
Percentage effect for an 18.18% shock to $\#$ *News*$_{t-1}$					
(the one-year effect of a one-SD advertising revenue shock to news production)					
OLS	0.40%	1.21%	0.59%	–2.55%	–4.41%
IV	1.08%	2.83%	1.74%	–3.82%	–7.21%
Mean of Dep. Var.	0.135	0.045	0.646	0.157	0.396
Controls	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y
N(Observations)	18,975	12,225	18,632	18,632	18,632
N(Firm)	3,223	1,782	3,051	3,051	3,051
N(Year)	12	12	12	12	12
KP F-stat	23.08	24.27	23.81	23.81	23.81

Notes. This table reports OLS and IV estimates for effects of media news production on measures of price informativeness, using the specification (9). *Price Informativeness*is constructed following Dávila and Parlatore (2023a) and Dávila and Parlatore (2023b). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of firm and year are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A4. News Production Affects Analyst Coverage and Forecast Error

	(1)	(2)	(3)	(4)
		Δ*Absolute Forecast Error*$_t$ (%)		
	$\Delta\#Analyst_t$	One-Year-Ahead	Two-Year-Ahead	Three-Year-Ahead
OLS				
$\Delta\ln(\#\ News_{t-1})$	0.239***	–0.315***	–0.220	–0.396
	(0.053)	(0.114)	(0.165)	(0.309)
IV				
$\Delta\ln(\widehat{\#\ News_{t-1}})$	0.358*	–0.708**	–1.333***	–1.346**
	(0.163)	(0.319)	(0.490)	(0.537)
Magnitude of effect for an 18.18% shock to $\#$ *News*$_{t-1}$				
(the one-year effect of a one-SD advertising revenue shock to news production)				
OLS	0.043	–0.057	–0.040	–0.072
IV	0.065	–0.129	–0.242	–0.245
Percentage effect for an 18.18% shock to $\#$ *News*$_{t-1}$				
(the one-year effect of a one-SD advertising revenue shock to news production)				
OLS	0.71%	–1.83%	–0.86%	–1.25%
IV	1.07%	–4.12%	–5.21%	–4.24%
Mean of Dep. Var.	6.107	3.122	4.655	5.777
Controls	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
N(Observations)	21,247	18,692	16,990	10,011
N(Firm)	3118	3168	2901	2122
N(Year)	12	12	12	11
KP F-stat	24.44	23.07	24.32	24.66

Notes. This table reports OLS and IV estimates for effects of media news production on the number of analyst coverage and absolute errors of analysts' forecasts on one/two/three-year-ahead earnings per share (EPS) normalized by lagged price per share, using the specification (9). See the table on page 47 for definition and construction of outcome measures. Standard errors double clustered at the level of firm and year are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Procyclicality of Advertisement and Media and Non-Media Revenue and Employment

	(1) $\Delta\ln(Ad_{i,t})$	(2) $\Delta\ln(Sales_{i,t})$	(3) $\Delta\ln(Emp_{i,t})$	(4) $\Delta\ln(Ad_t)$	(5) $\Delta\ln(Sales_t)$	(6) $\Delta\ln(Emp_t)$
$\Delta\ln(GDP_t)$	1.832***			1.748***		
	(0.319)			(0.222)		
$\Delta\ln(GDP_t) \times \mathbb{1}(Media)$		3.750***	0.926***		2.453***	0.701***
		(0.895)	(0.183)		(0.325)	(0.100)
$\Delta\ln(GDP_t) \times \mathbb{1}(Non\text{-}Media)$		2.054***	0.620***		1.675***	0.413***
		(0.270)	(0.068)		(0.325)	(0.100)
Coef. Diff. $Media - Non\text{-}Media$		1.696*	0.306*		0.778**	0.288***
		(0.896)	(0.159)		(0.331)	(0.102)
Firm FE	Y	Y	Y			
Sample	U.S. Compustat Panel			U.S. Time Series		
Time Span	1970-2022			1970-2022		
N(Observations)	93,249	319,819	271,919	52	104	104
R^2	0.157	0.168	0.167	0.544	0.366	0.325

Notes. This table reports OLS estimates for regressing annual growth rates of advertising expenditure, sales, employment on real growth rate of GDP, using a Compustat panel of U.S. public firms and the U.S. aggregate time series. Firm fixed effects are included in the panel regression. For panel regressions, standard errors double clustered at the level of firm and year are in parentheses. For time series regressions, Newey-West standard errors with six lags are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6. Top Five Rotemberg Weight Industries

Industry Name	SIC2	Rotemberg Weight α_g	*Growth Rate*$_g$	Just-Identified Coefficient β_g
Bank	60XX	0.216	–0.007	0.053
Retail	57XX	0.160	0.075	0.069
Insurance	63XX	0.096	0.017	0.018
Automobile	37XX	0.061	0.087	0.021
Real Estate	65XX	0.043	0.050	0.032

Table A7. Correlates of Industry Shares

	(1)	(2)	(3)	(4)	(5)
	Industry Shares (%)				
	Bank	Retail	Insurance	Automobile	Real Estate
ln(*Ad*)	–0.034	–0.061	–0.040	0.020	–0.059
	(0.058)	(0.054)	(0.054)	(0.057)	(0.063)
ln(# *News*)	–0.069	–0.132	–0.039	0.197	–0.230
	(0.307)	(0.217)	(0.204)	(0.221)	(0.244)
ln(# *Firms*)	0.133	0.348	0.054	–0.253	0.013
	(0.388)	(0.310)	(0.281)	(0.328)	(0.339)
Novel (%)	–0.005	0.006	–0.017	0.001	0.006
	(0.008)	(0.008)	(0.018)	(0.008)	(0.009)
Firm-Specific (%)	0.014	–0.015	–0.013	0.022	–0.003
	(0.040)	(0.031)	(0.036)	(0.037)	(0.031)
Sentiment	0.004	–0.009	–0.001	–0.016	–0.000
	(0.021)	(0.019)	(0.017)	(0.017)	(0.017)
$\mathbb{1}$(*Group*)	–0.180	0.411	0.208	0.411	0.671
	(0.475)	(0.591)	(0.471)	(0.528)	(0.618)
$\mathbb{1}$(*Blog*)	–0.056	0.119	0.258	0.288	0.141
	(0.468)	(0.471)	(0.497)	(0.445)	(0.506)
Time FE	Y	Y	Y	Y	Y
N(Observations)	24,090	24,090	24,090	24,090	24,090
R^2	0.302	0.124	0.208	0.150	0.229