Risk From the Inside Out: Firm Insights from Employee News Consumption*

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Abstract

We use novel data covering two billion daily employee-article interactions across two million firms to characterize firms' exposures to macroeconomic risk. We find that, in the time-series, employees consume more macroeconomic news following the onset of bad times. In the cross-section, firms whose employees were reading more macroeconomic news ex ante are more exposed to changing aggregate economic conditions ex post. Consistent with the notion that firm-employee news consumption provides predictive insights into a firm's risk exposures, we also show that these firms try to hedge more, yet have higher costs of capital and subsequently lower investment and hiring rates.

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Firms, investors, and policymakers face the difficult task of allocating scarce resources in a continuously evolving economic landscape. Recognizing this challenge, a growing literature looks to gain timely insights into *investors*' concerns by analyzing the types of topics published by newspapers (e.g., Bybee, Kelly, Manela, and Xiu, 2023a), aggregate trends in readership (e.g., Cookson, Garcia, and Jarnecic, 2023b), and social media discourse (e.g., Cookson, Engelberg, and Mullins, 2023a). But can we measure *firms*' economic concerns, namely their exposures to risk, in such an environment? This paper answers this question by probing the minds of each firm's employees, assessing the types of news they consume on a daily basis.

While the information revealed by a firm's top executives is informative about a firm's prospects and risk (see, e.g., Hassan, Hollander, Van Lent, and Tahoun, 2019), it is less evident that rank-and-file employees' news consumption would provide similar insights. On the one hand, a firm worried about its risk exposure could task its employees to learn about and act upon those risks. Similarly, employees may read news about the state of the economy if they are concerned about their own human capital that is tied to firm prospects. In either case, the news that the average employee reads may provide insights into the risks the firm faces. On the other hand, if rank-and-file employees read content largely unrelated to their employer's business or prospects (e.g., sports and weather), then the news they consume will be uninformative.

This paper shows that a firm's employees' news consumption patterns is informative about a firm's risk exposure. We establish this fact exploiting a granular dataset that quantifies firm-employee demand for online news content across more than two million firms, four thousand online publishers, and two billion daily user-article interactions. We construct a novel firm-level measure of the degree to which employees are paying attention to macroeconomic news relative to other business-related news (henceforth, their "relative attention"). We use this measure to infer each firm's exposure to systematic risk, establishing two baseline facts.

First, in the time series, employees at a typical firm shift their attention towards consuming more macroeconomic news in the days following bad aggregate economic conditions. As published news articles are an equilibrium outcome of readers' preferences and the media's production technology (Mullainathan and Shleifer, 2005), it is reassuring but not altogether surprising that aggregate consumption of macroeconomic news is correlated with measures of economic conditions. Thus, second, we conduct a cross-sectional analysis that establishes that firms that were reading more macroeconomic news prior to the onset of an economic shock consume even more macroeconomic news after the shock. These highly exposed firms have higher costs of capital, engage in more risk management, and subsequently invest less in both physical and human capital. In short, our analysis shows that firm-level employee news consumption reflects both the *ex-ante* exposure to macroeconomic risks as well as the *ex-post* reaction to subsequent macroeconomic shocks.

Our motivation for measuring firm-level risk exposures through employee news consumption is rooted in the literature that elicits firm-level expectations from surveys of key corporate personnel (see, e.g., Weber, D'Acunto, Gorodnichenko, and Coibion, 2022, for a review). While the responses to these surveys often reflect the expectations of top executives, they are typically (i) conducted on a low-frequency basis (e.g., quarterly or annual), (ii) reflect only the narrow set of questions asked by the surveyor, and (iii) conducted anonymously such that these expectations cannot be linked to firm actions. Our ability to observe the news consumption of rank-and-file employees at firms can be thought to reflect an almost high-frequency (i.e., daily) survey in which each employee expresses their most salient concerns. We thus assume that an employee concerned about a particular risk would choose to read news about it, and that, if enough employees are both aware and concerned, then employee-aggregated reading will also reflect the high firm-level exposure to that risk.

Our data on employee reading of news articles is drawn from a consortium of over four thousand online publishers (hereafter referred to as "the Consortium"). Each of these publishers—which span a variety of news publications (e.g., the Wall Street Journal, Forbes, and Bloomberg) and trade periodicals (e.g, Hart Energy and Step Stone)—provide the Consortium with data on each user-article interaction (e.g., URL of the article, time of reading, external IP address). This allows the Consortium to link the nearly 2 *billion* daily interactions between 2016 and 2022 to specific firms. For example, the Consortium would observe the ten unique users at Company A reading the same article on a given day, while observing only one user at Company B reading two different articles.

The Consortium deploys a machine learning algorithm on the content to decompose each article into its essential topics.[1] Returning to the previous example, the Consortium may determine that the article read by Company A was 30% related to "inflation" and 70% related to "FOMC."

[1]The Consortium's primary business is to generate a signal of user *intent* to purchase an underlying product or service. The objective of this machine learning algorithm is to generate an accurate, topic-specific signal so that a client of the Consortium can better direct sales, marketing and advertising dollars towards a firm whose topic-related intent is high. The Consortium is thus economically motivated to fit the large corpus and diverse set of topics as well as possible. At present, the articles are decomposed into nearly 7,000 unique topics.

In contrast, the first article read by Company B was 100% related to "CPUs," and the second article was evenly split between "CPUs" and "Cloud Computing." After decomposing each article into topics, the Consortium aggregates topic interactions within each firm and day to produce a dataset of firm-topic interactions. In our example, the Consortium would uncover that Company A (Company B) was mainly focused on the "FOMC" ("CPU") topic for that day. This dataset forms the basis of our ensuing analysis.

While the set of news sources, articles, and topics covered in the Consortium's dataset is vast, we are primarily interested in the degree to which firms are paying attention to macroeconomic news. To define a constrained set of macroeconomic-related topics, we construct a corpus of macroeconomically relevant news in the spirit of the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016). Namely, we gather articles that mention keywords, such as "economy," from the Wall Street Journal, USA Today, and New York Times, among other publishers. We have the Consortium deploy its algorithm onto these articles to identify the subset of approximately 600 topics in their corpus that are related to the macroeconomy. Aggregating each firm's relative attention towards this subset of topics on a given day allows us to obtain a firm-by-day measure of how intensively employees are *consuming* macroeconomic-related news.

Do the typical firm's employees shift their attention towards macroeconomic-related news as business conditions deteriorate? We answer this question using a proxy that captures the proportion of macroeconomic relevant topics a firm's employees are paying attention to on a given day relative to other topics. We find that in the time-series relative attention to macroeconomic news is closely related to the underlying state of the economy. For instance, the typical firm reads more macroeconomic news in the days following an increase in the corporate default spread, but less macroeconomic news as the funding conditions of financial intermediaries improve. Firms' employees also read relative more macroeconomic-related news following a rise in economic uncertainty, measured using either the VIX, EPU, or Bekaert, Engstrom, and Xu (2022) uncertainty indices.

While these time-series results demonstrate that employees re-allocate their attention to macroeconomic news in response to fluctuating economic conditions, they do not tell us which firms are most likely to shift their attention in bad times and why. As noted above, the set of news articles published are an equilibrium outcome of the media's production decisions and readers' preferences. As such, the previous measure of attention confounds supply and demand for news. To distinguish between the two we use a procedure similar to *tf-idf* scores in computational linguistics (see, e.g., Gentzkow, Kelly, and Taddy, 2019, for an application of *tf-idf* scores in finance). In short, terms with high (low) *tf-idf* scores are those that are most (least) useful for differentiating the content of a given document from a corpus of documents. Similarly, we compute time-varying *topic frequency, inverse aggregate frequency* (henceforth, *tf-iaf*) scores for each macroeconomic topic. Topics with a high (low) *tf-iaf* score in a given period are those that are the most (least) useful for differentiating what firms are paying attention to in the cross-section of firms.

As an example of the intuition underlying these scores, consider the monthly release of the Consumer Price Index (CPI). Many employees will read articles about inflation around this time by virtue of there being a higher supply of such articles. Knowing that two firms — A and B — are reading about inflation will tell us little about which firm is more exposed to the macroeconomy. Consequently, inflation-related topics will have low *tf-iaf* scores during these times. However, if the employees of Firm B also intensely read other macroeconomic topics (e.g., interest rate swaps or duration management), then these topics will carry relatively high *tf-iaf* scores. We classify Firm B and its employees as being plausibly more exposed to macroeconomic risk than Firm A. This logic also underlies the use of *tf-idf* scores to measure political risk (Hassan et al., 2019).

Our primary measure of firm-level exposure to macroeconomic risk captures the proportion of firm-employee attention towards macroeconomic topics, where topics are now weighted by their *tf-iaf* scores. Using the weighted measure of news consumption, we perform a simple validation exercise. If our cross-sectional measure of a firm's relative attention to macroeconomic news (henceforth, CS-RA$_{i,t}$) reflect firm exposure to macroeconomic risk, then we would expect the macroeconomic news consumption of the employees of high CS-RA$_{i,t}$ firms to be the more sensitive to fluctuating economic conditions than that of low CS-RA$_{i,t}$ firms. The results from this exercise are economically and statistically stark. When the level of economic activity declines, or the uncertainty associated with economic conditions rises, the employees of high CS-RA$_{i,t}$ firms consume even more macroeconomic news than the employees of low CS-RA$_{i,t}$ firms. We further corroborate these results by conducting a high-frequency event study examining how employees of high versus low CS-RA$_{i,t}$ firms shift their macroeconomic news consumption around the onset of the COVID-19 pandemic, which is the most prominent economic shock in our sample.

The set of topics that are upweighted (downweighted) to maximize cross-sectional differences in macroeconomic reading seems to reflect the systematic risk exposures of firms. Two natural questions follow. First, are the firms with employees who are reading more macroeconomic news actively managing their risk exposures? Second, how do investors perceive the risks of these more exposed firms? In regards to the first question, we find that firms reading the most about macroeconomic risk are about 10% more likely to partake in hedging activity than low CS-RA$_{i,t}$ firms. This propensity increases by an additional about 20% in bad times. We measure hedging activity using the approach of Campello, Lin, Ma, and Zou (2011) and define bad times as periods in which the EPU index is in its top decile. These findings are robust to a variety of controls and industry-by-date fixed effects. The latter result is important as prior studies (e.g. Hassan et al., 2019) have linked hedging activity to industry-specific risk exposures and key macroeconomic events. This specification shows that the relationship holds even controlling for such events.

In regards to the second question, we find that the equity market perceives these high CS-RA$_{i,t}$ firms as particularly risky. Notably, the implied cost of capital measure of Gebhardt, Lee, and Swaminathan (2001) shows that high CS-RA$_{i,t}$ have costs of capital that are about 0.60% to 1.70% per annum larger than those of low CS-RA$_{i,t}$ firms. This difference in the cost of capital across firms is not driven by common shocks at a given point in time (e.g., the onset of the COVID-19 pandemic) or differences in the cost of capital across industries (i.e., the fact that durable goods manufacturers are riskier than non-durable goods manufacturers). Moreover, the association between the intensity of macroeconomic-related reading and the cost of equity capital survives when we control for both industry-by-time fixed effects and a battery of firm-level characteristics typically associated with risk (e.g., size, leverage, and profitability).[2]

Having shown that reading important macroeconomic news is related to the cost of capital, we next show it also predicts future firm-level corporate decisions. For instance, the firms with the highest relative attention measures invest about 7.0% (3.0%) per quarter less in physical capital (inventories) and have hiring growth rates that are 5% per annum lower than firms with the lowest attention to the macroeconomy. We establish these results by estimating firm-level panel regressions that control for (i) a comprehensive set of observable firm characteristics that are known to predict real firm outcomes, and (ii) a variety of fixed effects that account for unobservable differences

[2]We find qualitatively similar results when we examine differences in the cost of capital across firms using simple portfolio sorts and realized returns rather than a regression approach based on analyst-implied costs of capital.

between industries and across time.

We conclude our analysis by asking two questions about which kinds of firms allocate their attention towards macroeconomic news. First, since the asset-pricing literature has demonstrated that firms with certain characteristics are particularly risky (e.g., those with high profitability rates and low investment rates), does a firm's relative attention simply reflect its underlying characteristics? We show that the answer to this question is unequivocally "no." A variance-decomposition analysis shows that variation in observable characteristics explain very little variation in relative attention. Second, we ask whether changing economic conditions have a causal impact on a firm's relative attention to macroeconomic news. We use the instrumental variables approach of Alfaro, Bloom, and Lin (2018) to show that exogenous variation in aggregate uncertainty has a pronounced effect on the attention allocation of a firm's employees.

1 Related Literature

This paper contributes to several strands of literature in economics and finance. Our focus on measuring each firm's exposure to macroeconomic risk through employee news consumption is motivated by the extensive literature demonstrating that shocks to the level and volatility of macroeconomic variables, such as consumption growth, are key drivers of marginal utility. For instance, the frameworks in Bansal and Yaron (2004); Campbell and Cochrane (1999); Gabaix (2012) focus on shocks to the level of macroeconomic growth, whereas studies including Bloom (2009); Colacito, Croce, Liu, and Shaliastovich (2022), among others, focus on time-varying second moments.

First- and second-moment shocks also feature prominently in empirical studies (see, e.g., Bali, Brown, and Tang, 2017; Ludvigson, Ma, and Ng, 2021). Finding suitable proxies for firm exposure to macroeconomic risk, however, remains challenging. Return-based measures, such as the covariance between each firm's excess returns and consumption growth or the VIX index, are noisy estimates of investors', as opposed to firms', perceptions of macroeconomic risk. In contrast, our ability to measure the types of news that employees are consuming reflect a real-time measure of the salient concerns that each firm's employees face. Our premise — which we empirically verify — is that the employees of riskier firms allocate a greater amount of their attention towards reading macroeconomic news compared to the employees of less risky firms. Firm employee attention to macroeconomic news thus serves as a non-return-based measure of the firm's risk exposure.[3]

Our motivation for measuring firm-level risk exposures via non-traditional data stems from the growing literature that elicits firm risk from key accounting disclosures. For instance, early work by Israelsen (2014) examines firm-level risks by estimating topic models on SEC filings to measure the risks firms disclose, while more recent work by Mazumder, Pruitt, and Ross (2023) considers text embedding in these disclosures to infer *how* a firm discloses particular risks. In a similar vein, Hassan et al. (2019) uses natural language processing methods to measure political and non-political risk using discussions in earnings call transcripts. While the aforementioned methods provide insights into how key decision-makers view their firm's risk exposures, they suffer from the fact that the underlying disclosures are made infrequently (i.e., on a quarterly or annual basis). In contrast, news consumption is available on a daily basis. Although few employees are the key decision makers, our results show that general employee news consumption is still highly informative about their employer's risks.

While our paper focuses on employee news *consumption*, our results are also related to the strand of literature that estimates economic quantities via news *production*. Examples include Dougal, Engelberg, Garcia, and Parsons (2012), who estimate the causal effect news articles on returns, Manela and Moreira (2017), who develop a news-based measure of news-based volatility, Baker et al. (2016), who develop an uncertainty index, and Bybee, Kelly, Manela, and Xiu (2021), who show how news content can predict macroeconomic quantities and financial market returns. Our work also relates to Bybee, Kelly, and Su (2023b), who construct a factor model based on narratives in the media to explain cross-sectional returns. Closely related to our study is Cookson, García, and Jarnecic (2023c), who examine how the *aggregate* consumption of articles published by the Australian Financial Review responds to variations in market-wide and firm-specific returns. In contrast to their study, we exploit the fact that we observe the internet domain of each reader to study *firm-level* news consumption to show that reading has both reactive and predictive value in understanding a firm's risk exposure.

Finally, our paper is broadly related to the literature on attention allocations. This literature emphasizes the importance of attention in decision-making as it shapes the information that in-

[3]Other studies that use non-traditional data to examine firm behavior include Loughran and McDonald (2011), who measure the tone of financial disclosures through textual analyses, and Ben-Rephael, Carlin, Da, and Israelsen (2021), who use Bloomberg terminal usage to characterize the provision of effort of corporate executives.

dividuals use to make choices (see, e.g., Gabaix, 2014). However, while much of the literature has focused on how individual and professional investors allocate their attention when making decisions (see, e.g., Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016; Peng and Xiong, 2006; Van Nieuwerburgh and Veldkamp, 2010), little is known about the attention allocation of the firm employees who are responsible for most of the firm's operations. Notably, it is not a given that the employees of firms that are exposed to more macroeconomic risk will spend more time reading about these topics. Indeed, Chinco, Hartzmark, and Sussman (2022) argue that investors do not appear to consider consumption risk in investment decisions, despite the large academic literature on consumption-based asset pricing. When viewed against this backdrop, our evidence is consistent with the notion of rational attention; specifically, rank-and-file employees of riskier firms are indeed more likely to pay attention to business-cycle risks.

2 Data

Our proprietary data comes from a company – "the Consortium" – that analyzes content in internet articles published across thousands of media sites (members). Although the Consortium's primary business objective is to supply clients with actionable signals of *intent* to purchase specific business-to-business products and services, the scope and variety of topics covered by their text corpus is broad. The topic breadth stems from the Consortium's diverse member pool spanning numerous industries and businesses. Members range from generalist publishers, including The Wall Street Journal, Forbes, and Bloomberg, to more specialized and niche content providers such as Hart (energy), StepStone (private equity), and Quin Street (consumer products). Figure 1 presents a small fraction of the approximately 4,000 publishers that supply the Consortium with its data.

The Consortium's members are publishers who supply raw readership data; in return, they receive analytics providing insights into user (i.e., readers) engagement with their published content. Members are also part owners of the Consortium and so share profits from the Consortium's core business. On a typical day, the Consortium observes over two *billion* user interactions, garnering rich perspectives on employees' daily reading habits across public, private, and non-profit firms. For each interaction, the Consortium logs several data points, including the URL of the specific online content being read, the user's external IP address, and their cookie data. Leveraging the

URLs of each online article, the Consortium employs a BERT-based algorithm to decompose each article into topics.[4] The Consortium uses the supplied IP addresses and cookie data to associate users with domains; thus linking topic interactions to specific firms. This process provides us with granular data on the degree to which each firm (i.e., domain) is paying attention to specific topics on a daily basis.

2.1 Topic Decomposition

The Consortium's algorithms distill individual news articles into their key topics - combinations of words and associations that are learned using a set of training corpora and validated by humans. These topics come in two varieties (see, e.g., Gentzkow et al. (2019) for an overview of these textual analysis methods). "Specific" topics are created with the purpose of providing insights to client firms that sell particular products or services. For example, a biotechnology firm may request information on which companies are researching "RNA sequencing" and "cancer genomics," to guide its sales and fundraising teams. On the other hand, "general" topics, which are learned from a broader corpus of articles, are created to enhance the fit of the Consortium's natural language processing (NLP) algorithm, i.e., subsume common variation in reading across users (e.g., articles about politics, vacations, and sports). One would assume that interactions with these "general" topics offer limited insights into firm-specific business operations.

Each article is potentially a combination of many topics. For instance, a piece covering "RNA sequencing" and "cancer genomics" may also reference the "U.S. Food and Drug Administration (FDA)." The Consortium's NLP algorithm generates a proportionality score indicating the significance of each topic in an article. In the previous example, the Consortium's algorithm may determine that 50% of the article relates to "RNA sequencing," 45% to "cancer genomics," but only 5% to the FDA. Re-training the Consortium's NLP algorithm on the set of daily *user-article* interactions to, e.g., expand the set of topics is both financially expensive and time-consuming. We thus take the topic decomposition as a fixed component of our analysis.

After running its NLP algorithm on the high-dimensional dataset, the Consortium constructs a lower dimensional dataset of daily *domain-topic* interactions. Prior to this, the Consortium applies

[4] BERT, which stands for **B**idirectional **E**ncoder **R**epresentation from **T**ransformers, is a large language model developed by Google Research in 2018 (see Devlin, Chang, Lee, and Toutanova, 2018, for more details).

several filters to streamline the data and focus solely on meaningful content interactions, including bot-detection and proportionality thresholds. For example, topic proportionality must not only be sufficiently high on a per article basis, but also repeat with high enough historical frequency for the interaction to be included. On a typical day, this *domain-topic* dataset features roughly two million domains and 7,000 topics. Finally, as we are interested in understanding what the allocation of employee-time in the cross-section tells us about firm risk, we focus on the number of employees that interact with a given topic each day rather than the number of interactions with a topic. This choice further de-emphasizes the anomalously large number of interactions that may come from a bot.

Figure 2 illustrates this process and shows a fictional domain (xyz.com) with three users on 11/17/2018. Each user reads the same Wall Street Journal (WSJ) article, one user also reads an article on microchip.com, and another user also reads an article by Bloomberg. Each publisher feeds this user-article interaction data to the Consortium, who apply their NLP algorithm to determine that the microchip.com article is entirely about CPUs, the WSJ article is a 30%/70% split between inflation and the Federal Open Market Committee (FOMC), and the Bloomberg article is a 20%/80% split between inflation and politics. The Consortium then aggregates these interactions across users and topics. On this day, three users at xyz.com were focused on FOMC and inflation-related news, whereas only one was focused on CPU and Politics.

This dataset of domain-topic interactions provides us with details on the set of topics that each firm is paying attention to daily. However, directly using this daily data in our analyses is problematic because reading activity displays a variety of intra-week effects. For example, there are significantly fewer user-article interactions on weekends than on weekdays, and a different composition of topics read on Mondays versus Fridays. Figure OA.3.1 in the Online Appendix highlights this intra-week pattern in reading by showing that on an average Tuesday, 93 unique users per firm (across all roughly 2 million domains) interact with the Consortium's data, while on Fridays, the number falls to 83. We address these intra-week patterns in reading by either applying day of week fixed effects or aggregating the daily domain-topic interaction data into lower frequencies, such as quarterly or annually, when conducting our analysis.

2.2 Exploring the Data

The Consortium's raw data covers user-level interactions with each topic. This taxonomy, the members of the Consortium, and the number of covered firms, however, has evolved over time. Panel A of Table 1 provides an overview of this evolution and presents annual summary statistics for (a) the number of unique domains in the data, (b) the number of topics in the Consortium's taxonomy, and (c) the cross-sectional distribution of employee attention across topics.

There are two takeaways from Panel A, which covers both public and private firms. First, there is a substantial degree of cross-sectional and time-series heterogeneity in the Consortium's coverage of firms and topics. The number of domains (topics) covered by the Consortium has increased from about 650,000 (2,500) in 2016 to about 2.1 million (7,400) in 2022. This trend reflects the fact that the Consortium has increased both its member base over time and the set of topics it covers. Second, Panel A also shows that the distribution of the number of topics that firms pay attention to in any given week is highly positively skewed. The mean (median) firm pays attention to about 330 (130) topics per week. A skewness of around four suggests that a majority of firms engage with just a small subset of the topics.

Panel B repeats the exercise after matching the Consortium's dataset to the CRSP/Compustat universe of firms — the set of domains over which we conduct our empirical analyses in Sections 4 and 5.[5] Employees of public firms pay attention to a broader array of topics. The mean (median) number of topics a public firm pays attention to is around 2,800 (2,900). Consequently, the skewness of the firm-topic distribution diminishes among public firms. Comparing the results in Panel A to those in Panel B suggests that the number of topics that a firm pays attention to is inherently correlated with the firm's size.

Table 1 shows that the number of firms that interact with the Consortium's data and the number of topics that the Consortium covers generally increase over time. These changes in the composition of the Consortium's data could potentially distort the time-series dynamics of a firm's attention to any particular topic. We address this issue by focusing on cross-sectional variation in

[5] We only include firms with a CRSP share code of 10, 11, and 12 and a CRSP exchange code of 1, 2, or 3. This confines our analyses to the public equity of firms listed on the NYSE, AMEX, and NASDAQ exchanges. Moreover, we link firms in the CRSP/Compustat universe to the Consortium's dataset via the firm's domain(s). While we remove financial firms and utilities from all empirical tests that involve the CRSP/Compustat universe, we still report attention-related statistics for firms in these industries in Tables 1 and 2 for the purpose of completeness.

relative attention to topics across firms on a given date. This ensures that our results are immune to problems associated with changes in (i) the Consortium's algorithm used to decompose articles into topics, and (ii) the technological landscape (e.g., the possibility that users read more news simply because a faster version of the Wall Street Journal app becomes available).

Visualizing the topics. While the Consortium's raw data typically features over 7,000 individual topics, a careful analysis of the Consortium's taxonomy indicates that some topics are more related to one another than others. To illustrate this point, the Consortium provided us with category labels associated with each topic. For example, the individual topics such as "M&A," "M&A due diligence," and "capital injection" fall under the "corporate finance" category, whereas the "succession planning" and "layoffs" topics fall under the "staff departure" category.

To provide a sense of the types of topics covered by the Consortium's data, we count how many topics are associated with each category on a randomly selected week in the middle of the sample period (11/17/2018). We present these counts as a word cloud in Figure 3 in that category labels are weighted such those more prominently featured are a larger set of topics. The figure shows that certain categories (e.g., technology and financial services) tend to feature many more topics than other categories (e.g., urban planning). The distribution of topics across categories is not uniform; it is comforting that it mirrors industries that are a larger proportion of the economy, assuaging concerns of inherent industry biases in the data.

Summary statistics by industry. As the category coverage tilts towards finance, business services, and technology, we report the quality of firm matches between the CRSP/Compustat universe and the Consortium's data. Table 2 shows summary statistics by industry groups. We match each firm to one of 17 2-digit NAICS industry codes. While we report statistics for financials and utilities, we remove these sectors in our empirical analysis following convention in the literature.

The last row of this table shows that we can successfully match 86% of the 4,198 firms that exist in the CRSP/Compustat universe between 2016 and 2022. The matched firms are typically larger, representing an average of about 88% of the aggregate market capitalization. Non-price-based measures of firm size, such as the number of employees, show that the matched firms comprise approximately 85% of the total number of employees in the CRSP/Compustat universe. The second to last column also indicates that the employees within an industry interact with about 45% of the topics on average in the Consortium's data on a given day.

The preceding rows of this table show the same summary statistics for each of the 17 industry groups. We observe a large degree of heterogeneity: our sample includes only 10 agriculture-related firms but 1,760 manufacturing-related firms. That said, our matched sample still includes the bulk of each industry's market capitalization. For instance, the 10 agricultural firms in our sample represent 99% of the total market capitalization of the agriculture sector. This pattern is generally consistent across industries, with notable exceptions being the education sectors, with only 65% of its total market capitalization matched. Lastly, the table reveals varying levels of attention paid to topics by firms in each sector. While firms in education only interact with about 15% of topics on a given day, the employees of the typical retail-based firms interact with over 68% of topics.

Additional statistics. For the sake of brevity, Section OA.4 in the Online Appendix provides a battery of additional summary statistics and descriptions of the Consortium's data. We thoroughly examine the distribution of *domain-topic* interactions and show that many topics are only marginally informative about a firm's business line(s). Unsurprisingly, a large proportion of the online reading activity of the average firm is spent on current events. For example, in the week ending on November 17, 2018, the preponderance of online time was spent on general topics including "South by Southwest," a popular festival and conference related to music and film, and "Call of Duty," a popular video game which had released a new version shortly before this date. A key insight from this analysis is that rudimentary measures of firm-level attention, such as the total number of interactions scaled by assets or the number of employees, are most likely uninformative about the firm's economic exposures, something we address in the next section.

3 Motivating our Measure of Exposure to Macroeconomic Risk

In this section we show statistical evidence that the composition of reading by firms has a strong relationship to macroeconomic risk. Section 3.1 uses a set of time-series analyses to demonstrates that the average firm's relative attention to macroeconomic conditions is highly correlated with fluctuations in well-know proxies that capture the state of the business cycle, including the corporate default spread, the VIX index, and the EPU measure proposed by Baker et al. (2016). Our study, however, also seeks to understand how firm-level attention to macroeconomic-related news in near real time can be used to measure differences in *exposure* to macroeconomic risk. In Section

3.2 we formulate a data-driven method to differentiate between topics that are informative and uninformative about a firm's economic exposure to macroeconomic risk, notwithstanding the average employee's focus on reading about general news and events.

3.1 Attention to Macroeconomic-Related Topics

As noted above, firms pay attention to a broad array of topics. To constrain their attention to only macroeconomic-related topics we first create a sample corpus of articles using a procedure similar to that of Baker et al. (2016). This corpus includes more than 2,500 articles published by the Wall Street Journal (WSJ), the Economist (segmented by six section tabs), Financial Times (FT), Federal Reserve Beige Books (segmented in 12 regions), Federal Reserve Notes, and the Bank of International Settlements. We retain articles that include the terms "*economic*," "*economics*," "*economical*," and "*economy*." We then have the Consortium deploy its proprietary NLP algorithm onto this macroeconomic-related corpus. The topics that emerge from this exercise are an approximate 600 topic subset of the roughly 7,000 total topics in the Consortium's taxonomy.

The key difference between our approach and that of Baker et al. (2016) is that their corpus is generated by further intersecting the search terms with both "*uncertainty*" and other policy-related terms. This distinction is important for two reasons. First, the Consortium supplies our data at the topic-level. As such, we cannot measure how much of a given article is related to economic uncertainty, specifically, versus economics, generally. Second, firm concerns about macroeconomic conditions could reflect worries about either a slowdown in economic growth (a first moment effect) or an increase in economic uncertainty (a second moment effect). It is thus an empirical question as to which of these quantities most closely relate to future variations in reading activity. Rather than distinguishing between mechanisms in this section, we focus instead on characterizing firm-level reading activity, broadly, and defer addressing this question to Section 5.1.

Panel A of Figure 4 shows the types of macroeconomic-related topics that emerge from this analysis (more prominently read topics are represented as bigger words). The set of popular topics that emerge from the articles underlying the corpus are related to a broad range of categories. In the language of Ludvigson et al. (2021), several prominent topics are related to the real side of the economy (e.g., "Consumer Spending," "Economic Growth," and "Economic Inequality"), while others are related to financial markets (e.g., "Exchange Rate," "Interest Rate," and "Market

Volatility"). This reflects the fact there is not just a single facet of macroeconomic risk. Rather, the articles underlying the corpus reflect a wide variety of concerns that market participants face.

To illustrate how average reading of the macroeconomy changes in the time series, we first designate $Total$, $Macro$ and $Other$ as the sets of total topics, macroeconomic-related topics, and the remaining set of other topics, respectively,

$$Macro \cup Other = Total \qquad \text{and} \qquad Macro \cap Other = \varnothing.$$

For each firm, we stack its reading into vectors associated with $Macro$ and $Total$. Each element j is the number of the firm's employees reading that topic. Topics not read by a firm's employees are given a value of zero. For reasons that will become obvious in the next section we refer to these vectors as a firm's topic-frequency or $\boldsymbol{tf}$ vector. Our measure of attention to the macroeconomy for firm i at time t is the dot product of the macroeconomic and total vector of reading,

$$\text{TS-RA}_{i,t} = \cos\left(\boldsymbol{tf}_{i,t}^{\text{Macro}}, \boldsymbol{tf}_{i,t}^{\text{Total}}\right) = \frac{\boldsymbol{tf}_{i,t}^{\text{Macro}} \cdot \boldsymbol{tf}_{i,t}^{\text{Total}}}{\|\boldsymbol{tf}_{i,t}^{\text{Macro}}\| \times \|\boldsymbol{tf}_{i,t}^{\text{Total}}\|}, \tag{1}$$

where $\|\boldsymbol{v}\|$ are the Euclidean (or ℓ^2) norm of vector $\boldsymbol{v}$. As the elements of $\boldsymbol{tf}_{i,t}^{Macro}$ are members of $\boldsymbol{tf}_{i,t}^{Total}$ and equation (1) is bounded between zero and one, TS-RA$_{i,t}$ effectively represents the proportion of macroeconomic-related to total reading by firm i at time t.

We focus on *relative* attention because of the highly non-linear relationship between firm size and attention to topics. For instance, a large corporation such as Microsoft, with a workforce of 150,000 employees, will naturally consume more information than a smaller corporation like Malibu Boats, with 600 employees. However, a smaller, but still large corporation, such as Red Hat, does not necessarily engage with significantly fewer topics than Microsoft, despite being a tenth of its size. We provide a graphical illustration of this relationship by plotting the average log length of $\boldsymbol{tf}_{i,t}^{Macro}$ and $\boldsymbol{tf}_{i,t}^{Total}$ versus log firm size in Figure OA.3.2. Due to the non-linearity reading cannot be compared across firms by simply dividing $\boldsymbol{tf}_{i,t}^{Macro}$ by size proxies such as the number of employees, assets, or market capitalization. What is also clear in the figure, however, is that both the length of $Macro$ and $Total$ follow similar patterns across the distribution; the dot product of the two vectors thus does not show as strong of a relationship with size.

We next show that during periods of poor economic times, the employees tend to read more macroeconomic- versus other business-related news. We illustrate this fact by plotting TS-RA$_{i,t}$ aggregated across all public firms at time t,

$$\widetilde{\text{TS-RA}}_t = \frac{\overline{\boldsymbol{tf}}_t^{Macro} \cdot \overline{\boldsymbol{tf}}_t^{Total}}{\|\overline{\boldsymbol{tf}}_t^{Macro}\| \times \|\overline{\boldsymbol{tf}}_t^{Total}\|}, \tag{2}$$

where $\overline{\boldsymbol{tf}}_t = \frac{1}{N_t}\sum_{i=1}^{\mathcal{N}_t} \boldsymbol{tf}_{i,t}$ and N_t is the number of public firms at time t.

Figure 5 demonstrates that there is a substantial amount of time-series and cross-section heterogeneity in the degree to which firms pay attention to macroeconomic conditions. The solid blue line in the figure reports the time series of $\widetilde{\text{TS-RA}}_t$ from equation (2). On average, employees allocate about half of their attention to macroeconomic topics across the sample. Their attention to these topics, however, rises substantially during "bad" times, such as the political uncertainty surrounding the 2016 Presidential elections and in the wake of the COVID-19 pandemic in mid-2020. The proportion of attention towards macroeconomic-related topics for the average firm peaked around 62% during these periods. The dashed blue lines report the average values of TS-RA$_{i,t}$ among firms with a relative attention measure that is 25% above or below the mean at each point in time. The takeaway from this analysis is that attention to macroeconomic conditions also varies widely across firms. For instance, while the mean firm allocated about 60% of its attention towards macroeconoic news in mid-2020, a substantial number of firms had proportions greater (less) than 0.75 (0.45).

Given that a firm's reading about macroeconomic conditions is likely to reflect the employees' concerns about the state of the economy, we expect $\widetilde{\text{TS-RA}}_t$ to covary with the business cycle. As motivation, Figure 6 plots the time series of $\widetilde{\text{TS-RA}}_t$ alongside the corporate default spread (top panel) and the EPU index of Baker et al. (2016) (bottom panel). To aid comparability, each variable is standardized. The average firm's employees pays relatively more attention to macroeconomic conditions when either the corporate default spread or the EPU index are relatively high. Although the dynamics of $\widetilde{\text{TS-RA}}_t$ and these business-cycle proxies are highly correlated, they are not perfectly aligned. For instance, $\widetilde{\text{TS-RA}}_t$ spikes prior to the onset of the COVID-19 pandemic in early 2020, and tends to rise, but not as much as either alternative proxies, at the start of the COVID-induced recession of March 2020. The fact that employee reading about macroeconomic news is not perfectly aligned with variables that measure different aspects of aggregate macroeconomic conditions opens the possibility that our measure, which captures the consumption of news, contains additional firm-level information.

To statistically clarify the relationship between macroeconomic conditions and employee reading, we next regress $\text{TS-RA}_{i,t}$ onto the realization of various business-cycle variables,

$$\text{TS-RA}_{i,t} = \text{Day-of-Week}_t + \beta \cdot \text{MacroV}_{t-1} + \epsilon_{i,t}, \tag{3}$$

where MacroV_{t-1} is a proxy for macroeconomic activity at time $t-1$, measured using either the corporate default spread, the intermediary capital ratio of He, Kelly, and Manela (2017), the WTI oil returns, the EPU index of Baker et al. (2016), the CBOE's VIX index, or the macroeconomic uncertainty index of Bekaert et al. (2022). While the first three variables are closely related to the level of economic activity, the latter three are tightly linked to the notion of economic and financial market uncertainty. The regressions are conducted at a daily frequency and include day-of-week fixed effects to control for the substantial intra-week seasonality in reading data (see Section 2). All business-cycle variables are standardized. As such, the coefficient values reflect the change in a firm's relative attention after a one-standard-deviation change in each underlying proxy for macroeconomic activity. Finally, standard errors are clustered at both the firm and date level.

Table 3 presents the results of regression (3) in columns (1), (3) and (5). For example, Panel A shows that the typical firm increases its relative attention to macroeconomic news by about 0.015 (i.e., 1.5 percentage points) in the days following a one-standard-deviation increase in the corporate default spread. Moreover, firms generally read less about macroeconomic conditions in the days following improvements in the health of financial intermediaries and increases in the oil price. Panel B shows that firms also read more about macroeconomic conditions in the days following increases in uncertainty. For example, the typical firm's relative attention increases by 0.007 (0.013) when the VIX (EPU) index spikes. Interestingly, the economically largest relationship between reading and macroeconomic conditions holds with the uncertainty measure of Bekaert et al. (2022), which structurally separates variations in uncertainty from variation in risk aversion.

3.2 Cross-sectional differences in exposure to risk

While the previous section shows that $\widetilde{\text{TS-RA}}_t$ has a positive time-series correlation with several proxies for economic conditions, we are primarily interested in understanding what employee reading activity tells us about cross-sectional differences in firm-level exposures to macroeconomic shocks. A complication, however, arises when exploring this idea: most of the relative attention to macroeconomic topics, which is captured by $\text{TS-RA}_{i,t}$, is common across firms (see Panel A of Figure 4). This common component of reading can relate to both the supply of news (e.g., publishers write more articles and firms mechanically read more articles related to macroeconomic conditions in bad times) and the demand for news (e.g., employees worried about the their uninsurable labor risk read more about macroeconomic conditions in bad times). To identify the cross-sectional differences in risk exposure that we are interested in studying, we thus need to differentiate between topics that are more or less informative about a firm's latent risks.

On each day of the sample period, we differentiate between topics by adopting an approach from the field of document retrieval in computer science. Tasks, such as search operations, depend on word sequences within a query to extract related documents from a large corpus. Central to this process is the concept of the *tf-idf* (term frequency-inverse document frequency) score, where each word w within a document d is assigned a score defined as:

$$\textit{tf-idf}_{\,d,w} = \underbrace{\frac{\#\text{ Word in Document}}{\text{Total Words in Document}}}_{\text{Term frequency (tf)}} \times \underbrace{\frac{\#\text{ Documents in Corpus}}{\#\text{Documents featuring Word}}}_{\text{Inverse document frequency (idf)}}. \tag{4}$$

The *tf-idf* scoring mechanism emphasizes the importance of unique words while downplaying the importance of common ones. For example, prepositions frequently appear *within* (i.e., have high *tf*) and *across* (have low *idf*) documents. This widespread use diminishes the usefulness of prepositions in distinguishing between documents in the corpus. Consequently, prepositions generally have low *tf-idf* scores.

We build on this idea to propose a novel measure for differentiating between informative and uninformative topics for a firm. We refer to this measure as the *topic frequency-inverse aggregate frequency*, or *tf-iaf*, score. The scoring strategy downweights common topics, such as those associated with current events, that pervade reading across firms, and upweights topics with high readerships within each firm. This enabls us to identify topics that distinguish a firm's reading activity from those of other firms. We define this score for topic j and firm i at time t as:

$$
\begin{aligned}
\textit{tf-iaf}_{i,j,t} = {} & \underbrace{\begin{pmatrix}\text{Number of Employees at Firm } i \\ \text{Interacting with Topic } j \text{ at time } t\end{pmatrix}}_{\text{Topic frequency (tf)}} \quad \times \\
& \underbrace{\begin{pmatrix}\text{Average Fraction of Employees Across All} \\ \text{Firms Interacting with Topic } j \text{ at time } t\end{pmatrix}^{-1}}_{\text{Inverse aggregate frequency (iaf)}} \\
& \equiv \textit{tf}_{i,j,t} \times \textit{iaf}_{j,t},
\end{aligned} \tag{5}
$$

where topic j is either in the macroeconomic or other subset of topics on date t. Here, the *tf* component is the number of total users within a firm interacting with a topic on a given day. This component is identical to the inputs in equation (1), which places a higher importance on topics with a larger number of interactions. In contrast, the *iaf* component down weights the topics that receive a large number of interactions across all firms. This effectively places a lower weight on topics that all firms are reading because of the availability of news at time t and allows us to focus on topics that better reflect a firm's demand for news. For example, if many publishers write about the unemployment rate on the first Friday of each month when the Bureau of Labor Statistics (BLS) releases its employment data, and most employees at firms are reading about this current event, then employment-related topics will receive low *iaf* scores on those days.

With this logic in mind, we measure firm i's exposure to macroeconomic risk on day t via the degree to which its employees are paying attention to differentiated macroeconomic topics relative to differentiated other business topics,

$$
\text{CS-RA}_{i,t} = \frac{\boldsymbol{\textit{tf-iaf}}_{i,t}^{Macro} \cdot \boldsymbol{\textit{tf-iaf}}_{i,t}^{Total}}{\|\boldsymbol{\textit{tf-iaf}}_{i,t}^{Macro}\| \times \|\boldsymbol{\textit{tf-iaf}}_{i,t}^{Total}\|}. \tag{6}
$$

$\boldsymbol{\textit{tf-iaf}}_{i,t}^{Macro}$ is the vector of firm specific *tf-iaf* weights on macroeconomic topics from equation (5), whereas $\boldsymbol{\textit{tf-iaf}}_{i,t}^{Total}$ is the firm-specific vector of *tf-iaf* weights on the total reading vector. The time index t represents attention to each set of topics over a daily (or lower) frequency. We refer to this quantity as our cross-sectional measure of firm i's *relative* attention towards macroeconomic conditions at time t, or $\text{CS-RA}_{i,t}$.

Motivational evidence. To show that CS-RA$_{i,t}$ meaningfully distinguishes between firms with high and low exposures to macroeconomic risk, we perform a daily event study around the onset of the COVID-19 pandemic in early 2020. Specifically, we estimate CS-RA$_{i,t}$ on February 26th, 2020, which was the day of the first non-travel-related infection of COVID-19 in the United States. This variable remains constant across our event study.

We then map this variable to be uniformly distributed over the interval $[-1, 1]$ (to remove the effect of any potential outliers in reading) and compute a weighted average value of $\widetilde{\text{TS-RA}}_t$ from equation (2) among firms with positive and negative values of CS-RA$_{i,2/26}$. Within each group, the absolute value of CS-RA$_{i,2/26}$ determines the weight is placed on the reading of firms within each portfolio. Subtracting the weighted average of positive from negative transformed CS-RA$_{i,2/26}$ allows us to evaluate how the macroeconomic-related reading of each group changed as concerns over the COVID-19 pandemic evolved.

The results, which are reported in the left-hand side of Figure 7, show that prior to February 26, high CS-RA$_{i,2/26}$ firms tended to allocate about four percentage points more of their relative attention to macroeconomic topics. As concerns related to the pandemic spread throughout March, these same firms increased their reading of macroeconomic news by a statistically significant amount. By March 17, a few days after the Trump Administration declared a nationwide emergency and issued additional travel bans against non-U.S. citizens, high CS-RA$_{i,2/26}$ firm were allocating about 7 percentage points more of their relative attention towards macroeconomic news, a quantity almost double the unconditional difference.

The fact that the relative attention of firms that are highly exposed to the macroeconomy, as determined by CS-RA$_{i,2/26}$, increased upon the onset of a macroeconomic shock is consistent with the notion that this variable reflects a firm's exposure to macroeconomic risk. An additional implication of this risk-based narrative is that the returns of the highly exposed CS-RA$_{i,2/26}$ firms should deteriorate once the macroeconomic shock is realized. The right-hand side of Figure 7 plots the difference in cumulative returns of high versus low CS-RA$_{i,2/26}$ firms and shows that this is indeed the case. The employees of firms that are highly exposed to macroeconomic conditions not only read more macroeconomic news upon the onset of the COVID-19-related recession, but also experienced significantly lower returns than low CS-RA$_{i,2/26}$ over the sample. Strikingly, these differences in reading and returns were flat before February 26th.

Statistical evidence. To establish that CS-RA$_{i,t}$ is a valid measure of firms' exposures to macroeconomic risk, we hypothesize that if a firm is more (less) exposed to economic conditions, then changes in the firm's relative attention to macroeconomic news should coincide more strongly (weakly) with changes in common proxies for economic conditions. That is, firms with high (low) values of CS-RA$_{i,t}$ in the recent past are likely to read relatively more (less) about macroeconomic news when economic conditions worsen (improve).

$$\text{TS-RA}_{i,k,t} = \alpha_{k,t} + \beta\text{CS-RA}_{i,k,t-1} + \gamma\text{MacroV}_{t-1} \times \text{CS-RA}_{i,k,t-1} + \epsilon_{i,k,t}. \tag{7}$$

Here, TS-RA$_{i,k,t}$ (CS-RA$_{i,k,t-1}$) is the time-series (cross-sectional) measure of the relative attention of firm i in industry k on day t, and MacroV$_{t-1}$ is one of the same six proxies for macroeconomic conditions underlying equation (3). Moreover, $\alpha_{k,t}$ is an industry-by-time fixed effect, in which the index k corresponds to the 3-digit NAICS industry of firm i. These fixed effect subsume both the average effect of macroeconomic conditions on relative attention, as quantified by estimating equation (3), and the day-of-week fixed effects included in the aforementioned equation.

The key parameters of interest are β and γ. The former parameter reflects any unconditional differences in relative attention to macroeconomic news between firms in the same industry with different exposures to economic conditions. The latter parameter estimates the degree to which firms with high versus low exposures to macroeconomic conditions change the composition of their reading on day t due to changing macroeconomic conditions on day $t-1$. To minimize the effect of outliers and focus on cross-sectional differences in exposure between firms, we map CS-RA$_{i,k,t-1}$ to lay in the interval $[0, 1]$ on each day t. As a result, the estimated value of γ reflects how relative attention changes between firms in the 0^{th} to 100^{th} percentile of CS-RA$_{i,k,t}$.[6] We present the results of this analysis in the second and third rows of Panels A and B in Table 3.

To begin, all specifications show that the employees of firms that are highly exposed to macroeconomic conditions read substantially more macroeconomic news. Moving from the lowest to the highest value of CS-RA$_{i,k,t-1}$ increases the proportion of macroeconomic news consumed by more

[6]Specifically, if CS-RA$_{i,t-1}$ denotes the raw relative attention for firm i between $t-1$ and t, then its rank transformation is $F(\text{CS-RA}_{i,t-1}) = \text{Rank}\left(C_{i,t-1}\right)/(N_t+1)$, where N_t is the number of firms at time t, $\text{Rank}\left(\min_{i=1,\dots,N_t} C_{i,t-1}\right) = 1$ and $\text{Rank}\left(\max_{i=1,\dots,N_t} C_{i,t-1}\right) = N_t$. This transformation implies that the α-quantile of $F(\text{CS-RA}_{i,t-1})$ is α. For notational simplicity, we continue to refer to the rank transformed value as CS-RA$_{i,t-1}$ in our tables and regression specifications.

than 6%. Second, the estimated values of γ in columns (2) and (4) suggest that the employees of high CS-RA$_{i,k,t-1}$ firms also tend to read relatively more macroeconomic news in the days following an increase in the corporate default spread or a decrease in the health of the balance sheets of financial intermediaries, two signals for weak economic conditions. Focusing on intermediary capital shows that the employees of highly exposed firms reduce their relative attention to macroeconomic news by almost 3% in the days following a one-standard-deviation increase in the intermediary capital ratio, an effect that is almost 50% larger than the unconditional effect in Column (3).

While the relation between the composition of reading and risk exposure is corroborated when we examine changes in the corporate default spread in Column (2), Column (6) suggests that firms that read more about macroeconomic risk in the day following an increase in oil prices, which are often considered good times. First, although the sign of this relation is inconsistent with the results in Columns (2) and (4), its economic magnitude is relatively small. Second, as discussed in Alfaro et al. (2018) the effects of shift in oil prices on firm-level prospects is highly heterogeneous. For example, falling oil prices are unambiguously negative for oil producers, but positive for airlines.[7]

Finally, Columns (2), (4), and (6) in Panel B show that a similar results emerge when we include a measure of macroeconomic uncertainty on the right-hand side of equation (7). As economic uncertainty increases, measured using either the VIX, EPU, or Bekaert et al. (2022) uncertainty index, then high CS-RA$_{i,t}$ firms tend to increase their reading of macroeconomic topics by 1.0 to 2.0% more than low CS-RA$_{i,t}$ firms. Consistent with the results in Panel A, this shows that CS-RA$_{i,t-1}$ captures heterogeneity in how firm employees change the composition of their reading in response to a change in macroeconomic conditions—i.e., CS-RA$_{i,t-1}$ on day $t-1$ for firm i is a timely reflection of the firm's exposure to macroeconomic risk at time t.

3.2.1 Discussing and dissecting the relative attention measures

The preceding analyses delivers two takeaways: (i) firm employees change their attention to macroeconomic news in response to changes in economic conditions, and (ii) firms with high CS-RA$_{i,t}$ shift reading towards macroeconomic news during bad times more so than those with low CS-RA$_{i,t}$. This raises several follow on questions. Is there a change in the set of "salient" topics due to the *tf-iaf* adjustment? If so, does this change tell us anything important about the firm? In this section

[7]We exploit this heterogeneity when differentiating the effects of first- and second-moment shocks in Section 5.1.

we explore the distribution of topics across both TS-RA$_{i,t}$ and CS-RA$_{i,t}$ measures. We then use the insights gleaned to develop a framework to better understand the economic content of the measures.[8]

To illustrate the effect of the *tf-iaf* adjustment we first focus on non-macroeconomic topics. Consider the topic clouds presented in Figure 8. The figures in the top (bottom) row display the reading for the chemicals manufacturing (NAICS 334) (computer and electronics manufacturing industry (NAICS 325)) industry. The word clouds in the first column are constructed using the average topic frequency within each industry for the week ending November 17, 2018. These figures show virtually no differences in reading between the two industries. Prominent topics include "Live Streaming," "South by Southwest," "Blu-Ray," "United States Secret Service," and "Call of Duty." In the parlance of the *tf-iaf* scores, these topics, however, will also have low inverse aggregate frequency (*iaf*) scores because all employees seem to interact with these topics often.

The second column of Figure 8 demonstrate how these raw word clouds change when we weight each topic by its *tf-iaf* score from equation (5). The salient topics are now very industry specific. For instance, we see that the "Cancer Genomics," "Drug Discovery," and "Angiogenesis Inhibitors" topics are important for firms in the chemicals sector, which includes pharmaceutical firms, whereas the "Cisco ACI," "Remote Desktop Protocol," and "Software Defined Perimeter" topics are important for firms in the computer industry. The procedure enhances the weight of topics such as "Cancer Genomics" ("Cisco ACI") because many read this topic within the chemicals (computing) industry, but few read this topic outside the industry. Broadly speaking, the *tf-iaf* adjusted topics that emerge are closely related to the production and investment decisions of firms in each industry.

We also apply the *tf-iaf* adjustment to the set of topics drawn from the macro corpus as move from TS-RA$_{i,t}$ to CS-RA$_{i,t}$. Panel B of Figure 4 shows the *tf-iaf* weighted macro-related word cloud for the week ending November 17, 2018. While the raw word cloud in Panel A of Figure 4 shows that many firms read about "Quantitative Easing," "Consumer Spending," and "Economic Growth," these prominent topics are relatively uninformative in distinguishing reading about macroeconomic risk in the cross section of firms. Rather, what distinguishes reading between firms are finance-related terms that come in two broad categories: (i) topics such as "credit risk,"

[8]Similar to how the cross-sectional asset-pricing literature examines how heterogeneity in firm characteristics (e.g., book-to-market) reflect differences in risk exposures across firms, we examine what differences in firm-employee reading, measured using equation (6), tell us about heterogeneity in firm-level risk (see, e.g., Zhang, 2005).

"exchange rate," and "duration management" that closely relate to firm risk management, and (ii) topics such as "Basel II" and "International Accounting Standards Board" that closely relate to regulatory compliance. Both categories of topics are generally related to corporate hedging and risk mitigation activities. While these finance-related terms emerge as important macro-related topics, we reiterate that both finance and utility firms are excluded from both the main analysis and the set of firms underlying these word clouds.

Theoretical framework. How does CS-RA$_{i,t}$, which seems to be more related to the proportion of mitigation- versus investment-related reading versus TS-RA$_{i,t}$, link to a firm's risk exposure? And does this measure tell us anything else about firm-level outcomes? A simple two-period framework helps answer these questions. In this framework, the firm's value today is equal to

$$\begin{aligned} V_t = &\text{Production}_t - \text{Mitigation Cost}_t \\ &+ E_t\left[M_t\left(\text{Production}_{t+1} + \text{Mitigation Benefits}_{t+1}\right)\right]. \end{aligned} \tag{8}$$

That is, it is a function of output today (Production$_t$) and the discounted value of output tomorrow ($M_t \cdot$Production$_{t+1}$). Firms are also given the ability to mitigate risk. While mitigation helps hedge realizations of bad states of the world tomorrow (Mitigation Benefits$_{t+1}$), it comes with a potentially heavy cost that is incurred today (Mitigation Cost$_t$). This implies a tradeoff for the firm: higher mitigation expenditure implies fewer resources for the firm to invest in next period's production. Moreover, riskier firms—specifically, those whose cash flows covary more with the business-cycle (captured by the stochastic discount factor, M_t)—will be incentivized to hedge (invest) more (less). In short, if CS-RA$_{i,t}$ reflects firm-level risk exposure, then this measure should (i) positively predict hedging and mitigation activity, (ii) positively predict the cost of capital, and (iii) negatively predict investments in capital. This intuition is related to that in the literature linking macroeconomic risk to risk mitigation (e.g., Brown, 2001; Hong, Wang, and Yang, 2023) and regulatory exposure (e.g., Kalmenovitz, 2022). The following sections examine the usefulness of CS-RA$_{i,t}$ for predicting prominent firm-level outcomes and show results that are consistent with main implications of this framework.[9]

4 Relative Attention and Firm Outcomes

This section conducts a set of empirical exercises to substantiate the informativeness of our relative attention measure in quantifying firm-level exposures to changing macroeconomic conditions. Sections 4.1 show that firms with high CS-RA$_{i,t}$ attempt to mitigate risk through either hedging or regulatory activity more aggressively than firms with low CS-RA$_{i,t}$. Section 4.2 build on this result by showing that these firms also tend to be riskier. Consistent with these higher hurdle rates, Section 4.3 shows that CS-RA$_{i,t}$ predicts lower sales, and investment and employment growth in subsequent periods.

4.1 Risk mitigation and compliance

Section 3.2.1 shows that a consequence of applying the *tf-iaf* weights from equation (5) to cross-sectionally differentiate macroeconomic-related reading across firms is that salient topics shift from aggregate concerns, such as "Quantitative Easing" (QE) and "Consumer Spending," towards topics related to firm efforts to mitigate risk and/or comply with regulatory authorities (e.g., "Duration Management," "Basel II," and "International Accounting Standards Board").

Hedging. To link this fact to firm behavior, we follow the methodology of Campello et al. (2011) to see how a firm's hedging activity correlates with CS-RA$_{i,t}$ over the past year. The hedging measure is generated by first counting the number of times each of the following hedging-related keywords are mentioned in a 10-K: "derivatives," "hedge," "financial instrument," "swap," "market risk," "expos," "futures," "forward contract," "forward exchange," "option contract," "risk management," and "notional." The total occurrence of these keywords is then divided by the total 10-K word count to derive a firm-year proxy of hedging intensity.

As Campello et al. (2011) note, hedging activity plays little role for a large fraction of firms. Consistent with this finding, around 25% of firms mention four or fewer hedging-related words in their 10-Ks. A small number of firms, however, frequently mention these words. To minimize the effects of outliers, we map our firm-level proxy for hedging to be the cross-sectional percentile or

[9] Section OA.2 of the Online Appendix formalizes this intuition in an economic model. An extension that includes employee learning also generates comparative statics that map to our results from Sections 3.1 and 3.2.

rank, denoted by $\mathbb{R}^{\text{Hedge}}_{i,t}$, such that it is uniformly distributed between zero and one in each year. We then designate $\mathbb{R}^{\text{Hedge}}_{i,t}$ to be our dependent variable of interest when examining the relation between hedging intensity and a firm's *tf-iaf* adjusted relative attention to macroeconomic risk:

$$\mathbb{R}^{\text{hedge}}_{i,k,t} = \psi_{k,t} + \beta_1 \text{CS-RA}_{i,k,t-1} + \beta_2 \mathbb{I}^{\text{high}}_{\text{epu}} \times \text{CS-RA}_{i,k,t-1} + \boldsymbol{Z'}_{i,k,t-1}\gamma + \varepsilon_{i,k,t}. \tag{9}$$

In this regression, $\text{CS-RA}_{i,k,t-1}$ is the average daily value of the relative attention measure of firm i in industry k over the year prior to the firm's fiscal year-end. We average over this time period as 10-Ks reflect firm activity over an entire year. Additionally, as discussed in Section 3.2, we also map $\text{CS-RA}_{i,t}$ to be between zero and one. The benefit of applying this transformation is twofold. First, the transformed measure of relative attention is less sensitive to the presence of outliers. Second, this transformation allows us to interpret the estimated values of β_1 and β_2 in equation (9) as the difference in the propensity to hedge between a firm paying the least versus the most attention to *tf-iaf* adjusted macroeconomic-related topics.

As a firm's propensity to hedge its risks can depend on factors such as the firm's asset base and indebtedness, the vector $\boldsymbol{Z'}$ contains firm-level controls, including those from Leary and Roberts (2014), the measure of financial constraints from Whited and Wu (2006), and lagged CAPM β, a common measure of a firm's exposure to aggregate risk.[10] $\psi_{k,t}$ reflect industry-by-time fixed effects that not only subsume unobserved heterogeneity in hedging activity, but also common economic shocks each industry may face at a given point in time (e.g., the possibility that hedging differs between technology and manufacturing firms at the onset of the COVID-19 pandemic). Certain specifications also include time and industry fixed effects separately. Finally, $\mathbb{I}^{\text{high}}_{\text{EPU}}$ is a dummy variable that takes on a value of one if the EPU index is in the top 10% of its unconditional distribution. We often focus on the interaction between $\text{CS-RA}_{i,k,t-1}$ and this dummy variable to examine if firm hedging activity is especially high during times of high macroeconomic uncertainty (i.e., in "bad times"). Standard errors are clustered by both firm and year.

Panel A of Table 4 presents the results. The first column displays the regression without controls and fixed effects. The coefficient on $\text{CS-RA}_{i,k,t-1}$ indicates that as a firm moves from

[10]The Leary and Roberts (2014) vector of controls include firm size, Tobin's q, profitability, leverage, and asset tangibility. CAPM β is estimated on a 250-day rolling basis. Section OA.1 in the Online Appendix provides details on the construction of these control variables, and Table OA.3.1 in the Online Appendix reports summary statistics.

the 0^{th} to 100^{th} percentile of the CS-RA$_{i,t}$ measure, the percentile rank of hedging-related words increases by approximately 15% (t-statistic of 3.09). In the second and third columns, we add date and industry-by-date fixed effects, respectively. The magnitude and statistical significance of the aforementioned effect drops only marginally. Column (4) of Table 4 augments Column (3) by including the interaction between relative attention and our high economic uncertainty dummy. Furthermore, to show that CS-RA$_{i,t}$ reflects firm-level risk beyond standard measure, we also include lagged CAPM β as a control. While the unconditional effect of relative attention remains similar to that reported in column (3), the interaction effect shows that high CS-RA$_{i,t}$ firms are especially likely to hedge their exposure to macroeconomic fluctuations in bad times. The coefficient on this interaction effect is 0.21 (t-statistics of 1.75). In Column (5) we add the control variables from Leary and Roberts (2014) and Whited and Wu (2006). The unconditional effect of relative attention reduces in economic magnitude and statistical significance, yet the interaction between relative attention and economic uncertainty remains economically sizeable and statistically robust. High CS-RA$_{i,t}$ firms are almost 17% more likely to actively hedge their risk in bad times compared to their low CS-RA$_{i,t}$ counterparts in the same industry and at the same point in time.

Compliance. While most topics in Panel B of Figure 4 are related to risk mitigation, several topics are also related to compliance. This implies that firms with high exposures to macroeconomic risk tend to have more onerous regulatory and legal burdens. We formalize this link by examining the relation between CS-RA$_{i,t}$ and the firm-level proxy for spending on regulatory compliance from Kalmenovitz (2022). Specifically, we repeat specification (9), but replace the left-hand side variable with each firm's regulatory intensity. Panel B of Table 4 report the results.

As each column in Panel B shows, the relation between a firm's relative attention to macroeconomic risk and its degree of regulatory intensity is positive and statistically significant. In Column (5), we present our most comprehensive specification that includes industry-by-time fixed effects and the firm-level controls discussed above. We exclude the β_2 coefficient from interacting CS-RA$_{i,t}$ with $\mathbb{I}_{\text{EPU}}^{\text{High}}$ as the data provided by Kalmenovitz is only well populated through 2019. This means the regression are run on data from May 2016 through December 2019, a relatively uneventful macroeconomic period. We find that firms that have the highest values of CS-RA$_{i,t}$ are required to comply with costlier regulation than firms with the lowest values of CS-RA$_{i,t}$. This difference in regulatory intensity is significant at the 1% level (t-statistic of 7.06). The preceding columns show stronger results in specifications that include fewer fixed effects and controls. Overall, this confirms that firms that spend more time reading about macroeconomic-related news tend to be subject to more regulatory oversight.

4.2 Cost of Capital Regressions

We next examine how our measure of firm-level macroeconomic risk covaries with firm-level discount rates. *If* fluctuations in macroeconomic conditions reflect fundamental risks that firms are differentially exposed to, then those with higher exposures should not only spend relatively more time reading about macroeconomic conditions (i.e., have higher values of CS-RA$_{i,t}$) but should also have higher costs of capital to reflect this increased risk. To shed light on this, we follow the approach of Gebhardt et al. (2001) to infer the cost of equity capital (henceforth, ICC$_{i,t}$) from equity analysts' earnings forecasts. Section OA.1 of the Online Appendix provides details on how we construct the measure. Given our data's short time period, we use implied costs of capital to minimize the effects of noise in realized returns. Table **??** in the Online Appendix shows that we obtain similar takeaways when we use realized returns instead.

We then regress the firm's quarterly cost of capital, ICC$_{i,t}$, on each firm's lagged measure of CS-RA$_{i,t}$ using a similar regression specification to equation (9), but controlling for characteristics that have been linked to returns. These characteristics include the CAPM β, firm size, Tobin's q (the inverse of value), profitability, and investment tangibility. We estimate these regression using data from the end of each earnings announcement month because it is around this point in time that analysts make the largest adjustments to earnings estimate for the coming quarters and year.

Results are presented in Table 5. The first column indicates a strong positive relationship between a firm's relative attention to macroeconomic news and ICC$_{i,t}$. Columns (2) and (3) add combinations of date and industry fixed effects to the regressions and show that the results remain economically and statistically significant at the 1% level even after accounting for fixed differences in ICC$_{i,t}$ across times and industries, respectively. The magnitude of the point estimates in Columns (1) to (3) suggests that a firm moving from the lowest value to the highest value of CS-RA$_{i,t}$ sees its cost of capital increase by about 110 to 150 basis points. While the magnitude of this effect falls when we consider industry-by-time fixed effects and additional controls in Columns (4) and (5), the basic fact remains the same: firms that pay more attention to macroeconomic-related topics have higher costs of capital than those that pay more attention to other business-related news.

4.3 Firm-level real outcomes

Since high CS-RA$_{i,t}$ are more exposed to macroeconomic risk and have higher cost of capital, one would expect this to translate into lower investment, sales growth and employment growth rates. That is, we expect that firms that allocate a relatively high proportion of their attention to macroeconomic-related topics will tend to implement more contractionary corporate policies. We establish this fact once again by using panel regression specification in equation (9) after replacing the dependent variable with various firm-level real outcomes. The point estimate β_1 now tells us how a firm's relative attention is related to corporate decisions the firm may take, conditional upon the comprehensive set of fixed effects and control variables discussed in earlier sections. β_2 captures how these actions may change during especially bad economic times.

Table 6 reports the results that a higher degree of attention to macroeconomic-related topics is indeed associated with a *contraction* in the average firm's future investment and sales. Importantly, this negative association between a firm's attention and real outcomes holds regardless of whether we include industry-by-time fixed effects, thereby capturing differences in relative attention within each industry, the comprehensive set of firm-level controls from Leary and Roberts (2014), the Whited and Wu (2006) measure of financial constraints, and CAPM β. Column (1) of the table, which features no fixed effects or control variables, shows that increases in relative attention to uncertainty are associated with a 4.0% decline in one-quarter ahead investment (t-statistic of -3.3), a 13.6% decline in one-quarter ahead sales (t-statistic of -9.3), and a 6.0% decline in one-year ahead employment growth (t-statistic of -4.7).[11] Adding time fixed effects to the baseline specification in Column (2) leaves these results largely unchanged and eliminates the concern that the results are driven by a limited number of times when all firms cut investment simultaneously (e.g., in the onset of the COVID-19 pandemic in March 2020). Similarly, the regression results in Column (3) shows that augmenting Column (2) with industry fixed effects, thereby accounting for fixed differences in investment opportunities across industries, does little to change the strong negative relation between macroeconomic-related news and investment rates.

[11] Table OA.3.2 in the Online Appendix considers which components of total assets firms adjust in response to deteriorating macroeconomic conditions; both short-term (i.e., inventory) and long-term (i.e., property, plant, and equipment) assets fall as the relative attention to macroeconomic news rises.

Columns (3) through (5) present the results of our most comprehensive empirical specifications. These specifications include industry-by-time fixed effects, thereby controlling for time-varying differences in investment opportunities across industries (e.g., the possibility that the average technology firm benefited from the onset of the COVID-19 pandemic while the average durable goods retailer suffered), the interaction of our measure with bad times (i.e., high uncertainty states), and a large set of firm-level control variables. The results in Column (3) indicate that the robust and negative association between attention to macroeconomic-related topics and investment, sales growth, and employment growth persists even after we account the unobservable heterogeneity in these real effects across industries in time and CAPM β.

Column (4) indicates that the predictive power of CS-RA$_{i,t}$ is particular strong during times of high uncertainty for all three real outcomes. Notably, at any given point in time, the average firm in each industry that is allocating most of its relative attention to macroeconomic news has an investment rate that is 1.70% per quarter less than the investment rate of the firm that is paying the least amount of attention to macroeconomic-related topics. During periods of high economic uncertainty, this difference exceeds 10% and is statistically significant at the 1% level. Column (5) repeats this specification after adding the battery of firm-specific controls. The unconditional relationship between CS-RA$_{i,t-1}$ is now statistically insignificant for asset growth and employment growth. It is, however, still strongly negative during periods of high uncertainty for both of these outcomes. Specifically, firms paying the most attention to macroeconomic-related topics have asset (employment) growth rates that are 11.8% (7.5%) lower than their peers during these times.

5 Dissecting the drivers of attention to macroeconomic risk

Our analyses thus far show that firms with employees that pay relatively more attention to macroeconomic conditions hedge more, have higher costs of capital, and subsequently invest less capital and produce less output. While the previous sections do not differentiate between whether employees are primarily concerned about first- or second-moment concerns, Section 5.1 shows that fluctuations in economic uncertainty are the primary reason why firms allocate their attention towards macroeconomic conditions in bad time times. We establish this by following the instrumental variables approach of Alfaro et al. (2018). The fact that uncertainty drives a firm's allocation of attention to macroeconomic conditions is also consistent with the theoretical framework in Section OA.2 of the Online Appendix that links firm risk exposures (β) to the degree to which firms choose to mitigate risk rather than invest. Moreover, Section 5.2 shows that high CS-RA$_{i,t}$ firms have return and accounting characteristics that are associated with risk (e.g., high market betas).

5.1 Relation to Uncertainty

Does time variation in firm uncertainty predict changes in employee reading of macroeconomic-related news? We assess this question using the following firm-quarter panel regression

$$\Delta\text{TS-RA}_{i,t} = \psi_{i,t} + \beta_1 \Delta\sigma_{i,t-1} + \beta_2 \text{Ex Returns}_{i,t-1} + \boldsymbol{Z}'_{i,t-1}\boldsymbol{\gamma} + \varepsilon_{i,t}. \tag{10}$$

In words, we estimate how the change in proportion of macroeconomic reading in the current quarter t relates to either firm excess returns or firm volatility over the previous quarter. Certain specifications also include combinations of time and firm fixed effects that we denote as $\psi_{i,t}$. We also add the firm-level controls from Leary and Roberts (2014), the financial constraints proxy from Whited and Wu (2006), and the CAPM β. Furthermore, as Figure 5 shows, TS-RA$_{i,t}$ has a high degree of persistence; we threrefore add the lagged value of ΔTS-RA$_{i,t}$ to help isolate the relation between excess returns (ExReturns$_{i,t-1}$), return volatility ($\Delta\sigma_{i,t-1}$), and reading. Following Alfaro et al. (2018), we estimate these quantities on a 250-day moving average basis. In addition, we apply the HAC-robust standard errors of Driscoll and Kraay (1998) with a lag length of four quarters to mitigate cross-sectional dependence and autocorrelation effects due to overlapping data.[12] All regressors are standardized such that each coefficient reflects the effect of a one-standard-deviation change in the independent variable of interest on ΔTS-RA$_{i,t}$.

Columns (1) through (3) of Table 7 present the results of regression (10). Column (1) shows a strong statistical relation between changes in either excess returns (first moment) or volatility (second moment) and macroeconomic-related reading. The resulting coefficients have the expected signs: a one-standard-deviation increase in volatility (excess return) relates to an almost 1% increase (0.6% decrease) in the proportion of macroeconomic reading. These magnitudes are similar to

[12] We focus on a quarterly panel as our sample only runs between May 2016 and June 2022. In contrast Alfaro et al. (2018) run regression specification (10) on an annual panel from 1993 to 2019 such that volatility and return estimates are non-overlapping.

those shown in Table 3 that relates reading to fluctuations in aggregate macroeconomic quantities. Column (2) adds both firm and date fixed effects to the regression and shows that the coefficient value associated with volatility is reduced but remains statistically significant. The fact that excess returns become statistically insignificant is the first indication that second- rather than first-moment innovations seem to be the primary driver of changes in firm-level reading of macroeconomic news. The same takeaways emerge from Column (3), which includes firm-level controls.

There is, however, a key endogeneity concern underlying the results of regression (10). Notably, an omitted variable could affect both *firm-level* volatility and a firm's relative attention to macroeconomic news. For example, higher idiosyncratic risk or lower stock returns could suppress non-macroeconomic reading if the employees of these firms refrain from reading news about the firm's main line of business (e.g., potential investment opportunities). This could cause $\Delta\sigma_{i,t-1}$ to predict an increase in $\Delta\text{TS-RA}_{i,t}$ due to higher idiosyncratic volatility rather than economic uncertainty.

We address this concern by using the instrumental variables approach proposed by Alfaro et al. (2018) to show that employee attention to macroeconomic news is indeed sensitive to fluctuations in economic uncertainty. While Section OA.1 of the Online Appendix provides full details on the estimation procedure, the crux of this approach involves three steps. First, we use an empirical asset-pricing model, such as the Carhart (1997) model, to remove the common component of stock returns. Second, we examine how each industry's model de-risked returns covary with aggregate variables, such as key currency returns. Finally, we instrument $\Delta\sigma_{i,t-1}$ using the absolute values of the industry-level exposures from the second step. The identifying assumption is that firm-level unobservables are uncorrelated with non-directional industry-level sensitives to aggregate economic conditions. Thus, 2SLS yields consistent estimates of the parameters in equation (10).

Columns (4) through (6) of Table 7 present the results. The results show that plausibly exogenous fluctuations in economic uncertainty continue to lead to increased employee attention to macroeconomic news. These effects are both economically large, in that a one-standard-deviation increase in uncertainty induces employees to allocate between 1% to 2% more attention to macroeconomic news, and statistically significant. This is in spite of the fact that we control for a battery of date and firm fixed effects in Column (6) as well as a battery of firm-level controls. Moreover, while the association between excess returns and readings becomes economically stronger, the sign and significance of this effect are inconsistent across specifications. This result is somewhat counterintuitive and may reflect that our short sample covers extraordinary times in the market (i.e., the COVID-19 shock). Overall, however, the results consistently show that employees reallocate their attention to macroeconomic news in the face of increased economic uncertainty.

5.2 Relation to firm-level characteristics

This section explores the asset-pricing implications of firms' relative attention to macroeconomic conditions. Given our short sample period, we focus on the relation between CS-RA$_{i,t}$ and several firm-level characteristics that the prior literature links to risk exposure: market beta, size, book-to-market ratios, profitability, and investment. These characteristics underlie the Hou, Xue, and Zhang (2014) and Fama and French (2015) models. We find that while firms that pay relatively more or less attention to macroeconomic-related topics feature economically and statistically significant differences in these characteristics, substantial unexplained variation in the drivers of CS-RA$_{i,t}$ remains. This indicates that CS-RA$_{i,t}$ varies for reasons beyond these common characteristics.

We show the relation between CS-RA$_{i,t}$ and these firm-level characteristics by sorting firms into either three or five CS-RA$_{i,t}$-ranked portfolios at the end of each calendar quarter. We then calculate the value-weighted average characteristic of each portfolio. Consistent with information revelation on accounting release dates, we update each firm's CS-RA$_{i,t}$ at the end of each announcement month. Table 8 reports the results of this analysis. Across both the tercile and quintile sorts in Panels A and B, respectively, we find that high CS-RA$_{i,t}$ firms have higher book-to-market ratios, higher profitability, and lower investment. These differences are significant at the 5% level. High CS-RA$_{i,t}$ firms also have higher market betas than low CS-RA$_{i,t}$ firms, although these differences are insignificant. While each of these characteristics is in line with the notion that high CS-RA$_{i,t}$ firms are riskier, the outlying characteristic is the difference in market capitalization, which is positive even though the size effect predicts a negative relation with returns.[13] Collectively, the strong relation between CS-RA$_{i,t}$ and these characteristics bolsters our confidence that CS-RA$_{i,t}$ is related to risk exposures.

The analysis underlying Table 8 focuses on the univariate relation between characteristics and

[13]While the CS-RA$_{i,t}$ measure does not line up correctly with the size characteristic, the size factor has had a close to zero return over the past two decades.

CS-RA$_{i,t}$. This makes it difficult to determine the marginal contribution of each characteristic in explaining variation in a firm's relative attention to macroeconomic conditions. Thus, Table OA.3.3 in the Online Appendix performs a simple variance decomposition of CS-RA$_{i,t}$. While we provide the full details in the Online Appendix, the key takeaway from this analysis is that firm-level characteristics explain relatively little variation in CS-RA$_{i,t}$. Without controlling for unconditional differences in attention between sectors (defined using two- or three-digit NAICS codes) or times, variation in characteristics explains about 12% of the variation in CS-RA$_{i,t}$. However, when we control for sector-by-date fixed effects, these characteristics explain less than 0.5% of the variation in relative attention. In fact, over 90% of the variation in CS-RA$_{i,t}$ is explained by firm-specific factors. This highlights the fact that knowledge of CS-RA$_{i,t}$ provides insights into firm-level risk exposures that are not reflected by traditional return- and accounting-based characteristics.

Finally, Table **??** in the Online Appendix builds on the evidence that CS-RA$_{i,t}$ is not simply a linear transformation of common asset-pricing characteristics by showing that high CS-RA$_{i,t}$ firms tend to earn larger returns, on average, than low CS-RA$_{i,t}$ firms. The unconditional difference in returns is 14 basis points per week, which is equivalent to about 7.5% per annum. While this result is not statistically significant (t-statistic of 1.36), we note that (i) this result is consistent with the positive relation between CS-RA$_{i,t}$ and implied costs of capital in Table 5 and (ii) noise in the time series of realized returns over our short sample period (i.e., 2016 to 2022) reduces our ability to establish statistically significant differences in returns. Columns (2) and (3) then show that this return is not explained by either the CAPM or the Fama and French (2018) three-factor model, but Columns (4) and (5) show that this spread becomes economically and statistically diminished when we consider the Fama and French (2015) five-factor model plus momentum.

6 Conclusion

This paper uses a high-dimensional dataset that reflects the daily internet news reading of the employees of public firms to characterize firm-level exposures to macroeconomic risk. Notably, and in the time series, we show that employees' attention to macroeconomic risk increases in periods following a deterioration in macroeconomic conditions, measured using either a decline in the level of macroeconomic activity or an increase in economic uncertainty. Second, and in the cross-section, we show that firms that spend relatively more of their time reading about macroeconomic conditions are (i) more likely to engage in corporate risk mitigation, (ii) have higher costs of equity capital, and (iii) tend to invest and produce less. These relations between employee reading, firm risk, and firm outcomes extend beyond typical firm characteristics, such as size, leverage, and asset tangibility, and often hold after accounting for differences in risk across industries and time periods.

The fact that employee attention to macroeconomic news is highly informative about firm-level risk exposures and outcomes is intuitive ex-post but not entirely obvious ex-ante. After all, if the average employee spends most of their time reading news on the internet that is unrelated to the risks or prospects of their employer, then a firm's relative attention to macroeconomic conditions will contain no useful information about the economic activity of the firm. In contrast, our results — which consistently find that employee readings respond to aggregate economic conditions and predict firm-specific actions — highlight that the attention of rank-and-file employees is useful for understanding the corporate policies that only a few key corporate personnel may ultimately be responsible for making. In some sense, this could reflect the fact that observing the news consumption of individual employees allows us to elicit the "wisdom of crowds" within each firm.

Our results, which directly link the business-relevant attention of employees to firm risk, stand in contrast to many papers that rely on surveys to infer the key concerns of firms and corporate personnel (e.g., Coibion, Gorodnichenko, and Ropele (2020)). Moreover, we contribute to a nascent literature that examines what kinds of news individuals choose to consume and why. While this paper focuses on how a firm's attention to macroeconomic news aligns with the firm's exposure to macroeconomic risk, asking whether employees pay attention to other sources of risk, such as climate and regulatory risk, provides interesting avenues for future research that could use these other kinds of news consumption to infer exposures to non-traded risks.

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Tables and Figures

Table 1: Summary Statistics
This table presents summary statistics for the number of firms (*domains*) covered by the data, the number of topics in the Consortium's taxonomy, and the cross-sectional distribution of firm-topic interactions for each year in our sample. Panel A reports results for all firms, while Panel B focuses on the CRSP-COMPUSTAT universe of firms. The cross-sectional distribution of firm-topic interactions is characterized by the mean, median, standard deviation (*SD*), and skewness, estimated using data from the last week of each year. The sample period is from June 2016 to July 2022.

(a) All firms

			Cross-sectional Firm-Topic			
Year	Firms	Topics	Mean	Median	SD	Skew
2016	651599	2407	204.27	111.00	274.88	3.02
2017	1935696	3227	477.77	256.00	582.79	2.02
2018	2051067	4804	444.62	176.00	687.69	2.95
2019	1713267	5500	262.84	76.00	567.97	4.83
2020	1960832	5869	306.06	105.00	587.48	4.49
2021	2053800	7392	301.77	86.00	642.63	5.01
2022	2124557	7395	295.76	83.00	630.07	4.98

(b) Public firms

			Cross-sectional Firm-Topic			
Year	Firms	Topics	Mean	Median	SD	Skew
2016	2609	2407	992.04	957.00	653.37	0.17
2017	2749	3227	2406.45	2864.00	964.07	-1.13
2018	2755	4804	3229.05	3820.00	1578.06	-0.71
2019	2786	5500	2933.25	3055.50	1962.48	-0.12
2020	2877	5869	3110.18	3185.00	2026.29	-0.10
2021	3181	7392	3426.36	3212.00	2505.42	0.13
2022	3267	7395	3410.00	3204.00	2465.62	0.15

Table 2: Summary Statistics and Characteristics by Industry

This table reports average industry characteristics across 17 North American Industry Classification (NAICS) 2-digit industries, providing insights into how firms in each industry interact with the Consortium's data. For each industry, we report summary statistics for all public firms (*Public*) and the fraction of public firms that we match to the Consortium's data (*Match (%)*). The statistics include the number of firms in each industry (*Firms*), the market capitalization of each industry (*Market Cap*), and the number of employees in each industry (*Employees*). Additionally, we report the fraction of topics in the Consortium's data that firms in each industry interact with (*Topics (%)*) and the average value of our cross-sectional relative attention measure (*Attention (%)*), as defined in Section 3.2. The topic- and attention-related statistics are first calculated at the firm level across all years and then averaged across all firms in each industry. The definition of each NAICS is available at the US Census website, `https://www.census.gov/naics/`.

	Firms		Market Cap		Employees		Topics	Attention
Industry	Public	Match(%)	Public	Match(%)	Public	Match(%)	(%)	(%)
Technical Services	116	86.44	4995060	96.40	21420	91.33	46.80	45.52
Information	423	77.75	14884940	67.70	14270	57.24	47.89	48.46
Education	27	56.44	1575222	64.95	8756	63.96	15.40	51.22
Agriculture	10	86.21	3332093	98.65	6524	98.39	42.84	51.78
Arts & Entertainment	24	87.59	2706848	98.07	9351	99.07	28.07	53.86
Wholesale	102	85.50	3729525	84.83	9669	88.11	35.80	56.65
Real Estate	259	81.95	5575583	94.57	2834	86.80	23.32	57.83
Manufacturing	1653	89.72	8080339	93.73	10247	90.75	44.58	58.37
Health Care	53	94.62	4256509	99.02	23369	98.49	45.49	58.71
Construction	54	91.93	2664172	98.26	7192	93.25	30.34	60.06
Waste Management	73	90.83	4996922	86.76	25932	95.56	38.04	61.26
Hotel and Food	66	87.66	7187891	92.72	40124	89.11	39.58	61.50
Utilities	91	85.32	11459666	92.70	7282	83.94	30.83	63.90
Transportation	128	75.23	8141457	91.44	18689	88.60	48.76	66.22
Oil & Gas	219	86.78	4245510	93.25	4305	89.15	28.69	69.27
Retail	132	86.87	17438184	84.17	62614	69.16	68.55	72.86
Finance	735	83.68	7194094	91.44	8132	91.70	48.56	74.70
All	4198	85.62	8212605	87.87	12605	83.66	44.98	61.30

Table 3: Sensitivity of Relative Attention to Fluctuations in Macroeconomic Conditions
The table reports how the time-series measure of relative attention to the macroeconomy from equation (1) changes in response to fluctuations in either the level of macroeconomic activity (Panel A) or economic uncertainty (Panel B). Columns (1), (3), and (5) of each panel display the results of estimating equation (3), where the dependent variable is each firm's value of relative attention from equation (1) and independent variables include one of the daily corporate default spread, the intermediary capital ratio from He et al. (2017), or the return on WTI oil in Panel A, and the daily value of the VIX index, EPU index of Baker et al. (2016), or macroeconomic uncertainty index from Bekaert et al. (2022) in Panel B. These regressions also include day-of-the-week fixed effects to subsume any fixed differences in attention across days of the week. Columns (2), (4), and (6) of these panels report the results of estimating equation (7), whereby we interact each macroeconomic variable with each individual firm's exposure to macroeconomic conditions, as defined by equation (6). The regressions in these columns also feature date-by-industry fixed effects. The sample period runs from May 2016 through June 2022. Standard errors are clustered by firm and date.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Moment Proxies						
	Def. Spread		Int. Capital		WTI Returns	
MacroV_{t-1}	0.0147***		−0.0176***		−0.0130***	
	[14.38]		[−16.66]		[−15.93]	
$\text{CS-RA}_{i,t-1}$		0.0649***		0.0661***		0.0648***
		[38.43]		[41.38]		[37.70]
$\text{CS-RA}_{i,t-1} \times \text{MacroV}_{t-1}$		0.0158***		−0.0279***		0.0087***
		[9.12]		[−17.45]		[5.94]
Observations	3,660,323	3,438,550	3,660,323	3,438,550	3,660,323	3,438,550
R^2	0.0141	0.1895	0.0197	0.1920	0.0116	0.1888
Panel B: Second Moment Proxies						
	VIX Index		EPU Index		BEX Index	
MacroV_{t-1}	0.0065***		0.0128***		0.0217***	
	[5.61]		[11.33]		[17.09]	
$\text{CS-RA}_{i,t-1}$		0.0651***		0.0651***		0.0649***
		[38.73]		[38.78]		[37.83]
$\text{CS-RA}_{i,t-1} \times \text{MacroV}_{t-1}$		0.0175***		0.0187***		0.0104***
		[9.80]		[9.02]		[7.07]
Observations	3,660,323	3,438,550	3,660,323	3,438,550	3,660,323	3,438,550
R^2	0.0043	0.1898	0.0111	0.1900	0.0286	0.1889
Day of Week FE	+		+		+	
Date × Industry FE		+		+		+

Table 4: Risk Mitigation, Regulatory Compliance, and Firm Attention to Macroeconomic Risk
The table presents regression results that examine the relation between firm-level exposure to macroeconomic risk and either hedging intensity (Panel A) or regulatory intensity (Panel B). These results are obtained by estimating equation (9). In Panel A, the dependent variable measures firm-level hedging intensity that we define using the approach of Campello et al. (2011). Specifically, we first count the number of hedging-related words that each firm mentions in its annual 10-K. We then scale this quantity by the total number of words in the firm's 10-K. To eliminate the influence of outliers, this hedging-intensity ratio is transformed to reflect each firm's cross-sectional percentile (or rank) of the hedging-intensity score. In Panel B, we measure a firm's regulatory intensity using the data constructed by Kalmenovitz (2022). Regressions include combinations of industry, date, and industry-by-date fixed effects, as well as a battery of control variables. These control variables include the set of variables from Leary and Roberts (2014), Whited and Wu (2006) proxy for financial constraints, and the CAPM β, a common proxy for a firm's exposure to macroeconomic risk. Panel A (Panel B) uses data from June 2016 through July 2022 (December 2020). All standard errors are clustered by firm and time.

	(1)	(2)	(3)	(4)	(5)
Panel A: Hedging Activity					
CS-RA$_{i,t-1}$	0.1484***	0.1142**	0.1226**	0.1130**	0.0106
	[3.09]	[2.26]	[2.17]	[2.16]	[0.78]
$\mathbb{I}^{\text{High}}_{\text{EPU}} \times$ CS-RA$_{i,t-1}$				0.2101*	0.1692**
				[1.75]	[2.56]
Observations	7,789	7,765	7,165	7,165	7,119
R^2	0.0195	0.1381	0.2081	0.2274	0.4202
Panel B: Compliance Activity					
CS-RA$_{i,t-1}$	19.5738***	13.6471***	14.5935***	14.3527***	8.7792***
	[8.52]	[7.21]	[7.64]	[8.01]	[7.06]
Observations	24,483	24,455	23,490	23,490	22,659
R^2	0.0242	0.4283	0.5538	0.5540	0.5970
Date FE		+			
Industry FE		+			
Date × Industry FE			+	+	+
CAPM-beta				+	+
Controls					+

Table 5: Implied Cost of Capital and Firm Attention to Macroeconomic Risk
This table shows the results of estimating equation (11) to examine the relation between a firm's implied cost of capital, measured using the approach of Gebhardt et al. (2001), and the firm's relative attention to macroeconomic risk (CS-RA$_{i,t}$), measured via equation (6). Regressions include combinations of industry, date, and industry-by-date fixed effects. All specifications also control for the CAPM β of each firm. Additionally, specification (5) also includes a set of asset-pricing characteristics related to each underlying firm. These characteristics include firm size, Tobins Q (the inverse of the book-to-market ratio), profitability, and investment tangibility. The data underlying this regression spans from 2016 through 2022, and all standard errors are clustered by firm and time.

	(1)	(2)	(3)	(4)	(5)
CS-RA$_{i,t-1}$	0.0166***	0.0164***	0.0110***	0.0113***	0.0062***
	[6.50]	[6.33]	[5.33]	[5.40]	[3.61]
CAPM $\beta_{i,t-1}$	−0.0030	−0.0025	−0.0070**	−0.0073***	−0.0075**
	[−1.20]	[−0.99]	[−2.65]	[−2.71]	[−2.65]
Size$_{i,t-1}$					0.0032***
					[3.54]
ROA$_{i,t-1}$					0.0085***
					[5.71]
Tangability$_{i,t-1}$					0.0015
					[1.26]
Tobin Q$_{i,t-1}$					−0.0068***
					[−5.75]
Date FE		+	+		
Industry FE			+		
Date × Industry FE				+	+
Observations	37,309	37,309	37,285	36,266	34,868
R^2	0.0087	0.0174	0.1045	0.1509	0.1790

Table 6: Real Outcomes and Firm Attention to Macroeconomic Risk
This table reports the results of estimating equation (9) to examine the relation between a firm's relative attention to macroeconomic risk (measured via equation (6)) and total asset growth (Panel A), sales growth (Panel B), and employment growth (Panel C). Asset growth, sales growth, and employment growth are defined in the Internet Appendix OA.1. The specifications include combinations of industry, date, and industry-by-date fixed effects. Additionally, specifications (4) and (5) control for each firm's CAPM β, a common proxy for a firm's exposure to macroeconomic risk. Additionally, specification (5) features both the set of controls from Leary and Roberts (2014) and Whited and Wu (2006) measure of financial constraints. The data underlying this regression spans from 2016 through 2022, and all standard errors are clustered by firm and time.

	(1)	(2)	(3)	(4)	(5)
			Panel A: Asset Growth		
CS-RA$_{i,t-1}$	-0.0406^{***}	-0.0326^{***}	-0.0334^{***}	-0.0170^{***}	0.0042
	[−3.30]	[−3.26]	[−3.37]	[−3.48]	[0.75]
$\mathbb{I}_{\text{EPU}}^{\text{High}} \times$ CS-RA$_{i,t-1}$				-0.1083^{***}	-0.1103^{***}
				[−3.47]	[−3.98]
Observations	53,846	53,811	52,691	52,691	40,564
R^2	0.0031	0.0235	0.0609	0.0632	0.1201
			Panel B: Sales Growth		
CS-RA$_{i,t-1}$	-0.1362^{***}	-0.1099^{***}	-0.1157^{***}	-0.1124^{***}	-0.0461^{***}
	[−9.25]	[−8.66]	[−9.28]	[−8.47]	[−3.96]
$\mathbb{I}_{\text{EPU}}^{\text{High}} \times$ CS-RA$_{i,t-1}$				-0.0543^{***}	-0.0143
				[−4.13]	[−0.69]
Observations	49,048	49,013	47,939	47,939	40,095
R^2	0.0050	0.0492	0.0997	0.0999	0.1362
			Panel C: Employment Growth		
CS-RA$_{i,t-1}$	-0.0624^{***}	-0.0445^{***}	-0.0364^{**}	-0.0214^{*}	0.0144
	[−4.69]	[−3.32]	[−2.64]	[−1.93]	[1.19]
$\mathbb{I}_{\text{EPU}}^{\text{High}} \times$ CS-RA$_{i,t-1}$				-0.0658^{***}	-0.0756^{***}
				[−6.36]	[−4.60]
Observations	11,068	11,027	10,362	10,362	8,388
R^2	0.0027	0.0435	0.0857	0.0878	0.1339
Date FE		+			
Industry FE		+			
Date × Industry FE			+	+	+
CAPM-beta				+	+
Controls					+

Table 7: Firm Reading and Uncertainty Shocks

This table shows the results of estimating equation (10) that examines the relationship between changes in risk and attention to macroeconomic-related news (ΔTS-RA$_{i,t}$). Regressions include a combination of firm and date fixed effects as well as the firm-level controls of Leary and Roberts (2014), Whited and Wu (2006), and CAPM β. The proxy for firm risk in columns (1) through (3) is the firm-level return volatility over a 250-day rolling period. In columns (4) through (6) we follow the approach of Alfaro et al. (2018), instrumenting firm-level return volatility with industry-level estimates of sensitivity with growth of various macroeconomic measures in an 2 stage leqst square analysis (see Online Appendix OA.1 for details). We t-statistics are estimated using the the HAC-robust approach of Driscoll and Kraay (1998) with a lag length of 4 quarters. The sample period runs from May of 2016 through June of 2022.

	Realized Volatility			Instrumented Moments		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔVolatility$_{i,t-1}$	0.0097***	0.0029**	0.0028**	0.0190**	0.0135*	0.0108**
	[4.27]	[2.47]	[2.83]	[2.08]	[2.01]	[2.77]
Ex Returns$_{i,t-1}$	−0.0055***	0.0012	0.0009	−0.0231	0.0423**	0.0304*
	[−3.36]	[1.35]	[0.86]	[−1.31]	[2.23]	[2.03]
Lagged Δ Reading	+	+	+	+	+	+
Date FE		+	+		+	+
Firm FE		+	+			+
Firm Controls			+			+
Observations	48,760	48,586	38,538	48,760	48,760	38,538
R^2	0.0788	0.0979	0.0833	0.0029	-0.1892	-0.0212

Table 8: Firm Attention to Macroeconomic Conditions: Portfolio Characteristics
The table presents the characteristics of portfolios formed by sorting firms on the basis of their relative attention to macroeconomic conditions, (CS-RA$_{i,t}$), measured via equation (6). Panel A (Panel B) reports the resulting of sorting the cross section of firms into tercile (quintile) portfolios at the end of each quarter from 2016 through 2022. For each portfolio, we report the value-weighted average values of five prominent asset-pricing characteristics: CAPM β, market capitalization, the book-to-market ratio, gross profitability, and asset growth. We also report the average difference in characteristics between the high CS-RA$_{i,t}$ portfolio and the low CS-RA$_{i,t}$ portfolio. The underlying data spans from 2016 through 2022, and brackets report t-statistics that are constructed using Newey and West (1987) standard errors.

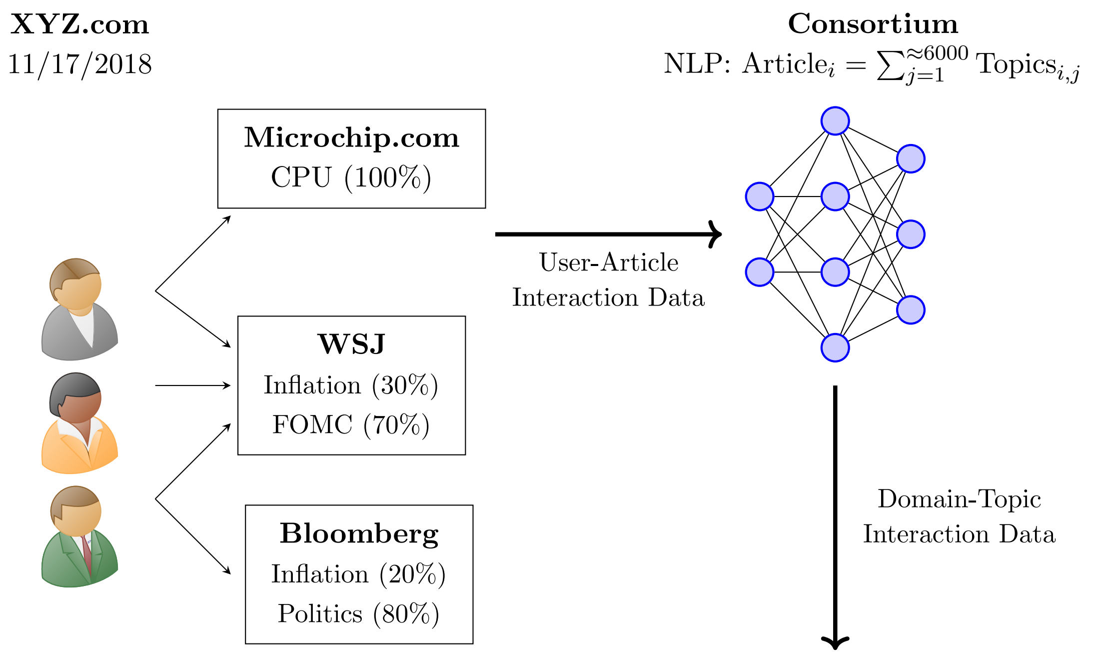
(a) Three CS-RA Portfolios

	Beta	Market Cap	Book to Market	Gross Profit	Asset Growth
Low ARA	0.9139	5.7593	0.9451	0.1380	0.3316
2	1.0184	6.7104	0.6591	0.2426	0.1969
High ARA	1.0428	7.5378	0.7058	0.2637	0.1236
High-Low	0.1289	1.7785	-0.2393	0.1257	-0.2080
t-stat	[8.00]	[9.12]	[-4.28]	[6.46]	[-3.67]

(b) Five CS-RA Portfolios

	Beta	Market Cap	Book to Market	Gross Profit	Asset Growth
Low ARA	0.8999	5.6863	1.0392	0.1277	0.3510
2	0.9520	6.0229	0.7629	0.1721	0.2821
3	1.0209	6.7290	0.6510	0.2447	0.1943
4	1.0461	7.2068	0.6710	0.2698	0.1437
High ARA	1.0398	7.7002	0.7265	0.2593	0.1162
High-Low	0.1400	2.0139	-0.3128	0.1316	-0.2347
t-stat	[8.52]	[9.67]	[-4.31]	[8.13]	[-3.88]

Figure 1: Visualizing the Consortium's Member Base
This figure illustrates a subsample of the Consortium's more than 4,000 members.



Date	Domain	Score	Topic
11/17/2018	xyz.com	3	Inflation
11/17/2018	xyz.com	3	FOMC
11/17/2018	xyz.com	1	CPU
11/17/2018	xyz.com	1	Politics

Figure 2: Visual Representation of the Consortium's data

The figure presents a stylized example of the Consortium's data generation process. Initially, users read various articles from a range of online publishers. The online publishers then provide this user-interaction data to the Consortium. Utilizing machine learning and natural language processing algorithms, the Consortium decomposes each article into a combination of its core topics (illustrated beneath each article). Subsequently, the Consortium aggregates the analyzed user-article interaction data across users and firms (depicted as domains) to generate domain-topic interaction data. This data encompasses several variables, such as the date of interactions, the domain of interactions, the user engagement with a specific topic, and an associated topic label.

Figure 3: Category Visualization

This figure presents a word cloud illustrating the prevalence of topic categories across the Consortium's dataset. Each topic in the dataset is associated with a specific category. Category labels are then weighted by the number of associated topics, making categories with more topics appear larger.

(a) Raw topic cloud

(b) *tf-iaf*-weighted topic cloud

Figure 4: Raw and *tf-iaf*-Weighted Topic Clouds for Macroeconomic Topics

This figure presents two topic clouds for the same set of macroeconomic-related topics. Panel A displays the raw topic cloud, showing the most read topics in aggregate. Panel B presents the *tf-iaf*-weighted topic cloud, highlighting the topics that are more informative in distinguishing reading about macroeconomic conditions across firms in the cross-section. We define the corpus of macroeconomic-related articles following the approach outlined in Section 3.2. Likewise, the *tf-iaf* weights are given by equation (5). The data underlying these topic clouds is from the week of 11/17/2018.

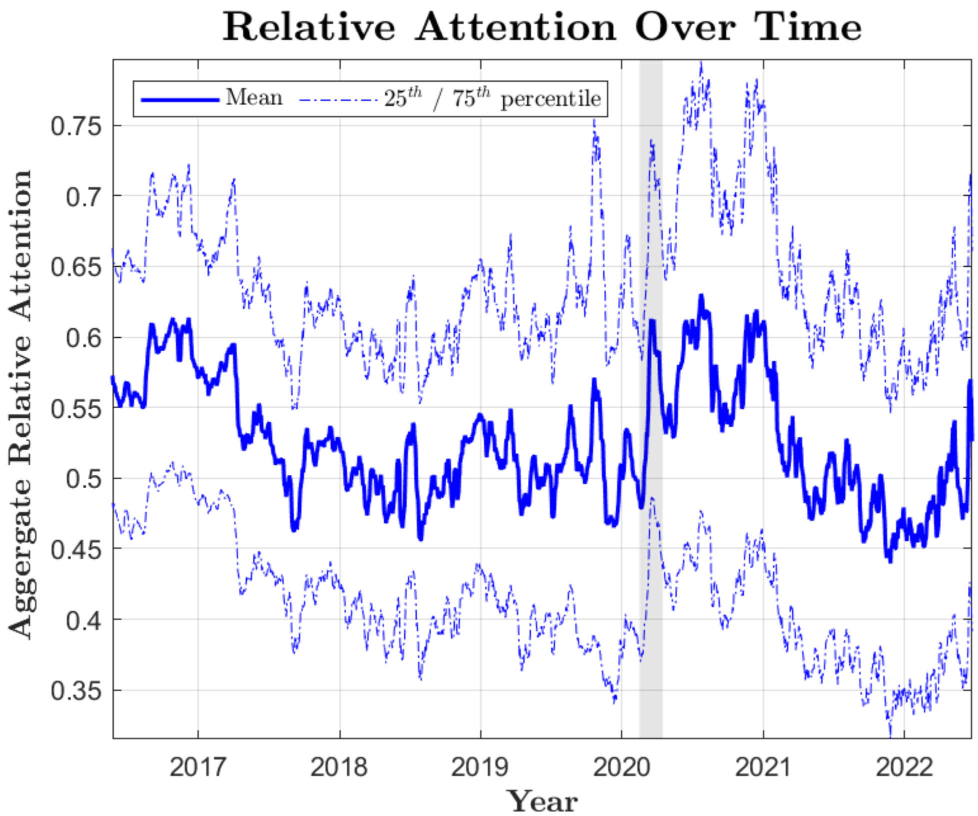


Figure 5: Aggregate Relative Attention ($\widetilde{\text{TS-RA}}_t$) and Macroeconomic Conditions
This figure displays the time series of raw relative attention to macroeconomic conditions, as defined in equation (2). The solid blue line displays the average value of $\text{TS-RA}_{i,t}$ across all firms (i.e., the time series of $\widetilde{\text{TS-RA}}_t$ from equation (1)), while the dashed blue lines reports the average value of $\text{TS-RA}_{i,t}$ across all firms with a value of $\text{TS-RA}_{i,t}$ that is greater (less) than the 75^{th} (25^{th}) percentile of $\text{TS-RA}_{i,t}$ at each time t. The underlying data is recorded at the daily frequency and ranges from 2016 through 2022. For visual clarity, the figure reports the five day moving average value of each quantity. The sample runs from May 2016 through June 2022.

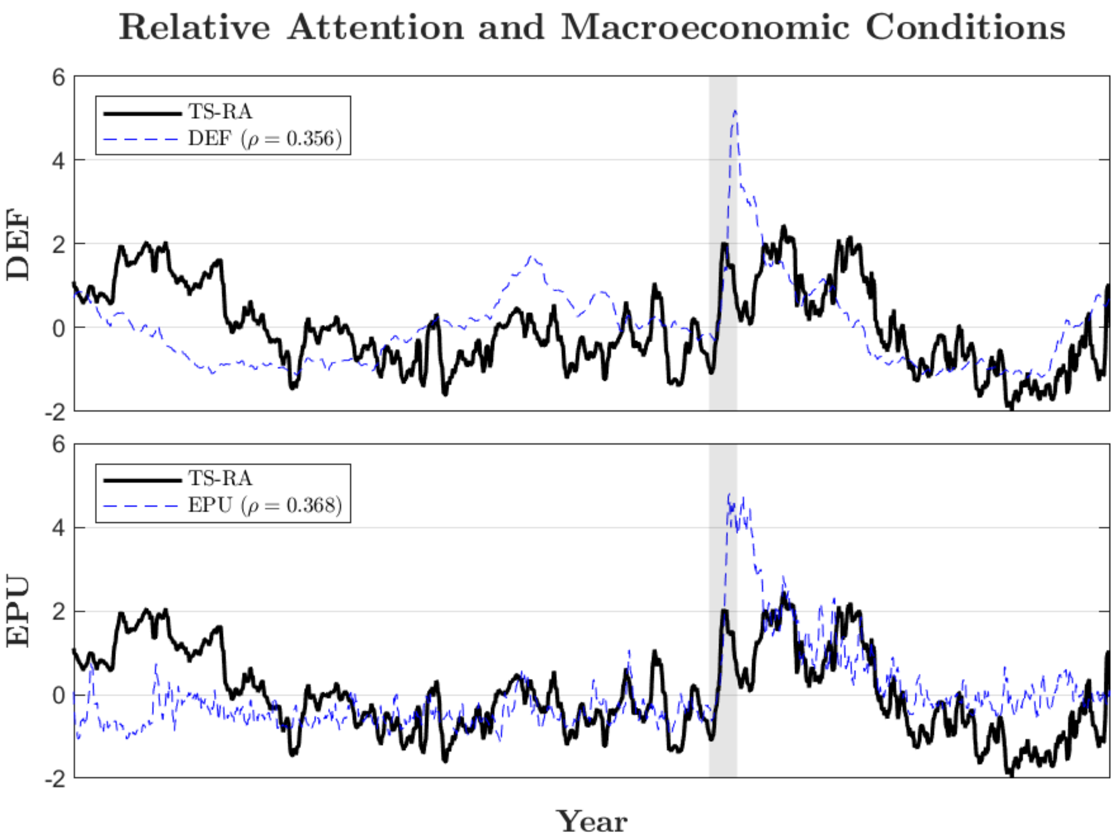
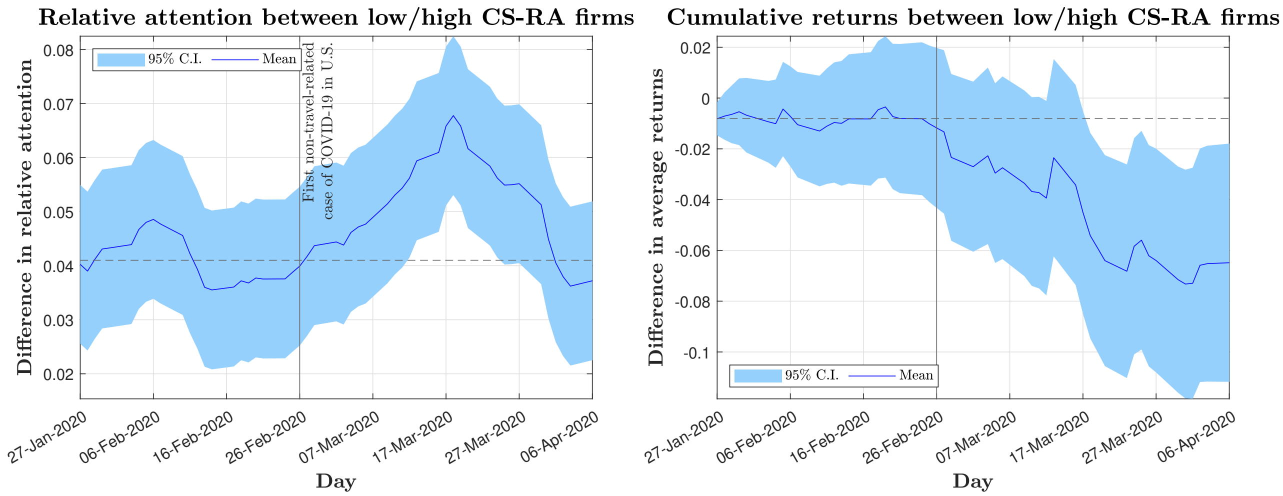


Figure 6: Aggregate Relative Attention ($\widetilde{\text{TS-RA}}_t$) and Macroeconomic Conditions

This figure displays the time series of raw relative attention $\widetilde{\text{TS-RA}}_t$ from equation (2) against the time series of two prominent variables that reflect the state of macroeconomics conditions: (i) the corporate default spread (DEF) and (ii) the Economic Policy Uncertainty index from Baker et al. (2016) (EPU). The underlying data is recorded at the daily frequency and ranges from 2016 through 2022. For visual clarity, the figure reports the five day moving average value of each quantity as well as the time-series correlation between $\widetilde{\text{TS-RA}}_t$ and each macroeconomic variable of interest. The sample runs from May 2016 through June 2022.



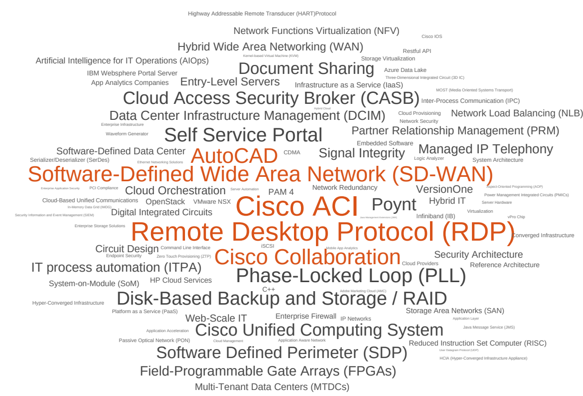
(a) Reading activity **(b) Returns**

Figure 7: Firm Relative Attention (TS-RA$_{i,t}$) Around the Onset of the COVID-19 Pandemic
The figure reports the results of a high-frequency event study in which we examine how the average firm's relative attention to macroeconomic conditions, as measured using (TS-RA$_{i,t}$) from equation (**??**), changes upon the onset of the COVID-19 pandemic in early 2020. The figure is constructed as follows. First, we estimate the value of CS-RA$_{i,t}$ for each firm on February 26th, 2020, which was the day the first nontravel-related case of COVID-19 was confirmed in the United States (depicted by the vertical black lines). Next, we transform CS-RA$_{i,t}$ to be uniformaly distributed over the interval of $[-1, 1]$. We then compute the value-weighted average value of $\widetilde{\text{TS-RA}}_{i,t}$ from equation (**??**) across all firms with a positive (negative) value of these transformed CS-RA$_{i,t}$ scores. For each group, greater weights are placed on firms whose relative attention is more extreme (i.e., close to either negative one or one). The left-hand side of the figure then plots the difference in $\widetilde{\text{TS-RA}}_{i,t}$ between firms with high and low amounts of relative attention to macroeconomic conditions. The right-hand side of the figure then plots the difference in the cumulative returns of these two groups, starting on January 27th, 2020. Each sub-figure also displays the following two quantities: (1) the shaded blue region depcits the 95% confidence interval associated with relative attention on the left-hand side and cumulative returns on the right-hand side; and (2) the horizontal dashed line represents the sample average of each difference between January 27th and February 25th, 2020, the period preceding the onset of concerns related to the COVID-19 pandemic

(a) **Raw topic cloud for Chemicals Manufacturing industry**

(b) ***tf-iaf*-weighted topic cloud for Chemicals Manufacturing industry**

(c) **Raw topic cloud for Computer and Electronics Manufacturing industry**



(d) ***tf-iaf*-weighted topic cloud for Computer and Electronics Manufacturing industry**

Figure 8: Raw and *tf-iaf*-weighted topic clouds for two industries

This figure compares the raw and *tf-iaf*-weighted number of interactions across topics for the Chemicals Manufacturing (NAICS 325) and Computer and Electronics Manufacturing (NAICS 334) industries. The figure highlights the difference in topic relevance between the two weighting methods. The *tf-iaf* weights employed for each industry are given by equation (5). The data underlying these topic clouds is from the week of 11/17/2018.

Online Appendix

OA.1 Variable Definitions

Asset growth. The asset growth rate is computed as the change in total assets (Compustat Quarterly item ATQ) between fiscal quarter t and $t-1$.

Asset tangibility. In analyses that feature quarterly data, asset tangibility is defined as the ratio of a firm's net property, plant, and equipment (Compustat Quarterly item PPENTQ) to the firm's total assets (Compustat Quarterly item ATQ) in fiscal quarter t. In analyses that feature annual data, asset tangibility is defined as the ratio of a firm's net property, plant, and equipment (Compustat Annual item PPENT) to the firm's total assets (Compustat Annual item AT) in fiscal year t.

CAPM $\boldsymbol{\beta}$. The CAPM beta is estimated on a firm-by-firm basis by running a regression of each firm's daily excess stock returns from CRSP onto the excess market return over the preceding 252 trading days.

Employment growth. The firm's employment growth rate is computed as the growth rate in the total number of employees (Compustat Annual item EMP) between fiscal years t and $t-1$.

Implied cost of capital (ICC). To construct this measure, we extract consensus estimates of earnings-per-share before extraordinary expenses ($FEPS_{t+i}$) at time $t+i$ from IBES, the book-value-per-share (B_t) at time t from Compustat, and the month-end stock price (P_t) at time t from CRSP. Our estimate of the ICC is then the solution to the following internal rate of return calculation:

$$P_t = B_t + \frac{FEPS_{t+1}/B_t - ICC_t}{(1+ICC_t)} \times B_t + \frac{FEPS_{t+2}/B_{t+1} - ICC_t}{(1+ICC_t)^2} \times B_{t+1} + TV_t. \tag{11}$$

The solution to this equation provides us with an estimate of a stock's ICC for each month, which is the frequency at which analysts update or reiterate their earnings forecasts in IBES.[14]

In general, only one- and two-year ahead earnings forecasts are reliably available. Hence, we project current earnings forward so as to estimate the terminal value term (i.e., TV_t) in equation (11). Following Pástor, Sinha, and Swaminathan (2008), we define the time-series of all analyst

[14] We rely on analyst forecasts rather than using predictive regressions (see, e.g. Hou, Van Dijk, and Zhang, 2012) due to our short sample and the large number of unanticipated events that occurred between 2016 and 2021 (e.g. the 2016 election results and the economic consequences of the COVID-19 pandemic).

estimated implied return-on-equity (i.e., $FROE_{t+\tau} = FEPS_{t+\tau}/B_{t+\tau-1}$) such that they converge to their long-run, pre-sample industry means (3-digit NAICS from 1995-2015) over a 15 year period,

$$TV_t = \sum_{\tau=3}^{14} \frac{FROE_{t+\tau} - ICC_t}{(1+ICC_t)^{\tau}} \times B_{t+\tau-1} + \frac{FROE_{t+15} - ICC_t}{ICC_t \times (1+ICC_t)^{14}} \times B_{t+14}, \tag{12}$$

where $FROE_{t+15}$ is the firm's industry (NAICS 3-digit) historical mean return-on-equity between 1995 and 2015 (i.e., before our sample). We follow the clean surplus methodology to estimate the future book values, where $B_{t+\tau} = B_{t+\tau-1} + FEPS_{t+\tau} \times (1 - \text{Payout Ratio})$. Like before, we estimate the historical long-run payout ratio using a firm's industry mean payout between 1995 and 2015.

Inventory growth. The inventory growth rate is computed as the change in inventories (Compustat Quarterly item INVTQ) between fiscal quarters t and $t-1$.

Investment growth. The physical investment growth rate is computed as the change in a firm's net property, plant, and equipment (Compustat Quarterly item PPENTQ) between fiscal quarters t and $t-1$.

Leverage. In analyses that feature quarterly data, leverage is defined as the sum of a firm's debt in current liabilities (Compustat Quarterly item DLCQ) plus long-term debt (Compustat Quarterly item DLTTQ) scaled by the firm's total assets (Compustat Quarterly item ATQ) in fiscal quarter t. In analyses that feature annual data, leverage is defined as the sum of a firm's debt in current liabilities (Compustat Annual item DLC) plus long-term debt (Compustat Annual item DLTT) scaled by the firm's total assets (Compustat Annual item AT) in fiscal year t.

Profitability. In analyses that feature quarterly data, profitability in fiscal quarter t is defined as the ratio of net income in fiscal quarter t (Compustat Quarterly item NIQ) to total assets in fiscal quarter $t-1$ (Compustat Quarterly item ATQ). In analyses that feature annual data, profitability in fiscal year t is defined as the ratio of net income in fiscal year t (Compustat Annual item NI) to total assets in fiscal year $t-1$ (Compustat Annual item AT).

Size. In analyses that feature quarterly data, firm size is measured using the natural logarithm of total sales (Compustat Quarterly item SALEQ) in fiscal quarter t. In analyses that feature annual data, firm size is measured using the natural logarithm of total sales (Compustat Annual item SALE) in fiscal year t.

Tobin's Q. In analyses that feature quarterly data, Tobin's q in fiscal quarter t is defined as the sum of the book value of total assets (Compustat Quarterly item ATQ) minus the book value of common equity (Compustat Quarterly item CEQQ) plus the market value of common equity (Compustat Quarterly item CSHOQ multiplied by the end of fiscal quarter stock price given by Compustat Quarterly item PRCCQ), all divided by the book value of total assets. In analyses that feature annual data, Tobin's q in fiscal year t is defined as the sum of the book value of total assets (Compustat Annual item AT) minus the book value of common equity (Compustat Annual item CEQ) plus the market value of common equity (Compustat Annual item CSHO multiplied by the end of fiscal year stock price given by Compustat Annual item PRCC), all divided by the book value of total assets.

Uncertainty-related Instrumented Variable. Need to fill in details.

OA.2 Model

To do: Start with a general overview (like 1-2 paragraphs) of what the purpose of this model is and why it's split into two separate sub-models? Like the start of next model says "We now turn to the employee part of the model." but we haven't used the "employee" in any of the preceding paragraphs, so the turn to the employee problem comes out of left field. Long story short, I think we need to add more context to before going into the specific details.

We start with the following firm objective function:

$$\max_{h,i} \quad \pi_0 + E[\overline{m}\pi_1] - \frac{\beta}{2}\text{Var}[\pi_1], \tag{13}$$

where π_t is the firm profits at time t and β captures the sensitivity of a firm's profits to the single aggregate shock in this model. As we explain below, the single source of risk this price-taking firm faces is the price that the market is willing to pay for its output in the future. The functional form for this objective function derives from combining the Euler Equation with an assumption that fluctuations in next period profits are entirely aggregate in nature (see, e.g. Acharya, Lochstoer, and Ramadorai, 2013).Can we add mroe details here? The variable $\overline{m}$ is the discount factor. All decisions are made at time $t = 0$, and the model resolves at time $t = 1$.

There are two choices for the firm to make: h and i. The variable h denotes how much the firm chooses to hedge or mitigate risk, whereas the variable i reflects how much the firm chooses to invest in next period's production. Intuitively, and as we highlight below, hedging activity is costly for the firm to undertake, but a larger choice of h reduces the firm's uncertainty about the future output price. Similarly, increasing i also reduces profits at $t = 0$, but increases the amount of output the firm has available to sell at the prevailing output price at $t = 1$.

The key measure of risk in the model is σ, which is the expected variation in next period's output price. For a specific firm, this is scaled by risk exposure, β. This is a little unclear, what do we mean by this exactly? Below we derive a comparative static that shows, ceteris paribus, that an increase in β corresponds to an increase in h/i. In other words, firms with higher macroeconomic exposure attempt to mitigate that risk more aggressively as a fraction of firm investment.

As in Hong et al. (2023), we assume an Ak model for production, whereby the output the firm produces at time t is $y_t = Ak_t$. Here, k_t is capital available for the purpose of production at time t and $A > 0$ is the productivity of capital. The law of motion of capital is given as:

$$k_1 = i + (1 - \delta)k_0, \tag{14}$$

where δ is a depreciation rate.

We assume the following structure for the firm's profits in each period:

$$\pi_0 = p_0(y_0 - i) - \frac{\kappa_p}{2}h^2, \quad \text{and,} \tag{15}$$

$$\pi_1 = p_1 y_1 + (\mu_p - p_1)\, h. \tag{16}$$

In words, these equations state that the firm jointly chooses to invest and/or mitigate risk at period 0. The choice to mitigate, however, carries a quadratic cost with scaling parameter $\kappa_p > 0$. While hedging reduces the firm's profits in period zero, the benefit of risk mitigation is that the firm reduces the variance of its profit variance in period one. One could microfound this cost in a general equilibrium setup; for example, Acharya et al. (2013) emphasize limits to arbitrage from the perspective of the suppliers—e.g., financial intermediaries—of hedging instruments (e.g., futures contracts). As noted above, the output price in period one, p_1, is risky. This price has a mean μ_p and a standard deviation $\sigma > 0$.

Proposition 1. *There is a positive relationship between firm risk exposure β and the ratio h/i:*

$$\frac{\partial(h/i)}{\partial\beta} > 0. \tag{17}$$

The proof is in the next section of this appendix.

The positive relationship between the ratio of hedging to investment and the firm exposure to risk is intuitive: as exposure to risk escalates, firms are inclined to allocate a greater proportion of their resources towards risk management relative to their investments. This behavior is contingent on (i) mitigation activity being costly for the firm and (ii) the cost function (i.e., both the quadratic functional form and κ_p in our idealized setup) being on average the same across firms (see, e.g. Hong et al., 2023, for similar assumptions underlying firm-level mitigation activity).

Finally, a corollary follows from proposition 1.

Corollary 1. *h/i in the cross section of firms will relate*

1. *positively to hedging activity as $\frac{\partial(h/i)}{\partial h} > 0$, and*
2. *negatively to investment activity as $\frac{\partial(h/i)}{\partial i} < 0$.*

This can also be rationalized from an NPV perspective. Higher exposure to aggregate risk (i.e., β) imply higher higher hurdle rates and thus lower investment activity.

Is it worth adding something that links this back to CS-RA? In the paper itself we say that CS-RA reflects firm-level risk exposure, but here don't say that we view CS-RA serving as an empirical proxy for h/i.

OA.2.1 Extension to employee attention allocation

We now turn to the employee part of the model. The employees have similar problems to that of the firm, except they seek to maximize the following: Again, worth being explicit about what the firm is choosing to solve this maximization problem?

$$\max \quad c_0 + E[\overline{m}c_1] - \frac{\beta}{2}\text{Var}[c_1], \tag{18}$$

where c_t is consumption at time t, and the expectations and variances are subjective. The consumption of the employee at time 1 is given by $w + b\pi_1 + (y_1 - h)\,\xi$, where w is a constant wage component, and b measures the degree of exposure that employee earnings are exposed to firm profits (e.g., pay increases tied to success of the firm), and ξ is the residual riskiness of the employee's pay. This residual component can be thought to capture human capital risk or employment risk outside of only the firm's profits. The employee is uncertain about this term, but can, from their perspective, reduce this uncertainty by learning about the aggregate environment. ξ is distributed $\sim N\left(0, (\sigma_\xi/\tau)^2\right)$, where τ is thus the strength of the employee signal. In addition, p_1 and ξ have a correlation of ρ. Intuitively, when aggregate risk increases the employee feels even greater uncertainty. Furthermore the employees uncertainty is scaled by the firm's residual risk after choosing h. Employee consumption is then:

$$c_0 = w + b\pi_0 - \frac{\kappa_\tau}{2}(y_1 - h)^2(\tau - 1)^2. \tag{19}$$

$$c_1 = w + b\pi_1 + (y_1 - h)\xi. \tag{20}$$

Note that obtaining the signal incurs quadratic costs controlled by κ_τ. The $\tau - 1$ term above means that at $\tau = 1$ the employees are both not reducing uncertainty nor incurring the associated cost. The employee chooses τ to optimize their objective function.

Proposition 2. *If $\rho > 0$, there is a positive relationship between the precision of the signal acquired, τ, and both the size of the residual volatility, σ_ξ, and exposure to aggregate risk, β:*

$$\frac{\partial \tau}{\partial \sigma_\xi} > 0. \tag{21}$$

$$\frac{\partial \tau}{\partial \beta} > 0. \tag{22}$$

$$\frac{\partial^2 \tau}{\partial \sigma \partial \beta} > 0. \tag{23}$$

The proof of this is below in the next section of this appendix.

Our model reveals the response of employees in the face of heightened risk for the firm either in the form of higher aggregate risk or firm-specific exposure. In short, employees become motivated to acquire more accurate and precise information in order to better smooth their consumption profile. This behavior aligns with rational risk-aversion strategies, where individuals seek to reduce uncertainty by improving their knowledge of the factors affecting their well-being.

Finally, a corollary follows from proposition 2.

Corollary 2. *As $\frac{\partial(h/i)}{\partial \beta} > 0$ and $\frac{\partial \tau}{\partial \beta} > 0$ then also $\frac{\partial \tau}{\partial(h/i)} > 0$.*

Again, worth being explicit about what this "employee problem" is meant to map to the in the data? We don't really mention anything about the employee problem in the text on page 24, we only mention the predictions of the firm's problem, don't we? So it's not clear what the main takeaway from this sub-model is...

OA.2.2 Model Proofs

Proof of Proposition 1. We calculate the expected period 1 discounted profits:

$$E[\overline{m}\pi_1] = E[\overline{m}(p_1(y_1 - h) + \mu_p h)] = E[\overline{m}p_1 y_1],$$

where we use the fact that $E[\overline{m}p_1] = \overline{m}\mu_p$. So the producer problem is to solve:

$$\max_{i,h}\ p_0 y_0 - ip_0 - \frac{\kappa_p}{2}h^2 + E[\overline{m}p_1 y_1] - \frac{\beta}{2}\mathrm{Var}[p_1(y_1 - h)] \tag{24}$$

$$\text{subject to } y_1 = A(i + (1-\delta)k_0). \tag{25}$$

Then we should have:

$$\max_{i,h}\ p_0 y_0 - ip_0 - \frac{\kappa_p}{2}h^2 + E[\overline{m}p_1 A(i + (1-\delta)k_0)] - \frac{\beta}{2}\mathrm{Var}[p_1(A(i + (1-\delta)k_0) - h)]$$

Given that $p_1 \sim N\left(\mu_p, \sigma^2\right)$, we can write the above problem as:

$$\max_{i,h}\ p_0 y_0 - ip_0 - \frac{\kappa_p}{2}h^2 + E[\overline{m}p_1 A(i + (1-\delta)k_0)] - \frac{\beta}{2}\sigma^2\left(A(i + (1-\delta)k_0) - h\right)^2$$

This yields the first order conditions (FOC):

$$[i]:\quad -p_0 + E[\overline{m}p_1 A] - \beta\sigma^2(A^2(i + (1-\delta)k_0) - Ah) = 0 \tag{26}$$

$$[h]:\quad -\kappa_p h + \beta\sigma^2\left(A(i + (1-\delta)k_0) - h\right) = 0 \tag{27}$$

To verify that this represents a global maximum:

$$V_{ii} = -\beta\sigma^2 A^2 < 0$$

$$V_{hh} = -\kappa_p - \beta\sigma^2 < 0$$

$$\text{and}\quad V_{ih} = V_{hi} = \beta\sigma^2 A$$

Such that the determinant of the hessian is:

$$D(H) = (-\beta\sigma^2 A^2)(-\kappa_p - \beta\sigma^2) - (\beta\sigma^2 A)^2$$

$$= \beta\sigma^2 A^2\kappa_p + \beta^2\sigma^4 A^2 - \beta^2\sigma^4 A^2$$

$$= \beta\sigma^2 A^2 \kappa_p > 0.$$

These results hold as long as $\kappa_p > 0$. We then solve the $[i]$ FOC w.r.t. i:

$$i = \frac{E[\overline{m}p_1 A] - p_0}{\beta\sigma^2 A^2} - (1-\delta)k_0 + \frac{h}{A}.$$

Plugging this into the $[h]$ FOC:

$$h = \frac{E[\overline{m}p_1 A] - p_0}{A\kappa_p},$$

which means

$$i = \frac{E[\overline{m}p_1 A] - p_0}{\beta\sigma^2 A^2} - (1-\delta)k_0 + \frac{E[\overline{m}p_1 A] - p_0}{A^2\kappa_p},$$

and

$$\frac{h}{i} = \frac{\frac{E[\overline{m}p_1 A] - p_0}{A\kappa_p}}{\frac{E[\overline{m}p_1 A] - p_0}{\beta\sigma^2 A^2} - (1-\delta)k_0 + \frac{E[\overline{m}p_1 A] - p_0}{A^2\kappa_p}}.$$

The derivative w.r.t. β:

$$\frac{\partial(h/i)}{\partial\beta} = \frac{\frac{(E[\overline{m}p_1 A] - p_0)^2}{\sigma^2 A^3\kappa_p}}{\left(\frac{E[\overline{m}p_1 A] - p_0}{A^2\sigma^2} - \beta(1-\delta)k_0 + \beta\frac{E[\overline{m}p_1 A] - p_0}{A^2\kappa_p}\right)^2} > 0. \qquad \square \tag{28}$$

Proof of Proposition 2. Using the distribution of p_1 and ξ, we write the employee problem as:

$$\max_{\tau} \quad w + b\pi_0 - \frac{\kappa_\tau}{2}(y_1 - h)^2(\tau - 1)^2 + E[\overline{m}(w + bp_1 y_1 + (y_1 - h)\xi)]$$

$$-\frac{\beta}{2}\left(b^2(y_1 - h)^2\sigma^2 + 2b(y_1 - h)^2\rho\sigma\sigma_\xi/\tau + (y_1 - h)^2\sigma_\xi^2/\tau^2\right) \tag{29}$$

The FOC is:

$$-\kappa_\tau(\tau - 1) + \beta(b\rho\sigma\sigma_\xi/\tau^2 + \sigma_\xi^2/\tau^3) = 0$$

Calculating the comparative static w.r.t. β we have:

$$\frac{\partial\tau}{\partial\beta} = \frac{b\rho\sigma\sigma_\xi/\tau^2 + \sigma_\xi^2/\tau^3}{\kappa_\tau + \beta\left(2b\rho\sigma\sigma_\xi/\tau^3 + 3\sigma_\xi^2/\tau^4\right)} > 0. \tag{30}$$

Similarly, calculating the comparative static w.r.t. σ_ξ we have:

$$\frac{\partial\tau}{\partial\sigma_\xi} = \frac{\beta\left(b\rho\sigma/\tau^2 + 2\sigma_\xi/\tau^3\right)}{\kappa_\tau + \beta\left(2b\rho\sigma\sigma_\xi/\tau^3 + 3\sigma_\xi^2/\tau^4\right)} > 0. \tag{31}$$

$$\frac{\partial^2 \tau}{\partial \sigma \partial \beta} = \frac{\kappa_\tau b \rho \sigma_\xi / \tau^2 + \beta b \rho \sigma_\xi^3 / \tau^6}{\left(\kappa_\tau + \beta \left(2 b \rho \sigma \sigma_\xi / \tau^3 + 3 \sigma_\xi^2 / \tau^4\right)\right)^2} > 0. \qquad \square \tag{32}$$

That is, all three are positive as long as $b > 0$ and $\rho > 0$.

OA.3 Additional Tables and Figures

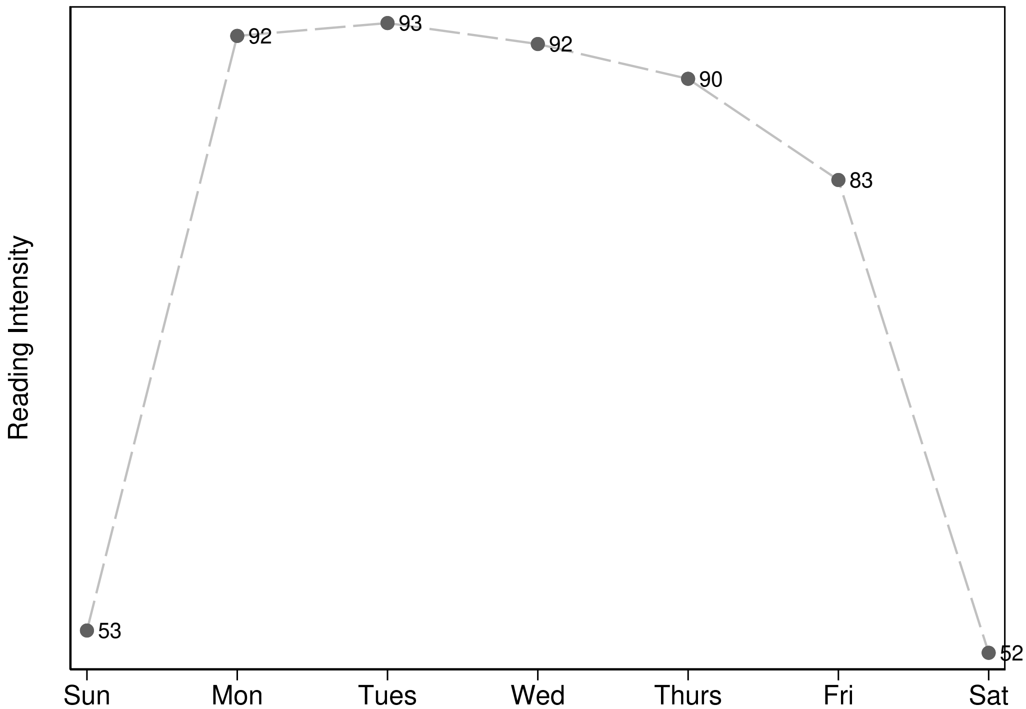


Figure OA.3.1: Average number users per day of the week
The figure plots the average number of unique users at each firm that interact with the Consortium's data on each day of the week. The set of domains over which these numbers are averaged cover both private and public firms from 2016 to 2022.

Table OA.3.1: Summary Statistics (Controls).
The table presents the summary statistics associated with the key real outcomes and control variables employed in Section 4. Here, "N" refers to the total number of observations for each variable, "SD" denotes the variable's standard deviation, and "p25" ("p75") refers to the 25^{th} (75^{th}) percentile of the variable's distribution. All data are quarterly, except for the employment growth rate, which is annual, and spans 2016 through 2022.

	N	Mean	SD	p25	Median	p75
Asset growth	52764	0.0363	0.1985	-0.0315	0.0042	0.0405
Employment growth	11554	0.0680	0.2949	-0.0476	0.0215	0.1224
Sales growth	48320	0.0882	0.4823	-0.0576	0.0244	0.1153
Log(Sales)	48640	4.7980	2.6002	3.3425	5.1538	6.5673
Tobin's q	52764	2.5606	2.2098	1.2267	1.7824	3.0016
Profitability	49521	-0.0296	0.1021	-0.0376	0.0032	0.0188
Leverage	52454	0.2695	0.2432	0.0529	0.2353	0.4084
Tangibility	51965	0.2378	0.2417	0.0605	0.1437	0.3355

Table OA.3.2: Real Outcomes and Firm Attention to Macroeconomic Risk: Additional Evidence
This table reports the results of estimating equation (9) to examine the relation between a firm's relative attention to macroeconomic risk (measured via equation (6)) and inventory growth (Panel A) and the growth rate of net property, plant, and equipment (Panel B). Each of these variables is defined in the Online Appendix OA.1. The specifications include combinations of industry, date, and industry-by-date fixed effects. Additionally, specifications (4) and (5) control for each firm's CAPM β, a common proxy for a firm's exposure to macroeconomic risk. Additionally, specification (5) features both the set of controls from Leary and Roberts (2014) and Whited and Wu (2006) measure of financial constraints. The data underlying this regression spans from 2016 through 2022, and all standard errors are clustered by firm and time.

	(1)	(2)	(3)	(4)	(5)
Panel A: Inventory growth					
CS-RA$_{i,t-1}$	-0.0370^{***}	-0.0351^{***}	-0.0352^{***}	-0.0293^{***}	-0.0128^{**}
	[−5.84]	[−5.58]	[−5.59]	[−5.36]	[−2.43]
$\mathbb{I}_{\text{EPU}}^{\text{High}} \times$ CS-RA$_{i,t-1}$				-0.0537^{***}	-0.0469^{***}
				[−7.30]	[−4.74]
Observations	37,648	37,621	36,579	36,579	30,890
R^2	0.0025	0.0294	0.0916	0.0922	0.1148
Panel B: PPENT Growth					
CS-RA$_{i,t-1}$	-0.0834^{***}	-0.0720^{***}	-0.0747^{***}	-0.0731^{***}	-0.0306^{***}
	[−3.89]	[−4.59]	[−4.54]	[−3.66]	[−3.29]
$\mathbb{I}_{\text{EPU}}^{\text{High}} \times$ CS-RA$_{i,t-1}$				−0.0069	−0.0040
				[−0.35]	[−0.21]
Observations	53,002	52,967	51,855	51,855	40,539
R^2	0.0044	0.1228	0.1972	0.1972	0.2397
Date FE		+			
Industry FE		+			
Date × Industry FE			+	+	+
CAPM-beta				+	+
Controls					+

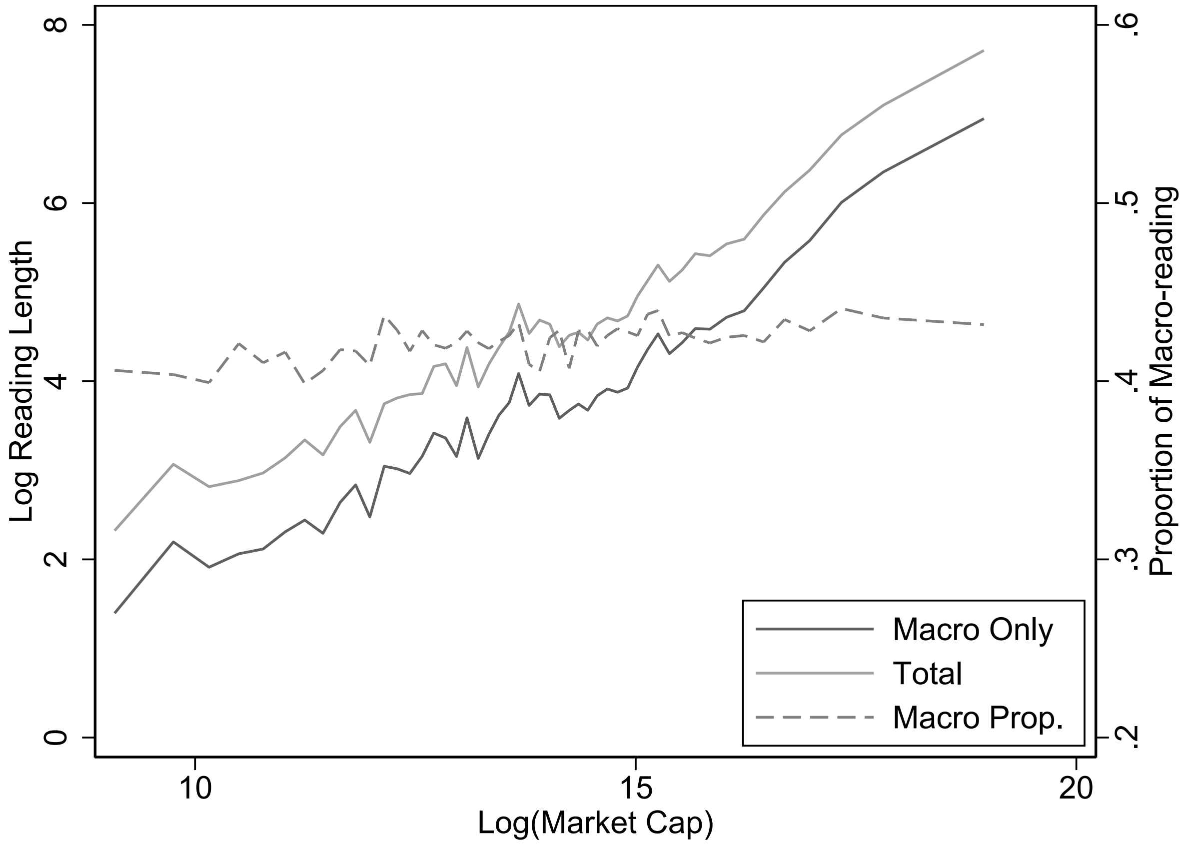


Figure OA.3.2: Relationship between Firm Size and Reading.
Did not touch this table/figure or caption The figure presents the relation between firm reading and firm size, measured by the natural logarithm of a firm's market capitalization. We measure the amount of reading a firm allocates towards uncertainty-related and total news. Specifically, we compute the amount of reading by computing the average length of $\boldsymbol{tf}_{i,t}^{Unc}$ and $\boldsymbol{tf}_{i,t}^{Total}$ from equation (1). We then plot the length of each of these vectors as a function of firm size. Beyond plotting the amount of reading firms of various sizes allocate to each type of reading, the figure also plots the cosine similarity between the two vectors as a function of firm size. The data underlying this analysis ranges from 2016 through 2022.

Table OA.3.3: Variance Decomposition by Fixed Effects and Firm Characteristics
The table presents a variance decomposition of the firm's relative attention to macroeconomic risk (i.e., CS-RA$_{i,t}$ from equation (6)) based on projections of CS-RA$_{i,t}$ on various combinations of fixed effects and firm characteristics. The variance of CS-RA$_{i,t}$ is decomposed into the variation attributable to firm characteristics, sector fixed effects, sector-by-date fixed effects, and firm fixed effects. The firm characteristics we consider include CAPM β, size, the book-to-market ratio, gross profitability, and asset growth. The sector fixed effects we consider reflect either 2-digit NAICS codes or 3-digit NAICS codes. The column denoted "No Fixed Effect" considers the possibility that all variation in CS-RA$_{i,t}$ is attributed to the firm-level characteristics. The data underlying this analysis ranges from 2016 through 2022.

	2-digit NAICS	3-digit NAICS	No Fixed Effect
Sector FE	2.42%	5.84%	
Sector × Date FE	24.60%	24.96%	
Firm-specific	72.98%	69.20%	
Permanent difference across firms, within sector-date	42.67%	39.69%	
Across firm-time residual	30.31%	29.51%	
Characteristics:			
Beta	1.75%	1.28%	1.43%
Size	4.99%	4.69%	5.15%
Book-to-Market	0.04%	0.05%	0.14%
Gross Profitability	0.81%	0.66%	0.80%
Asset Growth	0.27%	0.26%	1.04%
Characteristic Total	7.86%	6.94%	8.57%
Number of Sectors	64	247	

OA.4 Detailed Description of the Raw Attention Data

In this section we provide an overview of the Consortium's *domain-topic* dataset, which is used in the bulk of our empirical analyses. The main takeaway from this section is that while the Consortium's dataset covers a wide variety of topics (more than 7,000 in 2022), the majority of these topics are generally uninformative about each firm's business line(s). With this in mind, in Section 3.2 we propose a data-driven method for dealing with these uninformative, general, topics that encompass topics related to politics, entertainment, and sports.

To illustrate the fact that the vast majority of domain-topic interactions are only marginally informative about what a firm does, Figure OA.4.3 explores the distribution of topics for the Computer and Electronics Manufacturing sector (3-digit North American Industry Classification System (NAICS) code 334) during the week ending on November 17, 2018, a week that falls roughly in the midpoint of our sample period. The y-axis in this figure is a normalized measure of the intensity with which the employees of the firms in this sector are interacting with each topic in the given week. This normalized measure of the attention allocated to topic t is defined as

$$\text{NormInteractions}_t = \frac{\sum_{i \in \mathcal{I}} \text{Interactions}_{i,t}}{\max_t \left(\sum_{i \in \mathcal{I}} \text{Interactions}_{i,t} \right)}, \tag{33}$$

where $\text{Interactions}_{i,t}$ corresponds to the number of unique users at each firm i interacting with topic t in the given week. As this measure is scaled by the maximum number of unique interactions across all topics in a given week, $\text{NormInteractions}_{i,t}$ is a scalar that ranges from one (for the topic with the most interactions in a given week) to zero (for any topics with zero interactions in the given week). Numbers between these two extremes represent the amount of attention a given topic receives *relative* to the topic with the highest number of interactions in that week. The x-axis in this figure is then the rank associated with each topic's normalized attention score. These ranks are ordered from the topic with the most interactions, which has a rank of one, to the topic with the least number of interactions. In presenting these normalized interactions we truncate the rank at 250 to highlight the steep decline in attention as we move from the most popular topic to the less popular topics in a given week.

The topics with the most interactions towards the left of the figure are related a group of topics we consider to be current events. These high-interaction topics, which include "South by

Southwest," "Call of Duty," and "US Secret Service," were highly relevant topics in the week underlying this exercise and appeared, for example, as headlines on the splash page of major publishers, such as USA Today. Figure OA.4.4 shows an example of three article headlines published by the Consortium's members for three of the top 10 topics underlying Figure OA.4.3.

The first headline highlights a pitch submission deadline for an event that takes place in March 2019 at the South By Southwest music festival, an event with a heavy tech presence that attracts hundreds of thousands of attendees each year. The second headline is regarding a new multiplayer map in the newest version of Call of Duty, a popular online video game. Finally, during the week in question, former President Trump was in Europe. A controversy erupted when the US Secret Service suggested that then President Trump avoid an event due to inclement weather. This goes to show that many of the topics with a high number of interactions in any given week very likely reflect news and current affairs. Untabulated analyses result in similar takeaways when we focus on sectors other than technology and different points in time.

As we move to the right of Figure OA.4.3, and the rank increases along the x-axis, we see a steep decline in the relative amount of attention paid to the topics with a rank between 150 to 250. Although these topics still draw more user interactions than the 5,750 or so other topics in the Consortium's dataset in the given week that we do not plot, these topics with a rank between 150 and 250 still only attract about 10% of the interactions dedicated to the more popular current events described above. Yet, these topics are still very general in nature and cover "Miami, Florida," a popular retirement destination, "Traditional IRA," a common retirement savings account, and "Environment for Aging," an event on senior living design. These results once again highlights how many of the topics with a high number of interactions are very general in nature and do not necessarily reflect details on the business line(s) of the underlying firms.

This begs the question, can we use the Consortium's data to glean any novel insights about a firm's attention to economically relevant news, such as firm risk mitigation, when most employees' attention is concentrated on common and current events? To demonstrate that the answer to this question is "yes," Figure OA.4.5 presents a histogram of interactions across the entire distribution of topics for firms in the computer and electronics sector (NAICS 334). Here, the x-axis reports the degree of topic interaction from topics with the least (zero) to most (one) interactions. The y-axis displays the proportion of topics that fall within some topic interaction interval.

Figure OA.4.5 indicates that the vast majority of the mass of the topic distribution is concentrated among topics that have a relatively low number of interactions. In fact, about 85% of the topics that firms in the computer and electronics sector interacted with during the week of 11/17/2018 received less than than 20% of the interactions dedicated to the 10 most popular topic in the sector that week (i.e., “Live Streaming,” “Google +,” “South By Southwest,” “Call of Duty,” “ US Secret Service,” etc.). For instance, topics inherently related to firms in the computer and electronics sector such as “disk-based backup and storage,” “circuit design” and “cloud access security broker” each received about 5% or less of the interactions dedicated to “South by Southwest” and “Call of Duty” that week. Likewise, while topics related to business-relevant risks that we want to focus on, such as “credit risk,” “exchange rate,” and “cost of capital,” received relatively more attention than “circuit design,” these risk-related topics still received far less attention than many current events.

Overall, Figure OA.4.3 confirms that the Consortium’s data can indeed help us to glean novel insights about a firm’s attention to economic uncertainty, provided that we are careful to account for the fact that the bulk of the average employee’s attention is, unsurprisingly, dedicated to reading about current events. A corollary from this figure is that simple metrics of firm attention, such as the amount of total reading per employee, are very likely uninformative about the economic environment in which the firm is operating.

Consequently, Section 3.2 develops an intuitive measure of a firm’s attention to the risk that immunizes against the aforementioned concern in two steps. First, we define a set of topics that reflect uncertainty-related news, articles, and events. Second, we develop a measure of attention to these uncertainty-related topics that implicitly down weights interactions with topics that are common across all firms. This weighting scheme is motivated by the large literature on natural language processing (e.g., Gentzkow et al. (2019)) and essentially down weights a firm’s attention to topics that all other firms are also reading about (e.g., “Call of Duty”) and up weights topics that are more likely economically relevant and firm-specific (e.g., “Credit Risk” for all firms and “Circuit Design” for firms in the computer and electronics sector).

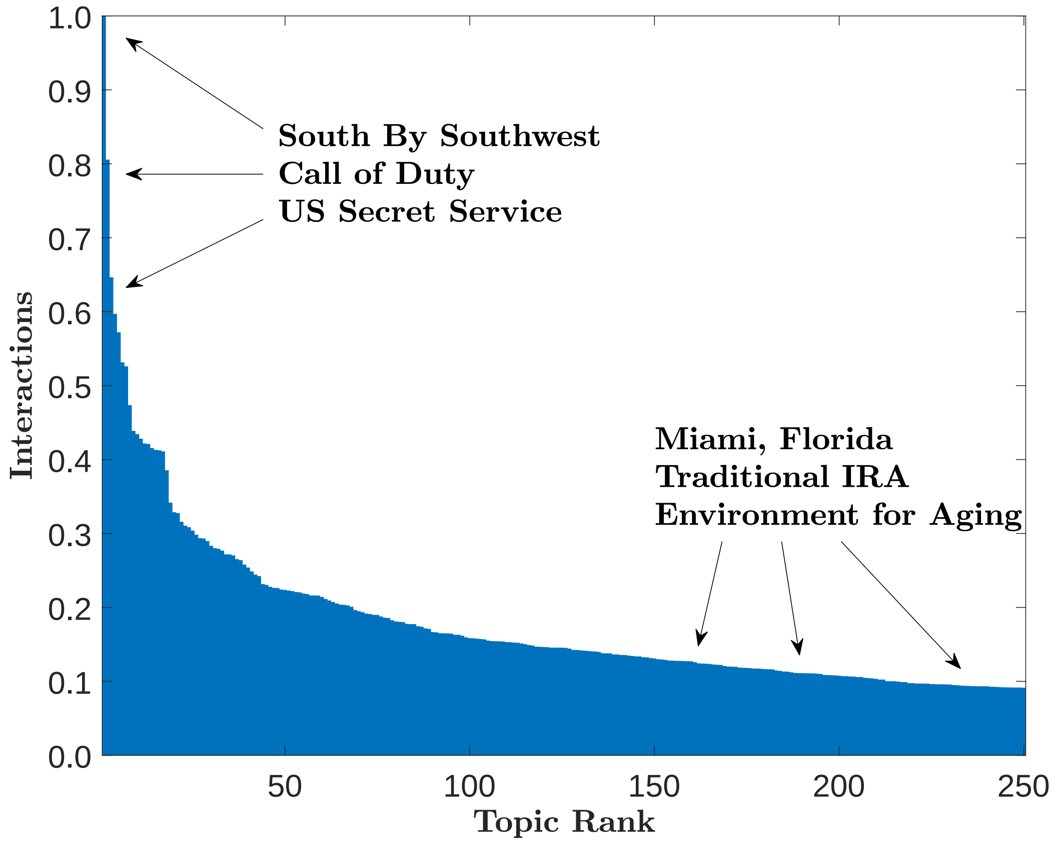


Figure OA.4.3: Bar chart of normalized attention to topics.
This bar chart represents the normalized number of interactions, defined according to equation (33), on the y-axis and rank of various topics across all firms in the North American Industry Classification (NAICS) code 334 industry — the Computer and Electronics Manufacturing industry — during the week ending 11/17/2018 on the x-axis.

(a) *South By Southwest Pitch Event*

Startup Funding Options, Media Exposure & More at SXSW Pitch – Final Deadline November 18 **By Jordan Roberts 11/8/2018**

(b) *Call of Duty Release*

NOVEMBER 13, 2018

by Call of Duty Staff

NUKETOWN COMES TO BLACK OPS 4

Forecast for November 20: Snowy, with a chance of mushroom clouds. Bundle up and hunker down, because Nuketown is coming back and it's better than ever.

(c) *US Secret Service News*

President Trump blames Secret Service for canceling cemetery trip in France

David Jackson

USA TODAY

Published 9:02 a.m. ET Nov. 13, 2018 | **Updated 1:46 a.m. ET Nov. 14, 2018**

Figure OA.4.4: News Headlines from 11/08/2018.
This figure captures a sample of headlines from Consortium publishers associated with 3 top topics from the week ending 11/08/2018. Panel (a) is a headline highlighting a submission deadline for a competitive South By Southwest VC pitch competition. Panel (b) highlights the release of an addition to the new release of Call of Duty. Panel (c) is a current events article about the US Secret Service.

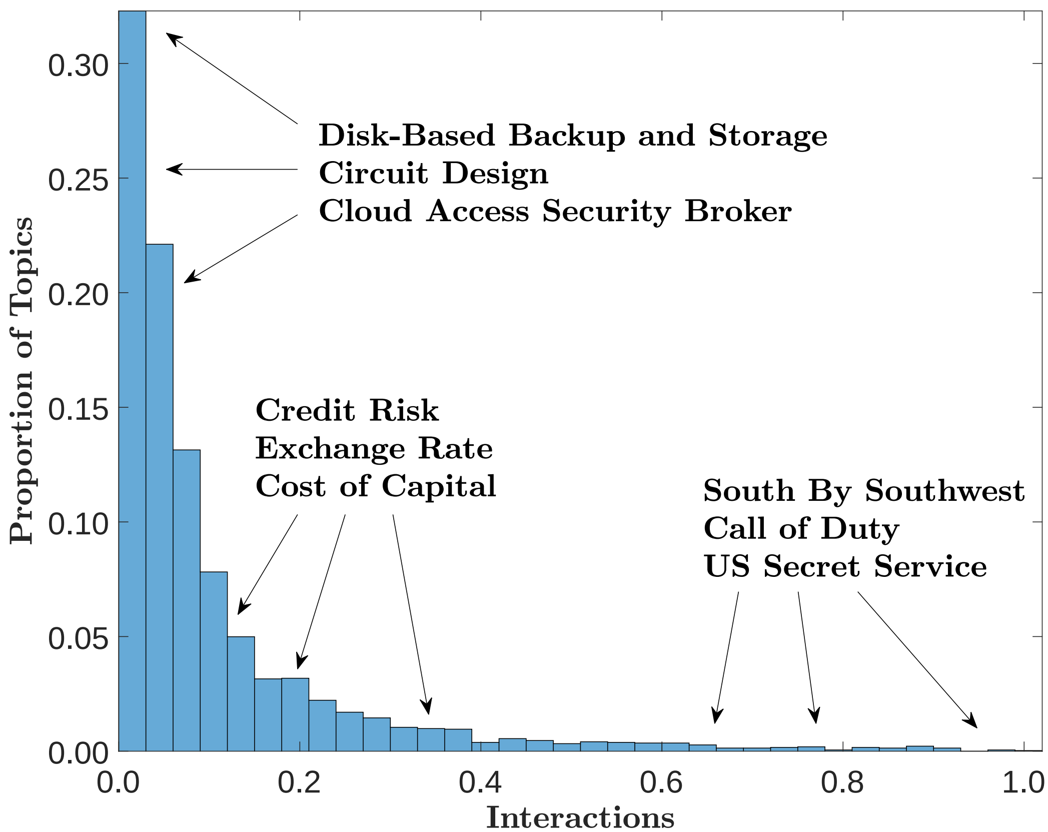


Figure OA.4.5: Histogram.
This figure is the histogram of topic interactions for all firms in NAICS 334 (Computer and Electronics Manufacturing) during the week ending 11/17/2018. We normalize the number of interactions with each topics by the number of interactions with the most popular topics in the given week (see equation (33). This measure of normalized interactions ranges from zero, for any topics with no interactions, to one, for the single topic with the most interactions.

OA.5 Risk Exposures and Pricing Errors

Table OA.5.4: Fama and French Regressions of CS-RA Sorted Portfolio

Did not touch this table/figure or caption This table presents the risk exposures and pricing errors of a long-minus-short portfolio formed on the basis of each firm's relative attention to uncertainty, measured using equation (6). Specifically, we sort the cross section of firms at the end of each quarter t into 5 portfolios formed on the basis of $ARA_{i,t}$. We hold each portfolio through the following quarter end, at which point in time all portfolios are rebalanced. We compute the value-weighted return of a self-financing portfolio that buys the set of firms with the highest quintile $ARA_{i,t}$ and sells the set of firms with the lowest quintile $ARA_{i,t}$. We then regress the value-weighted returns of these portfolios onto a constant (Column (1)), the excess market return (Column (2)), the Fama and French (1993) three-factor model (Column (3)), Fama and French (2015) five-factor model (Column (4)), and the Fama and French (2015) five-factor model that also features the momentum factor (Column (6)). The table reports exposure of the portfolio to each risk factor as well as the portfolio's pricing error (α). The time-series regression is estimated using weekly data from 2016 through 2022 and t-statistics, reported in brackets, are computed using Newey and West (1987) standard errors.

(a) Panel A: Sorts Using Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
α	0.0379	0.0487	0.0473*	0.0339	0.0223	0.0223
	[1.23]	[1.62]	[1.85]	[1.45]	[1.01]	[1.01]
MKTRF_t		−0.0814***	−0.0486***	−0.0414***	−0.0113	−0.0113
		[−4.47]	[−4.26]	[−3.79]	[−1.20]	[−1.20]
SMB_t			−0.2951***	−0.2344***	−0.2084***	−0.2088***
			[−11.22]	[−8.86]	[−10.24]	[−9.87]
HML_t			0.2349***	0.1738***	0.0606***	0.0596***
			[13.91]	[10.36]	[3.67]	[3.12]
RMW_t				0.2571***	0.2659***	0.2654***
				[9.55]	[11.38]	[11.12]
CMA_t					0.3807***	0.3818***
					[11.76]	[11.41]
UMD_t						−0.0016
						[−0.12]
Observations	1,534	1,534	1,534	1,534	1,534	1,534
F-stat	.	20.0114	92.7200	93.1830	103.3557	86.3204

Table OA.5.4: **Fama and French Regressions of CS-RA Sorted Portfolio**—(Continued)

(b) Panel B: Sorts Using Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
α	0.1000***	0.1022***	0.0974***	0.0749***	0.0679***	0.0681***
	[2.86]	[2.93]	[3.44]	[3.07]	[2.86]	[2.89]
MKTRF_t		−0.0161	0.0316*	0.0437***	0.0618***	0.0618***
		[−0.67]	[1.95]	[2.96]	[4.21]	[4.54]
SMB_t			−0.4370***	−0.3350***	−0.3194***	−0.3073***
			[−18.32]	[−14.97]	[−15.04]	[−14.68]
HML_t			0.1542***	0.0517***	−0.0164	0.0136
			[8.07]	[3.06]	[−0.88]	[0.66]
RMW_t				0.4319***	0.4372***	0.4501***
				[14.57]	[14.43]	[14.86]
CMA_t					0.2288***	0.1963***
					[6.83]	[5.86]
UMD_t						0.0483***
						[3.09]
Observations	1,534	1,534	1,534	1,534	1,534	1,534
F-stat	.	0.4459	113.4331	148.3137	131.8178	112.0885