When Micro Firms Speak Macro: Evidence on Firms' Macroeconomic Disclosures

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Abstract

We develop a firm-year measure of the sensitivity of corporate performance to aggregate shocks using 10-K disclosures. We document that macroeconomic disclosures are: (i) concentrated in the MD&A and Risk Factor sections of the 10-K after 2005; (ii) rise over time, consistent with the documented increase in the role of the macroeconomy in explaining firm-level performance, and; (iii) vary within firm, highlighting the importance of estimating a firm-year measure. Macroeconomic disclosures outperform existing numerical and text-based proxies used to identify bellwether firms—companies whose fundamentals are powerful predictors of changes in future economic activity. Moreover, we document substantial information spillovers related to earnings announcements across bellwether firms identified using macroeconomic disclosures. Overall, we demonstrate that macroeconomic disclosures are informative and provide an effective way to estimate firms' time-varying exposure to aggregate conditions.

1. *Introduction*

In this paper we examine firms' disclosures about macroeconomic conditions to develop a time-varying measure of the sensitivity of corporate performance to aggregate shocks (macro sensitivity hereafter). Our goal is twofold. First, we exploit 10-K disclosures to create a measure of macro sensitivity, an important source of systematic variation in firm performance, which has been challenging to estimate. Second, we show that macro disclosures provide an effective tool with which to identify "bellwether firms": companies whose performance is a leading indicator of future economic activity. There is extensive research on the role of bellwether firms in the economy. Prior academic work employs a variety of measures to identify such firms. Several studies use the time-series correlation between firm-level earnings and macroeconomic factors such as Gross Domestic Product (e.g., Hutton, Lee, and Shu, 2012; Bonsall, Bozanic, and Fischer, 2013). Others employ size as a bellwether proxy and find that earnings of large firms predict future economic activity (e.g., Konchitchki and Patatoukas, 2014b). More recent work develops and employs industry-based measures (Ali, Amiram, Kalay, and Sadka, 2023; Binz, Mayew, and Nallareddy, 2022). These existing proxies are characterized by three primary limitations, which are not mutually exclusive. First, they are relatively static (i.e., stable over time). This attribute is highly problematic because firms' sensitivity to systematic risk is time-varying (e.g., Fama and French, 1995; Fama and French, 1996; Ang and Chen, 2007; Ball, Sadka, and Sadka, 2009; Ball, Sadka, and Tseng, 2021). Second, correlation-based proxies require several data points at the firm level (e.g., 10 years) and therefore likely inject survivorship bias into the measurement of the construct. Finally, some proxies are primarily industry-based rather than firm specific.

We develop a new measure to address the limitations of existing proxies. We use textual disclosures about macroeconomic conditions within 10-K filings to generate a firm-year measure that captures firms' macro sensitivity. We propose a disclosure-based measure that captures the relative frequency of macroeconomic terms within annual corporate reports, which allows our measure to vary by year and firm. Therefore, our measure is less prone to survivorship bias relative to alternative proxies. The measure we propose is simple, interpretable, and objective.

To estimate our measure, we identify frequent macroeconomic terms within an external sample of Wall Street Journal "Economic News" articles, and count the occurrences of those terms within our primary sample of 10-K filings. This approach is easy to replicate and benefits from an out-of-sample validation of the macroeconomic terminology by using a source that is not based on firms' disclosures.

We use our textual measure to examine firms' macro disclosures.[1] We document an increasing time trend in the relative proportion of macroeconomic discussions within 10-K reports. This evidence is consistent with the rising correlation between macroeconomic conditions and firm performance, and the amplification of firms' connectedness over time (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Aobdia, Caskey, and Ozel, 2014; Acemoglu and Azar, 2020; Sadka, Sadka, and Tseng, 2023).[2] Furthermore, we find that managers discuss macroeconomic conditions in several different sections of the regulatory filing. On average, 85% of the disclosures are spread across five sections of the 10-K. The "MD&A" section accounts for a relatively large fraction of macroeconomic disclosures, both before (29%) and after (25%) the introduction of the "Risk Factors" section in 2005. Prior to 2005, a substantial proportion (20%) of macroeconomic terms were disclosed within the "Business" section. Interestingly, we document that macroeconomic disclosures appear to have "re-located" to the "Risk Factors" section which accounts for 22% of the discussions after 2005. Overall, this evidence highlights: (i) the increasing prevalence of macro disclosures within corporate reports, and; (ii) the importance of examining the entire 10-K rather than a specific section, as managers provide context about similar topics throughout the report.

We further document desirable time-series properties of our disclosure measure. The serial correlation of macro disclosure reveals that approximately 40% of firm-level macro disclosures vary

[1] We use the terms macroeconomic disclosure and macro disclosure interchangeably throughout the manuscript.
[2] Acemoglu and Azar (2020) shows analytically how technological improvements in a small industry can generate sizable macroeconomic effects, because firms source inputs from an increased number of suppliers over time.

each year. Therefore, it is unlikely that macroeconomic disclosures are primarily "boilerplate" or repetitive. Additionally, we document that the firm-level correlation across common macroeconomic words is relatively low (20% on average). This evidence suggests firms are exposed to different macro factors in different periods, as opposed to a constant set of factors over time, confirming that macro sensitivity is time varying due to differential exposures to distinct aggregate shocks.

Next, we validate the ability of our measure to capture time-varying sensitivities to aggregate shocks. Each year, we sort our observations into quartiles using the lagged macroeconomic disclosure measure. For each quartile, we regress the portfolio's earnings growth on contemporaneous macroeconomic indicators such as growth in Gross Domestic Product (real and nominal), inflation, and industrial production. Our measure identifies firms whose earnings are more strongly related to macroeconomic conditions. The magnitude of the coefficients and the *R*-squared increases monotonically across the quartiles. For example, the explanatory power when regressing earnings on nominal GDP growth rises from 8% in our low macro-disclosure portfolio (i.e., quartile 1) to 35% in the high macro-disclosure portfolio (i.e., quartile 4). We find similar results using inflation and industrial production.

To illustrate the value of our proxy, we benchmark the macroeconomic disclosure measure against several existing numerical and text-based proxies. We employ: (i) a bellwether metric based on the correlation between firms' earnings and an array of macroeconomic factors, including Gross Domestic Product (e.g., Hutton et al. 2012; Bonsall, et al., 2013); (ii) company size (e.g., Konchitchki and Patatoukas, 2014b), and; (iii) CAPM Beta. We also use alternative textual metrics. We measure risk disclosures employing distinct word lists or dictionaries utilized by: (i) Campbell, Chen, Dhaliwal, Lu, and Steele (2014), (ii) Kravet and Muslu (2013); (iii) Loughran and McDonald (2011), and; (iv) Hassan, Hollander, van Lent, and Tahoun (2019). Our measure significantly outperforms all the alternative proxies in its ability to identify firms' macro sensitivity.

Taken together, our findings point to a distinct role for firm-level macroeconomic disclosures. We find that firms' disclosures reveal their macro sensitivity. Interestingly, in unreported tests, we fail to find that macro disclosures predict future macroeconomic conditions. Therefore, our measure captures macro *sensitivity* rather than managers' views about the future state of the economy. In other words, macro disclosures reflect how changes in macroeconomic conditions affect the firm, rather than describing expected changes in overall macroeconomic conditions.

Finally, we examine the bellwether nature of firms with higher levels of macroeconomic disclosures. In our view, macro sensitivity is an important bellwether characteristic. Therefore, we expect macro disclosure to serve as a better tool with which to identify bellwether firms. We design two distinct sets of analyses to examine the relation between a firm's macro sensitivity and its potential classification as a bellwether firm. First, we test the ability of macro disclosure to identify portfolios of companies whose aggregate performance predicts future changes in macroeconomic conditions. Abdalla and Carabias (2022) suggests that the information content of aggregate earnings with respect to future GDP is mostly due to firms' special items.[3] Therefore, we study whether the ability of special items to predict future macroeconomic conditions is greater for firms that have more contemporaneous macro disclosures. We find strong evidence that special items of companies providing relatively more macro disclosure predict future economic conditions better than the special items of other firms. We find similar results using analyst forecasts as an alternative predictor of future economic performance (Choi, Kalay, and Sadka, 2016). The forecasted growth of firms with higher levels of macro disclosure better predicts future macroeconomic activity relative to the forecasted growth of low macro disclosure firms. Importantly, we find that macro disclosure identifies bellwether firms better than the alternative proxies. In fact, macro disclosure is the only measure that consistently exhibits a monotonic increase in explanatory power, and offers the largest out-of-sample R-squared, relative to the models that use the alternative proxies to identify bellwether firms.

Second, we predict substantial information transfers across bellwether firms as they are more likely to be affected by similar aggregate shocks. Therefore, we examine the market response to, and

[3] Abdalla and Carabias (2022) extends an emerging literature examining the role of aggregate earnings in capital markets (e.g., Kothari, Lewellen and Warner, 2006; Sadka, 2007; Sadka and Sadka, 2009; Konchitchki and Patatoukas, 2014a).

information spillovers around, earnings announcements for companies classified as bellwether firms, based on their level of macro disclosure. We follow the empirical framework in Pownall and Waymire (1989) and find results consistent with our expectations. The announcement returns of high-macro-disclosure firms are less sensitive to the focal firm's individual earnings news when relatively more news is announced concurrently by other high-macro-disclosure firms. We fail to find this relation for firms with lower levels of macro disclosure. This evidence confirms the presence of information transfers across high-macro-disclosure firms. Our finding is robust to controlling for economic determinants of macro disclosure, and the inclusion of firm fixed-effects to account for firm-level, time invariant, heterogeneity. Taken together, these findings allow us to partially attribute our results to the firm's disclosure per se, as opposed to its underlying fundamentals.

This paper contributes to the literature across several dimensions. First, our findings show that macroeconomic disclosures offer superior information about a firm's time-varying exposure to aggregate conditions. In this sense, we contribute to a growing literature that focuses on the information content of aggregate earnings (e.g., Konchitchki and Patatoukas, 2014a; and Abdalla and Crabias, 2022) and its increased importance over time (Kim, Schonberger, Wasley, and Land, 2020; Sadka, Sadka and Tseng, 2021). While prior work demonstrates the predictive ability of disclosure tone for future economic conditions (Jiang, Lee, Martin, and Zhou, 2019), we are the first to highlight the distinct role of macroeconomic disclosures in reflecting how changes in aggregate conditions affect a firm. Second, we contribute to the influential stream of research examining the role of bellwether firms in the economy (e.g., Bonsall et al., 2013). Our findings offer direct evidence on the bellwether nature of companies with relatively more macroeconomic disclosures, and demonstrate the superior ability of macro disclosure to identify bellwether firms relative to existing proxies. Third, to the best of our knowledge, this is the first paper to examine firm-level macroeconomic disclosures in 10-K filings, and find a markedly increasing time trend in the proportion of macroeconomic discussions. In this sense, our evidence contributes to the research studying the increasing role of the aggregate economy in individual firms' economic activities (Acemoglu and Azar, 2020; Acemoglu et al., 2012). Finally, our analysis links to, and extends, prior research assessing disclosure topics discussed within 10-K reports (e.g., Dyer, Lang, and Stice-Lawrence, 2017). To our knowledge, we are the first to conduct a systematic examination of the specific *sections* within the 10-K in which the relevant macroeconomic terms are located. Prior work that estimates textual measures utilizing the entire 10-K does not delineate between specific sections.

The paper proceeds as follows. In section 2 we develop our predictions. Section 3 discusses measurement choices and data. Section 4 examines macroeconomic disclosures and their properties. Section 5 reports analyses on the economic implications of macro disclosures. Section 6 concludes.

2. *Hypothesis Development*

In this paper, we stress the importance of creating a time-varying measure of a firm's macro sensitivity. We chose to utilize textual disclosures within 10-K regulatory filings for two primary reasons: relevance and data availability. 10-K reports represent the most comprehensive source of companies' annual disclosures. If macroeconomic conditions affect firm performance, and managers provide disclosures regarding the firm's exposure, we expect the disclosure to appear within the annual filings. Additionally, because these are mandated filings, they are available for a large cross-section of U.S. firms and are thus less subject to sample selection issues.

The importance of creating a time-varying (i.e., yearly) measure of macro sensitivity stems from two primary issues. First, the economic drivers of aggregate shocks are time-varying in nature. For example, different recessions reflect different underlying economic factors. In 2001, the economic contraction was led by "high-tech" firms, while the 2007-2009 recession was mainly driven by financial institutions and triggered by an economic shock to the housing market. Therefore, different aggregate shocks that are directionally consistent (e.g., lead to an economic slowdown), can have varying effects on a firm depending on its sensitivity to the shock's underlying forces.[4] In turn,

[4] We consider differences in firms' sensitivity to macroeconomic conditions generalizable to any aggregate shock, not only recessions.

the changing nature of aggregate shocks generates heterogeneity in the sensitivity of firms' earnings to macroeconomic conditions

Second, even when holding the aggregate shock constant, firms' macro sensitivity can vary with its operating and financing choices. Consider, for instance, a technological shift from a carbon-based electric grid to a nuclear and/or wind power-based grid. Firms' energy consumption will no longer be sensitive to oil prices, changing the nature of the aggregate shocks the firm is exposed to. Similarly, a transportation company that switches its fleet to electric vehicles as part of its strategy can mitigate its sensitivity to fluctuations in fuel prices. Thus, firms' strategic and operating decisions can impact their sensitivity to the same macroeconomic shock, in this example oil prices. To summarize, macro sensitivity can vary across firms and over time. Therefore, a firm-year measure is likely to serve as a more powerful tool with which to capture firms' macro sensitivity.

We note that the construct of time-varying sensitivity to macroeconomic shocks is well established in portfolio theory and empirical asset pricing (e.g., Fama and French, 1995; and Fama and French, 1996). While portfolio betas which reflect sensitivities to aggregate risk factors are fixed within a portfolio, companies' sensitivity to those risk factors varies as firms move across different portfolios over time. Unlike the empirical estimation of sensitivities to aggregate risk factors, our approach yields a firm specific firm-year measure rather than a portfolio-level measure.

We believe that our disclosure-based measure is better suited to estimate a firm's macro sensitivity relative to the existing bellwether and textual based proxies for the following reasons. First, a disclosure-based measure would vary by firm and year, thus capturing the time-varying nature of macro sensitivity. Second, a disclosure-based metric is less likely to suffer from survivorship bias. Third, our measure differs from other textual disclosure measures developed by prior research because we are the first to focus on the specific construct of macro sensitivity, and do not limit our analysis to specific sections in the 10-K. Therefore, we predict our macro disclosure measure to capture firms' macro sensitivity better than existing text-based proxies related to more generic constructs or other specific risks such as political uncertainty (Campbell et al., 2014; and Hassan et al., 2019).[5]

Our prediction is further motivated by recent macroeconomic literature that documents the increased role of aggregate economic conditions in explaining company performance (Acemoglu and Azar, 2020; Acemoglu, et al., 2012). Consistent with this literature stream, in this paper we also ask whether, and to what extent, managers' propensity to provide macroeconomic disclosures within regulatory filings offers insights into the firm's macro sensitivity.

We note considerable tension in our prediction. On the one hand, if a firm's performance becomes more sensitive to the aggregate economy, we expect the manager to provide more macroeconomic information within the firm's corporate disclosures that accurately reflect the firm's macro sensitivity. On the other hand, managers are not professional economic forecasters. Information intermediaries, such as analysts, are conjectured to possess superior macroeconomic information (e.g., Darrough and Russell, 2002; Piotroski and Roulstone, 2004; Kadan, Madureira, Wang, and Zach, 2012; Hutton et al., 2012; Ali et al., 2023). Furthermore, firms' disclosures may simply be repetitive or "boilerplate" in nature, and thus not informative about temporal variations in the firm's exposures to different macroeconomic shocks. In sum, the extent to which annual financial reports include discussions about macroeconomic exposures, and whether those disclosures are informative, is an empirical question.

To empirically test our predictions, we proceed as follows. First, we construct and validate a disclosure-based measure capturing firms' time-varying macro sensitivity. Next, we conduct detailed analyses to examine the properties of our measure to ensure its ability to capture time-varying exposure to aggregate shocks. Our validation tests exploit macro disclosures to identify companies whose performance is more highly associated with contemporaneous aggregate changes in economic

[5] This is because these alternative text-based measures are not aimed at capturing a conceptual construct that coincides with exposure to aggregate shocks. For example, we note that a company's sensitivity to macroeconomic shocks may vary regardless of its exposure to political risk.

activities. In addition to the validation tests, we benchmark macro disclosure against a wide range of existing numerical and text-based proxies to demonstrate its effectiveness.

Finally, we examine the bell whether nature of firms with higher levels of macro disclosure. In our view, the contemporaneous correlation between changes in aggregate earnings and changes in economic activity (e.g., real GDP) is in itself an important bellwether characteristic. Therefore, we predcit: 1) that macroeconomic disclosures contain relevant information for identifying companies whose performance is highly predictive of *future* changes in the aggregate economy (i.e., bellwether companies), and; 2) the existence of significant information transfers and spillovers across high macro disclosure firms due to their bellwether nature.

3. *Data and Descriptive Statistics*

3.1 Data and Measurement

We use three primary data sources. Textual data is extracted from (i) 10-K filings obtained from the *SEC EDGAR* database, and (ii) *Wall Street Journal* (WSJ) "Economic News" articles downloaded from the *Dow Jones Factiva* repository. Firms' financials are primarily from *WRDS Compustat* (annual files) and *CRSP* (daily files). Macroeconomic data is obtained from the *Bureau of Economic Analysis* at the U.S. Department of Commerce.

We construct a measure of macroeconomic disclosure using textual analysis of a firm's 10-K filing. First, we download 10-K reports filed between 1994 and 2021 with valid CIK, GVKEY, and PERMNO identifiers and a minimum length of 500 words. We exclude 10-K Amendments, 10-KSB, and 10-KSB Amendments. We also exclude all financial firms (i.e., SIC codes 6000-6999) due to their unique business model and reporting rules. Finally, we drop observations with missing Compustat or CRSP items and lagged disclosures (i.e., a 10-K report in year *t-1*). We obtain a large sample of 86,624 firm-year observations with valid disclosure and financial data; the sample selection details are reported in Table 1.

To create the macroeconomic disclosure measure, we count the number of occurrences of one and two-word phrases (i.e., "unigrams" and "bigrams") that depict macroeconomic conditions within 10-K filings. Our approach is similar, for example, to Li, Lundholm, and Minnis (2013) and Bushman, Hendricks, and Williams (2015) that use textual analysis to measure a firm's competitive environment by counting the number of competition-related terms in firms' 10-K reports. We note two key measurement choices. First, we use a large sample of *Wall Street Journal* "Economic News" articles to identify terminology that is *a priori* related to the macroeconomy and therefore validate the chosen macroeconomic terms. Second, to control for the general propensity to disclose within a 10-K filing, we scale the total count of macroeconomic terms by the total number of words within the report. Thus, the resulting text-based measure of disclosed macroeconomic conditions is:

$$MacroDiscl = \frac{MacroWords}{10kWords}\ x\ 1{,}000$$

where *MacroWords* and *10kWords* are the total number of macroeconomic words and the total number of words in the 10-K, respectively. We multiply the ratio by 1,000 to enhance economic interpretability. Therefore, *MacroDiscl* measures the number of macroeconomic terms occurring in a 10-K report for each 1,000 words in the filing. Of note, we compute *MacroDiscl* using the entire 10-K report, excluding financial statement tables. In a series of sensitivity analyses, we estimate *MacroDiscl* using word counts from specific sections in the 10-K. The results from this analysis are reported in Section 4.6.

Our measure, *MacroDiscl,* is meant to capture the manager's perception of whether and to what extent current macroeconomic conditions affect their firm's performance. The measure assumes that a manager is relatively less likely to discuss macroeconomic conditions in their 10-K filing if the firm's performance is mainly idiosyncratic and unaffected by macroeconomic conditions. Furthermore, we conjecture that the level of macro-disclosure varies widely across firms and years based on a firm's macro sensitivity. Hence, a distinct characteristic of *MacroDiscl* is that it allows for variation in macro sensitivity across firms in a given year and across years for a given firm. In other words, we develop a measure that is meant to capture firm-level and time-varying *sensitivity* to macroeconomic conditions.

We identify macroeconomic words in three steps. First, we select the top 1% macroeconomic terms (by frequency rank) within a large sample of 22,993 *Wall Street Journal* "Economic News" articles published between 1994 and 2021. We exploit the *Dow Jones Factiva* categorization of WSJ articles and focus our data collection on "Economic News", a broad category including articles on the general macroeconomic environment, monetary policy, and domestic or international trade. We exclude short newspaper articles: those characterized by less than 5 sentences and 100 words. In particular, we focus on one and two-word phrases (i.e., "unigrams" and "bigrams") excluding "stop-words" (e.g., prepositions, conjunctions); see Frankel, Jennings, and Lee (2017). Next, we extract the top 1% most frequent one and two-word phrases within the sample of 86,624 10-K reports. Finally, we select the intersection of terms found in *both* the WSJ and 10-K samples and make those terms our target macroeconomic words. Appendix B includes the word list, while Appendix C reports three examples of 10-K macroeconomic disclosures. As previously noted, our assumptions are that: (i) the WSJ "Economic News" articles likely include terminology that is *a priori* related to the macroeconomy, and; (ii) the most frequent macroeconomic phrases are likely to be the most relevant.[6]

One advantage of using frequent words is that it increases the robustness of our results with respect to potential omissions. Relatively infrequent macroeconomic terms, while potentially informative, are unlikely to change our results because, by construction, these words are not frequently disclosed within 10-K reports. We confirm this expectation in the sensitivity analyses presented within Section 4.6.

[6] One could design a more accurate yet more complex procedure. For instance, relatively infrequent macroeconomic words could be informative about the macro sensitivity of the firm. To include the less frequent words, natural language processing research suggests applying weighting schemes such as TF-IDF (i.e., "Term Frequency-Inverse Document Frequency." See also Hassan, Hollander, van Lent, and Tahoun, 2019). We believe that increased sophistication and complexity comes at the cost of replicability and interpretability, which we consider key features of empirical research (e.g., Hail, Lang, and Leuz, 2020). We therefore opt for a reliable, objective, and easily interpretable procedure, and consider our results a lower bound for the role of annual reports in capturing firms' macro sensitivity.

3.2 Sample Statistics

Table 1 Panel B reports descriptive statistics for disclosure and firm characteristics in our sample. *MacroDiscl* has a mean (median) value of 1.77 (1.51), with a standard deviation of 1.17. The mean (median) number of macroeconomic and total words in our sample are 57 (42) and 31,032 (28,400), respectively. Similar to Li et al. (2013), both counts increase steadily over the sample period. To put *MacroDiscl* in the context of other firm disclosures, we compare it to the count of risk factor disclosure (i.e., $RFDiscl_{CEA}$) using the Campbell et al. (2014) word list. We find that the mean risk factor disclosure count is 47.82 suggesting that macroeconomic disclosures capture a construct that differs substantially from general risk disclosures. The median company has a *Size* (i.e., market capitalization) of $350 million and exhibits moderate *Leverage* (i.e., 17%) and *ROA* (i.e., 2%).

4. *Examining firm-year macroeconomic disclosures*

4.1 The time-series trend and location of macroeconomic disclosure

We use *MacroDiscl* to assess the time-trend of macroeconomic disclosures within 10-K reports. Figure 1 Panel A shows that the proportion of macroeconomic discussions increases remarkably over the sample period and spikes during economic recessions (i.e., in 2001 around the "tech bubble", during the 2007-2009 financial crisis, and in 2020 around the COVID pandemic). This is likely because recessions represent large shocks to aggregate economic activity. Thus, firms provide more macroeconomic disclosures during times of heightened economy-wide concerns. To offer confirmatory evidence that our measure captures meaningful variation related to the economic cycle, we plot the time-series mean counts for recessionary words (e.g., "recession" or "recessionary") in Appendix D. We find that recessionary word counts rise significantly during economic recessions and drop during growth periods. Overall, the combined evidence on the time trend in *MacroDiscl* provides additional support for our measure, which varies in a meaningful way with the business cycle.

Furthermore, we verify that the time-trend displayed in Figure 1, Panel A, is consistent throughout our sample. Each year, we sort observations into quartiles based on their level of *MacroDiscl* and then plot the mean of *MacroDiscl* for each quartile-year in Figure 1, Panel B. We find similar time trends in all four quartiles of *MacroDiscl*, suggesting that the time trend in is not driven primarily by the behavior of firms that provide the most macroeconomic disclosure, but rather by a more consistent increase across all sample firms.

Next, we investigate *where* macroeconomic disclosures are located within the 10-K. Our objective is to offer contextual evidence about disclosures that capture macro sensitivity. Therefore, we exploit the "HTML" formatting features and tags of regulatory filings to divide each 10-K report into 20 homogeneous sections (i.e., as per SEC rules: from *Item 1*, "Business" to *Item 15* "Exhibits, Financial Statement Schedules, and Reports on Form 8-K") and count the macroeconomic terms in each section.[7] Specifically, we scrape each document to identify a set of starting signals (e.g., "Item 7a", "Quantitative and Qualitative Disclosures About Market Risk") and ending signals (e.g., "Item 8", "Financial Statements and Supplementary Data") to delimit individual 10-K sections.[8] We then assess whether discussions about a firm's macro sensitivity is concentrated in a particular section of the report, or is more widespread—a fact that would justify our choice to analyze the entire filing. We note that our analysis links to and extends prior research that examines general disclosure topics within 10-K reports (e.g., Dyer et al., 2017). To the best of our knowledge, we are the first to offer systematic evidence about the specific *sections* in which disclosures in general, and, macroeconomic disclosures in particular, are located within the 10-K.

[7] The SEC regulatory framework (i.e., Section 13 or 15(d) of the Securities Exchange Act of 1934) requires that 10-K reports include Item 1-15, plus Item 1a, 1b, 7a, 9a, and 9b for a total of 20 sections.

[8] We also develop tailored conditional statements to handle cases of multiple starting and/or ending signals. Whenever a 10-K section cannot be identified with sufficient reliability, we exclude the document from the sample; this leads to the exclusion of approximately 15% of the total downloaded 10-K reports. We note that not all the current 10-K sections are mandated over our entire sample period; for example, "Item 1A" (i.e., "Risk Factors" section) is only mandated from 2005. Therefore, we do not drop documents for which we cannot identify a 10-K section, if the section is not mandatory in a reporting period. We confirm the reliability of our parsing strategy by manually checking the extracted sections for 50 distinct firms in different years.

Figure 2, Panel A, reports the average relative frequency of macroeconomic disclosures within each section of the 10-K. We find that macroeconomic terms are found in *several* locations throughout the 10-K, and that on average, 85% of the disclosures are spread across five sections. Therefore, we focus our analysis on these top-5 sections. We present results for two time periods, before and after the introduction of the "Risk Factors" section in 2005. We identify a relatively larger fraction of words within the MD&A section (i.e., "Item 7") both before (29%) and after (25%) the introduction of the SEC mandated "Risk Factor" section. Prior to 2005, a substantial percentage (20%) of macroeconomic terms was found within the "Business Description" section (i.e., "Item 1"). However, the macroeconomic disclosures appear to have "re-located" to the "Risk Factors" section after 2005, which accounts for 22% of the discussions. The remaining sections with a meaningful proportion of macroeconomic terms include market risk (i.e., "Item 7a") and footnotes (i.e., "Item 8"), each accounting for 15% of macro-related disclosures. All other sections include 15% of the terms, on average. Figure 2, Panel B, shows the time-series evolution of macroeconomic disclosures for these top-5 sections. Consistent with prior findings, we notice the increasing (decreasing) relevance of the "Risk Factors" ("Business Description") section, while the remaining sections exhibit a more consistent trend over time.

Our findings highlight the importance of examining the entire 10-K rather than a specific section. As noted above, we find that firms disclose their exposure to macroeconomic shocks throughout the financial statement and not just within the risk factor or MD&A sections. Below, we examine and show that excluding certain 10-K sections weakens the effectiveness of *MacroDiscl*, which highlights the need for a comprehensive analysis of the 10-K filing as opposed to focusing on a specific section or sections.

4.2 Within-firm variation of macroeconomic disclosure

We expect firm-level sensitivity to macroeconomic shocks to be time-varying, consistent with prior research. Several studies find that firms' systematic risk is time-varying (e.g., Ang and Chen, 2007; Ball et al., 2009; Ball et al, 2023). One notable example is the "Book-to-Market Effect," documented in Fama and French (1996). While portfolio betas are estimated for the entire estimation period, firms switch across book-to-market portfolios at regular intervals, which implies that firm-level sensitivity to risk factors is time varying. Thus, if a manager chooses to discuss macroeconomic conditions based on their private information about the firm's exposure to systematic variance, we should observe informative firm-level variation in *MacroDiscl* and its components (i.e., individual words). For this reason, we assess whether *MacroDiscl* exhibits within-firm variation which we consider to be a desirable attribute for a potential measure.

To test the time-varying nature of macro disclosures we proceed in two steps. First, we examine the serial correlation of *MacroDiscl* at the firm-level and plot the coefficients from firm-level AR (1) regressions in Figure 3. The mean (median) autoregressive coefficient on *MacroDiscl* at time *t-1* is 0.62 (0.63), suggesting that approximately 40% of firm-level macroeconomic disclosure amounts vary each period. This magnitude seems inconsistent with the notion that *MacroDiscl* is "boilerplate" in nature and provides initial evidence of managers' macro-disclosure choices over time.

Second, we examine firm-level time-series variation in the individual components (i.e., common words) of *MacroDiscl*. We report the results from this analysis in Table 2. While we find a generally positive correlation across words and phrases at the firm-level, the correlation is relatively low (on average, 20%). This evidence suggests firms are exposed to different macroeconomic components in different periods, consistent with our hypothesis that a firm's sensitivity to macroeconomic shocks is time varying due to differential exposures to distinct aggregate shocks.

4.3 Determinants of macroeconomic disclosure

In this section, we examine contemporaneous economic determinants of *MacroDiscl*. This analysis helps validate our measure by examining whether firms that are more likely to be affected by macroeconomic conditions provide more macroeconomic disclosures. In addition, we employ this analysis in subsequent tests (see Section 5), where we examine the incremental role of macroeconomic disclosures relative to other firm-level characteristics.

In particular, we estimate the following equation:

$$\begin{aligned} MacroDiscl_{i,t} = {} & \beta_0 + \beta_1 Size_{i,t} + \beta_2 Beta_{i,t} + \beta_3 IVol_{i,t} + \beta_4 CFVol_{i,t} + \beta_5 BM_{i,t} \\ & + \beta_6 Leverage_{i,t} + \beta_7 ROA_{i,t} + \beta_8 Segments_{i,t} + \beta_9 InstOwn_{i,t} \\ & + \beta_{10} HiMacro_{i,t} + \beta_{11} SPI_{i,t} + \beta_{12} Tone_{i,t} + \beta_{13} RFDiscl_{CEA\,i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where *MacroDiscl* is firm *i's* number of macroeconomic-related words per thousand words in year *t's* 10-K filing. We begin by studying the contemporaneous association of *MacroDiscl* with four proxies for historical risk, namely: 1) *Size* (the natural logarithm of firm *i*'s market capitalization at the beginning of filing year *t*); 2) *Beta* (the CAPM Beta derived from a one-factor market model estimated using daily returns over the year preceding the 10-K filing); 3) *IVol* (the standard deviation of firm *i*'s daily market-adjusted stock returns, measured over the preceding 12 months), and; 4) *CFVol* (the standard deviation of firm *i*'s annual operating cash flows scaled by total assets over the prior five years).

We further include general characteristics capturing firm's growth opportunities, complexity, operating performance, and information environment. Namely: 1) *BTM* (firm *i*'s book-to-market ratio measured at the beginning of the filing year *t*); 2) *Leverage* (firm *i*'s short-term plus long-term liabilities divided by total assets at the beginning of filing year *t*); 3) *ROA* (firm *i*'s net income for year *t* divided by beginning total assets); 4) *Segments* (the natural logarithm of one plus firm *i*'s geographic segments in year *t*), and; 5) *InstOwn* (the number of shares held by institutional investors in year *t*, scaled by total shares outstanding). We also add two variables that are meant to capture exposure to aggregate economic activity, namely *HiMacro* (the bellwether categorical variable employed by Bonsall et al., 2013), and *SPI* (firm *i*'s annual special items scaled by market capitalization in year *t*, following Abdalla and Carabias, 2022). Finally, we include two related disclosure measures: (i) The relative level of risk disclosure, $RFDiscl_{CEA}$, which equals the total number of risk words per 1,000 words in firm *i*'s 10-K filing in year *t,* following Campbell et al. (2014), and; (ii) disclosure sentiment measured using *Tone*, which equals the number of positive minus negative words from the Loughran and McDonald, 2011, dictionary scaled by the total number of words in the10-K. All variables are also defined in Appendix A. We include year and industry fixed-effects based on the Fama-French 48 industry classification in all the regressions. We cluster the standard errors by both firm and year.

We report univariate correlations and multivariate regression results in Tables 3 and 4, respectively. The two analyses offer generally consistent results. We find that *Size* and *CFVol* are positive and significant in all specifications suggesting that historical risk correlates with macroeconomic disclosures. At the same time, idiosyncratic volatility, *IVol*, is negatively associated with disclosures about systematic variance. *Beta*, interestingly, exhibits a positive univariate, but negative multivariate correlation with *MacroDiscl*. We also find that *BM*, *Leverage*, *Segments*, and *InstOwn* are positive and significant in all specifications.

Interestingly, we find that the coefficient on *ROA* is positive and significant, implying that firms do not appear to use macroeconomic conditions as an excuse for poor performances. This result is especially relevant as managers can "blame" external forces when performance is low regardless of the impact of the macroeconomy. Yet, we find the opposite. With respect to alternative measures, we document a positive and significant (insignificant) univariate (multivariate) correlation of *HiMacro* with macro-related disclosures, while special items, *SPI*, are strongly and negatively associated with *MacroDiscl*. Moreover, we find that risk factor disclosures, $RFDiscl_{CEA}$, have a strong positive relation with macroeconomic disclosures, which motivate a series of subsequent sensitivity analyses in Section 4.6. Finally, *MacroDiscl* is generally associated with a positive linguistic sentiment, again confirming that managers do not seem to "blame" the macroeconomy for poor performance. Overall, the findings are consistent with the notion that firms that are likely to exhibit greater macro sensitivity are more likely to discuss macroeconomic disclosures in their financial reports.

4.4 A first step towards identifying bellwether firms using macroeconomic disclosure

Having established a number of desirable properties related to macro disclosures, we examine macro disclosures' ability to capture the firm's *sensitivity* to changing macroeconomic conditions. In Section 5, we proceed to explicitly test whether companies with greater macro sensitivity measured using *MacroDiscl* can help predict future changes in the aggregate economy. Consistent with the forward-looking nature of 10-K disclosures (e.g., Li et al., 2013; Bushman et al., 2015), we hypothesize that a manager offering more extensive macroeconomic discussions in year *t-1* expects her company's future performance to exhibit higher macro sensitivity. To test the association between changes in future firm performance and changes in macroeconomic conditions, for each year *t* we sort observations into quartiles of *MacroDiscl* at time *t-1*. As we note above, one advantage of our measure is that it allows for within-firm variation in the level of macroeconomic disclosure across years. Hence, a firm is not classified as a high macroeconomic discloser across the entire sample period.

After grouping our firm-year observations into quartiles, we regress the value-weighted cross-sectional averages of all firm-level changes in operating income on contemporaneous (i) GDP growth (nominal and real), (ii) inflation rate growth, and (iii) industrial production growth. If managers are indeed more likely to discuss macroeconomic conditions when their firm's performance is less idiosyncratic, then we should observe a positive association between firm and macroeconomic performance in the highest quartile. We present the results in Table 5.

We document a positive and significant association between changes in operating income and changes in GDP, inflation rate, and industrial production for the highest quartile of *MacroDiscl.* More importantly, we observe a monotonic increase in the coefficients and *R*-squared across the quartiles of *MacroDiscl*. For example, the coefficient on real GDP increases from 0.03 to 0.12 and the *R*-squared rises from 0.08 to 0.29 when moving from the first to the fourth quartile. We find similar monotonic trends across all the proxies used to capture changes in the aggregate economy. Finally, statistical tests show that the differences in coefficients and *R*-squared between quartile 4 and quartile

1 are statistically significant at conventional levels. Our results suggest that *MacroDiscl* appears to capture the firm's sensitivity to changing macroeconomic conditions.

In untabulated analyses, we estimate equation (1) using terciles instead of quartiles and find similar results. We restrict our analysis to quartiles and terciles because our test requires us to construct "large" portfolios reflecting "aggregate" economic activity. Our approach is consistent with the conclusions in Ball et al. (2009) which examines common variation in earnings across firms. Since earnings tend to be more skewed than returns, due to large negative one-time charges, creating fewer and larger portfolios generates earnings portfolios that better reflect the systematic components of earnings. We acknowledge that our measure is likely to be less effective as we increase the number of portfolios, especially for the low macro-disclosure groups. This is because a relatively limited number of words, especially for low macro-disclosure firms, will easily move a company across portfolios, thus exacerbating measurement error.

In unreported analyses, we further test whether our disclosure measure is informative about overall changes in macroeconomic conditions, as opposed to the sensitivity to those changes (see Jiang et al., 2019). We fail to find evidence that aggregate macroeconomic disclosures predict future macroeconomic conditions. Thus, we conclude that *MacroDiscl* primarily captures managers' views about their firm's macro sensitivity rather than their predictions about future economic conditions.

Finally, we examine the time frame over which our measure is effective. If a firm's sensitivity to macroeconomic shocks is relatively stable, and firm disclosures are informative (as shown above), then one could use *MacroDiscl* in year t, to rank firms based on their sensitivity to macroeconomic shocks in periods $t+1$, $t+2$,…, $t+n$. The number of periods n reflects the degree to which the sensitivity to macroeconomic shocks is stable over time. A higher n indicates more stability over time, implying that a firm-year measure is likely *unnecessary*. In contrast, a lower n suggests that firms' macro sensitivity is time-varying in nature, which supports our prediction that a firm-year measure is optimal. Specifically, for each year t we sort observations into quartiles of *MacroDiscl* at time t, $t-1$, and $t-2$ and repeat the analysis presented in Table 5. We report these comparative results in Table 6. We find that the monotonic trend in the explanatory power disappears after two periods and is mostly u-shaped (except for inflation). These findings highlight not only that macro sensitivity is time varying, but also that the time-series variation is economically significant. Since this is the first study that we are aware of to create a firm-year measure of macro sensitivity, we present the first evidence that clearly documents significant firm-level time-series variation for this construct.

4.5 Comparison to alternative measures

In this section, we examine the relative ability of *MacroDiscl* to identify firms with higher levels of macro sensitivity compared to the ability of alternative existing measures. We benchmark macroeconomic disclosures against three numerical and four textual proxies. We first employ *HiMacro* which is based on the time-series correlation between firms' earnings and an array of macroeconomic variables, including Gross Domestic Product (e.g., Hutton et al. 2012; Bonsall, et al., 2013).[9] Next, we use *Size* (e.g., Konchitchki and Patatoukas, 2014b). Our final numerical proxy is *Beta* which should capture firm-level sensitivity to the market factor.

We also use the following four alternative textual proxies, which are meant to capture various dimensions of idiosyncratic and/or systematic risk: (i) $RFDiscl_{CEA}$, the total number of Campbell et al. (2014) risk words, (ii) $RFDiscl_{KM}$, the total number of Kravet and Muslu (2013) risk words, (iii) $RFDiscl_{LM}$, the total number of Loughran and McDonald (2011) uncertainty words, and (iv) *PRDiscl*, the total number of top-120 political risk bigrams identified by Hassan et al. (2019). All the counts are express per thousand words in firm *i's* 10-K filing.

[9] In particular, Bonsall et al. (2013), estimate the following equation: $e = \mu_e + B'M + m$, where e is the firm's earnings realization, μ_e is the constant, B' is the estimated sensitivity of the firm's earnings to the macroeconomic factor, *M,* which is a vector of macroeconomic factor realizations, and *m* is the firm-specific shock to earnings. This estimation aims to decompose the firm-level earnings into two components: (i) a firm-specific shock to earnings, and (ii) the sensitivity of the firm's performance to macroeconomic conditions. Thus, firms with the largest *R*-squared from this regression are those with the highest sensitivity to macroeconomic conditions. *HiMacro*, thus, equals one, two, three, or four if the firm's *R*-squared from the above regression is in the first, second, third, or fourth quartile respectively. In our empirical estimation, we use the same macroeconomic proxies for *M* as those used in Bonsall et al. (2013). Specifically, we employ the (a) corporate yield bond for AAA issuers, (b) consumer price index inflation rate, (c) housing starts, (d) industrial production index, (e) real Gross Domestic Product, (f) T-Bill rate (3-month), (g) T-Bond rate (10-year), and (h) unemployment rate. All these variables are sourced from the Federal Reserve Bank of Philadelphia.

We report the results in Table 7. Overall, we find that *MacroDiscl* dominates all the alternative proxies with respect to (i) the monotonic trend in the coefficients and *R*-squared across the quartiles of each proxy, and; (ii) the differences in *R*-squared between the fourth and first quartile. First, we note that the monotonicity of the coefficients and explanatory power is particularly important. In fact, in the presence of a non-monotonic relation, the bellwether proxy would lead to misclassification and render the examination of statistical differences between the highest and lowest groups of little value. For example, *Size* seems to offer relevant classification power only for the fourth quartile of its distribution, leading to misclassification in approximately 75% of cases.[10] Second, in the presence of a monotonic trend, the difference between the coefficients and *R*-squared in the fourth and first quartile helps establish the measure's ability to identify bellwether firms.

Interestingly, *MacroDiscl* offers substantial improvement relative to the alternative text-based proxies. For example, $RFDiscl_{CEA}$ provides a u-shaped pattern in explanatory power across sample quartiles. Specifically, when considering real GDP growth, the *R*-squared decreases from 0.32 in group 1, to 0.20 in group 2, to 0.14 in group 3, before finally increasing to 0.21 in group 4. $RFDiscl_{LM}$ and $RFDiscl_{LM}$ seem to have a negative relation with firms' macro sensitivity. For example, the explanatory power across sample quartiles sorted on $RFDiscl_{LM}$ for nominal GDP growth declines (non-monotonically) from 0.50 to 0.12 across the quartiles. Taken together, these results confirm the superior ability of *MacroDiscl* in identifying firms' time-varying sensitivity to aggregate economic shocks.

4.6 Sensitivity analyses

We test the sensitivity of our main findings in several ways. First, given the strong association of *MacroDiscl* with risk factor disclosures (that we document in both Sections 4.1 and 4.3), we repeat our primary analyses *excluding* macroeconomic terms found within the "Item 1A" (i.e., Risk Factors)

[10] We note that this evaluation approach is quite common within the finance literature (e.g., Fama and French, 1996). Several influential works, in fact, examine the statistical difference between "high" and "low" characteristic-based portfolio returns after assessing a monotonic trend across the relevant portfolios.

of 10-K reports. The findings are reported in Table 8. While the results become marginally weaker, highlighting that risk factor disclosures are indeed important sources of macroeconomic discussion, the tenor of our primary findings does not change. Even when we exclude the risk factor section, firms that discuss more macroeconomic conditions exhibit greater macro sensitivity. Second, we test the macroeconomic information content of individual 10-K sections. In particular, we extract macro-related terms from each 10-K section separately (e.g., "Business Description", "MD&A", "Risk Factors", etc.) and then use the count from a specific section to estimate macro disclosure. This exercise results in five section-specific measures of macro disclosure. We then repeat our primary analyses in Table 5 for each measure. In untabulated tests, we observe a general deterioration in the information content of macro disclosure when individual 10-K sections are utilized to compute our measure. None of the measures estimated using the stand-alone 10-K sections offers significant results. These findings highlight once again the importance of examining the entire 10-K rather than focusing on a single section, as managers provide contextual information about similar topics throughout the regulatory filing.

Third, we extend the macro-related terms included in our word list. Our focus on the top-1% more frequent unigrams and bigrams might lead to a loss of valuable macroeconomic information. For example, we observe that terms related to labor market conditions (e.g., "labor market", "unemployment") fall slightly below the 99th percentile threshold set, while still being potentially relevant. Therefore, we add these words to our list and repeat the primary analyses. The untabulated findings are very similar to those presented in Table 5. We find monotonic increases in the coefficients and R-squared across the quartiles of our disclosure measure for most of the proxies used to identify macroeconomic activity. Finally, in unreported tests, we also benchmark *MacroDiscl* against a measure based on the Campbell et al. (2014) risk words classified as "systematic." We continue to find that our measure dominates alternative benchmarks.

5. *Economic implications and applications*

5.1 Identifying Bellwether Firms

In this section, we employ *MacroDiscl* to identify potential bellwether firms, and then use the financial accounting information of the identified firms to *predict* future changes in the macroeconomy—thus confirming their bellwether nature. We examine two financial fundamentals that we expect to predict future changes in aggregate economic activity: (i) special items, and; (ii) forecasted earnings growth.[11] First, we follow Abdalla and Carabias (2022) who show that quarterly aggregate special items are strong predictors of future changes in quarterly GDP growth. Since *MacroDiscl* is developed using annual disclosures, we extend their analysis to the yearly frequency and examine whether the special items of firms with higher levels of macro sensitivity are better predictors of future GDP growth, compared to firms with lower levels of macro sensitivity. We define high (low) macro sensitivity firms as firms in the upper (lower) tercile of *MacroDiscl* in year *t*.

Next, similar to Choi et al. (2016), we employ analyst forecasts of annual earnings as a leading indicator of macroeconomic activity. For each firm-year in our sample, we obtain all the analyst forecasts of annual earnings per share for year *t+1*, issued within the first quarter following the release of the firm's 10-K for year *t*. Next, for each analyst, we retain the first forecast issued after the release of the firm's 10-K for year *t*, and use the median of these forecasts as the forecast consensus for each firm-year. Finally, we compute the forecasted growth for each firm-year as the difference between the forecast consensus for year *t+1* and realized earnings in year *t*.[12]

Using the same approach as before, we test whether the aggregate forecasted earnings growth of firms with higher levels of macro sensitivity is a better predictor of future GDP growth, relative to the aggregate forecasted earnings growth of firms with lower levels of macro sensitivity.

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[11] Abdalla and Carabias (2022) find that after accounting for serial correlation in GDP growth, only special items (as opposed to corporate earnings) predictive future changes in the macroeconomy. Therefore, we do not examine the ability of the identified firms' earnings to predict future economic activity. Furthermore, we do not examine management forecasts since the propensity to provide earning's guidance has declined substantially over time (e.g., Ali et al., 2023).

[12] In untabulated sensitivity analyses, we use forecasted earnings growth scaled by total assets per share (i.e., we scale the difference between forecasted EPS and actual EPS by total assets per share) as an alternative analyst-based leading indicator of macro activity. We find similar results and our conclusions remain unchanged.

In both tests, we continue to compare the information content of *MacroDiscl* with that of the alternative bellwether indicators. Specifically, for each measure, we sort observations every year into three terciles based on their level of the respective measure at time *t* (e.g., *MacroDiscl, RFDiscl*$_{CEA}$). We then use the portfolio-level special items and forecasted earnings growth to predict future economic activity in year *t+1*.[13] Given the predictive nature of this analysis, we use the *R*-squared from OLS regressions as our primary evaluation metric.

The results are reported in Table 9. When we sort observations using *MacroDiscl,* we find compelling results for both special items and forecasted earnings growth that depict large and monotonically-increasing *R*-squares across all the proxies used to estimate future economic conditions. For example, when predicting nominal GDP growth, the explanatory power increases from 0.25 to 0.60 for special items and from 0.13 to 0.58 for analyst forecasts. Importantly, we also confirm that *MacroDiscl* offers superior information content (i.e., bellwether identification) relative to alternative numerical and text-based proxies. In fact, the disclosure-based measure we propose is the only measure that consistently exhibits a monotonic increase in explanatory power. In addition, for the highest portfolio group (i.e., top tercile of *MacroDiscl*), our measure, overall, offers the largest out-of-sample *R*-squared, providing a leading indicator for the future state of the economy.

5.2 Macroeconomic disclosures and investor response to earnings surprises

In our final set of tests, we examine potential capital market implications of firms' macro sensitivity. In particular, given the bellwether nature of companies that provide more macro-related disclosures, and experience higher levels of macro sensitivity, we predict substantial information transfers across high-macro-disclosure firms around earnings announcements. We follow the empirical framework in Pownall and Waymire (1989) and examine both the market response to, and information spillovers from, earnings news across high-macro-disclosure firms *vis-à-vis* the rest of

[13] We sort observations into terciles for two primary reasons. First, to render the analysis more concise while conveying the primary economic insight. Second, to better reflect the "aggregate" nature of (and therefore better aggregate) firms' fundamentals into portfolios built using *MacroDiscl*. However, using quartiles leads to similar results.

our sample. Our goal is to test for the existence of informational spillovers across firms that have higher levels of macro sensitivity (identified using *MacroDiscl*).

For each company in our sample (i.e., the "focal firm"), we test the sensitivity of its earnings announcement returns to individual (i.e., firm-specific) and aggregate (i.e., portfolio-level) earnings news. We execute this test separately for firms in the fourth quartile of *MacroDiscl*, and the remaining firms in quartiles 1-3. Specifically, we estimate the following equation twice, first for firms in quartile 4, and next for firms in quartiles 1-3 of *MacroDiscl*:

$$\begin{aligned} R_{i,[0,1]} = \beta_0 + \beta_1 RM_{[0,1]} + \beta_2 dUX_{i,[0,1]} + \beta_3 dUX\_Agg_{j,[-1,0]} \\ + \beta_4 dUX_{i,[0,1]}\ x\ dUX\_Agg_{j,[-1,0]} + \eta_{i,t} \end{aligned} \tag{2}$$

$R_{i,[0,1]}$ is firm *i*'s two-day buy-and-hold stock return around its quarterly earnings announcement, where day 0 is the earnings announcement date. $RM_{[0,1]}$ is the two-day return on the value-weighted CRSP index, $dUX_{i,[0,1]}$ is the decile of earnings news for firm *i* (i.e., measured as the difference between actual earnings and the most recent median analyst forecast), $dUX\_Agg_{j,[-1,0]}$ is the decile of aggregate earnings news announced by firms *j* (i.e., firms in the same quartile of *MacroDiscl* as the "focal firm", *excluding* the "focal firm") immediately prior to firm *i* (i.e., on days [-1,0]), and $dUX_{i,[0,1]}\ x\ dUX\_Agg_{j,[-1,0]}$ is the interaction term between the prior two variables.[14] All regressions include date and either industry or firm fixed-effects. Standard errors are clustered by firm and date.

As previously described, we predict information transfers across firms in the fourth quartile of *MacroDiscl* to result in a negative and significant coefficient for the interaction term $dUX_{i,[0,1]}\ x\ dUX\_Agg_{j,[-1,0]}$. A negative coefficient implies that the announcement returns of the "focal firm" are less sensitive to its earnings news when the amount of aggregate news announced by other "bellwether" companies (as per *MacroDiscl*) is larger. We expect to find a smaller or zero coefficient for the interaction term when estimating the model for firms in the quartiles 1-3 of

[14] Of note, we estimate equation (2) using deciles of earnings news because the relation between announcement-day returns and earnings surprise is highly non-linear (e.g., Kothari, 2001). In addition, we define the deciles as ranging from 0 to 9, to enhance the interpretability of the coefficients.

MacroDiscl.[15] These results would confirm the presence of information transfers among firms with high levels of macro sensitivity.

The results are reported in Table 10. Consistent with our prediction, we find negative coefficients for $dUX_{i,[0,1]}\ x\ dUX\_Agg_{j,[-1,0]}$ when estimating our model for firms in the highest quartile of *MacroDiscl*. The coefficients are stable at -0.001, with *t*-stats of -5.54 and -3.52. The coefficient for the interaction term is zero and statistically insignificant for the remaining firms in quartiles 1-3 of *MacroDiscl*. Additionally, the difference in the coefficients across the partitions are statistically significant. This evidence confirms information transfers across firms with higher levels of macro sensitivity as captured by *MacroDiscl.*

We run additional tests to isolate the role of the macroeconomic disclosures as opposed to the inherent characteristics of firms with higher levels of *MacroDiscl*. First, we run the determinants model reported in Table 4 column (4) and extract the residual from the OLS regression. Next, we use the residual as our macroeconomic disclosure variable to sort companies into quartiles. Finally, we re-estimate equation (2) using the updated sample. By using the residual, and including firm fixed effects, we examine the *incremental* information content, if any, of the actual disclosure. These results are also reported in Table 10. We find similar results using the residual. The coefficients for the interaction term for firms in the fourth quartile of *MacroDiscl* remain stable at -0.001, with slightly lower t-stats of -2.56 and -1.99. Therefore, we conclude that our results are at least partially attributable to the information present in a firm's disclosure, as opposed to the firm's inherit characteristics. Overall, we confirm that *MacroDiscl* identifies bellwether firms and that investors consider these firms' macroeconomic disclosures as bellwether signals about the future state of the economy.[16]

[15] We expect spillovers to concentrate across firms that are highly exposed to macroeconomic shocks; this motivates our focus on companies classified in the fourth quartile of *MacroDiscl*. Consistent with the bellwether attributes of macroeconomic disclosures, we consider information transfers *a priori* less likely for low(er)-macro-disclosure firms.

[16] We follow Pownall and Waymire (1989) in our primary specification, and use raw stock return as the outcome variable. In untabulated analysis, we find similar results when employing cumulative abnormal stock returns as an alternative dependent variable.

6. *Conclusion*

In this paper, we develop a simple, interpretable, and objective textual measure that captures a company's propensity to provide macroeconomic discussions within 10-K reports. We demonstrate that macroeconomic disclosures enable us to identify (i) companies whose contemporaneous performance is highly correlated with current economic conditions (i.e., firms with higher levels of macro sensitivity), and (ii) firms whose fundamentals are strong predictors of future changes in economic conditions (i.e., "bellwether firms"). Overall, our findings offer new evidence about the fundamental role of accounting disclosures in identifying the time-varying nature of firms' macro sensitivity.

Our measure of macroeconomic disclosure outperforms a wide array of existing numerical and text-based proxies used to capture systematic risks and identify bellwether firms. Moreover, our measure allows us to document that firms have increased their propensity to disclose macroeconomic information in their corporate reports over the last few decades. These findings show that macro disclosures reflect changes in firms' economic landscapes. The results are consistent with recent findings in macroeconomics that document how the U.S. production network has become more connected over the past 50 years (Acemoglu and Azar, 2020; Acemoglu, et al., 2012).

We envision several applications and avenues for future research using the disclosure-based measure we develop. Naturally, future work can use macro disclosure to better identify bellwether firms within capital market and accounting research settings. Furthermore, macro disclosure can help examine strategic disclosure choices within regulatory filings—for instance, conditioning the analysis of macroeconomic discussions on the sign of the news. Finally, we believe our measure can shed light on the asset pricing implications of firms' exposure to time-varying aggregate shocks.

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Appendix A

Variable Descriptions

	Description	Source
Aggregate Economic Variables		
Δ *nGDP*	Yearly change in nominal U.S. Gross Domestic Product downloaded from Table 1.1.5 of the Bureau of Economic Analysis (BEA)	BEA
Δ *rGDP*	Yearly change in real U.S. Gross Domestic Product downloaded from Table 1.1.6 of the Bureau of Economic Analysis (BEA)	BEA
Δ *Inflation*	Yearly change in U.S. inflation downloaded from Table 1.1.9 of the Bureau of Economic Analysis (BEA)	BEA
Δ *IndProd*	Yearly change in U.S. total industrial production downloaded from the OECD Industrial Production Table	OECD
Experimental Variable		
MacroDiscl	Ratio of macroeconomic terms (as defined in Appendix B) to total words within a 10-K filing in year *t*. The ratio is multiplied by 1,000 for expositional purposes	EDGAR
Aggregate Firm Fundamentals		
Δ *OI*	Value-weighted cross-sectional average of all firm-level changes in operating income for year *t*, scaled by beginning of the year stock price	Compustat and CRSP
Special Items	Value-weighted cross-sectional average of all firm-level special items scaled by market capitalization	Compustat and CRSP
Forecasted Earnings Growth	Value-weighted cross-sectional average of all firm-level differences between the consensus analyst forecast of annual EPS for year *t+1,* and year *t* realized EPS To compute the consensus, we obtain all the analyst forecasts of annual EPS for year t+1, issued within the first quarter following the release of the firm's 10-K for year t. Next, for each analyst, we retain the first forecast issued after the release of the firm's 10-K for year t, and use the median of these forecasts as the forecast consensus for each firm-year	Compustat and I/B/E/S
Firm-level Fundamentals, Disclosure Characteristics, and Other Bellwether Proxies		
Size	Natural logarithm of a firm's market capitalization	CRSP
Beta	CAPM beta, using daily returns over the past 12 months	CRSP
IVol	The standard deviation of a firm's monthly market-adjusted stock returns, calculated over the previous 12 months. We use data on the value-weighted index including dividend distributions as our measure of market returns	CRSP
CFVol	The standard deviation of annual operating cash-flows divided by total assets, measured over a 5-year period	Compustat
BM	Book value per share / fiscal closing price	Compustat
Leverage	(Short-term liabilities + long term liabilities) / total assets	Compustat
ROA	Net income/total assets	Compustat

Segments	Natural logarithm of one plus the number of geographic segments in year *t*	Compustat
InstOwn	Number of shares held by institutional investors each year divided by the total number of shares outstanding	Reuters 13-F
HiMacro	The categorical variable developed by Bonsall et al. (2013) capturing firms' earnings sensitivity to aggregate economic activity. *HiMacro*, equals one, two, three, or four if the firm's *R*-squared from the Bonsall et al. (2013, p. 231) regression is in the first, second, third, or fourth quartile of its pooled distribution. *HiMacro* is computed using the vector of macroeconomic variables employed in Bonsall et al. (2013, p. 231)	Compustat
SPI	Annual special items scaled by market capitalization in year *t*	Compustat
Tone	Positive minus negative words from the Loughran and McDonald (2011) dictionary scaled by total 10-K words	EDGAR
$RFDiscl_{CEA}$	Ratio of Campbell et al. (2014) risk words to total words within a 10-K filing in year *t*. The ratio is multiplied by 1,000 for expositional purposes	EDGAR
$RFDiscl_{KM}$	Ratio of Kravet and Muslu (2013) risk words to total words within a 10-K filing in year *t*. The ratio is multiplied by 1,000 for expositional purposes	EDGAR
$RFDiscl_{LM}$	Ratio of Loughran and McDonald (2011) uncertainty words to total words within a 10-K filing in year *t*. The ratio is multiplied by 1,000 for expositional purposes	EDGAR
PRDiscl	Ratio of top 120 political risk bigrams identified by Hassan et al. (2019) to total words within a 10-K filing in year *t*. The ratio is multiplied by 1,000 for expositional purposes	EDGAR
Variables for Market Reaction Tests		
Ret [0,1]	Firm *i*'s two-day buy-and-hold stock return around its quarterly earnings announcement. Day 0 is the earnings announcement date	CRSP
CAR [0,1]	Firm *i*'s two-day cumulative abnormal stock return around its quarterly earnings announcement. Day 0 is the earnings announcement date	CRSP
RM	Two-day return on the value weighted CRSP index	CRSP
dUX	Decile of earnings news for firm *i*, measured as the difference between actual earnings announced on day "0" and the most recent analyst forecast consensus. We compute the forecast consensus using the median estimate. Deciles range between 0 and 9 to enhance interpretability	Compustat and I/B/E/S
dUX_Agg	Decile of aggregate earnings news announced by firms *j* (i.e., firms in the same quartile of *MacroDiscl* as the "focal firm" *i*, excluding the "focal firm") measured in the [-1,0] window relative to firm *i*'s earnings announcement date. Deciles range between 0 and 9 to enhance interpretability of the coefficients	Compustat and I/B/E/S

Appendix B

Macroeconomic Terms included in *MacroDiscl*

	Percentile Rank	
Unigrams	*10-K Sample*	*WSJ Sample*
Macro, Macroeconomic/s, Macroeconomy	Top 1%	Top 1%
Import/ing/ed, Export/ing/ed	Top 1%	Top 1%
Inflation, Deflation	Top 1%	Top 1%
GDP, GNP	Top 1%	Top 1%
Recession	Top 1%	Top 1%
Currency	Top 1%	Top 1%
FED	Top 1%	Top 1%
Bigrams	*10-K Sample*	*WSJ Sample*
Economic condition/environment/downturn/factor/trend/ growth/activity/development/slowdown/instability/ uncertainty/recovery/climate/data/cycle/ crisis/indicator/output/expansion	Top 1%	Top 1%
Capital/credit/global/international/exchange/emerging/bear/ bull market	Top 1%	Top 1%
Market/credit/global/international/exchange/economic/ risk	Top 1%	Top 1%
Global/international/emerging/general economy	Top 1%	Top 1%
Foreign exchange/investor/investment	Top 1%	Top 1%
Federal reserve, Central bank	Top 1%	Top 1%
Gross domestic/national	Top 1%	Top 1%
Monetary/fiscal policy	Top 1%	Top 1%
Interest/discount rate	Top 1%	Top 1%
Business cycle	Top 1%	Top 1%
Global trade	Top 1%	Top 1%

This table reports the macroeconomic terms included in the text-based disclosure measure. These terms represent the intersection of the top 1% most frequent macroeconomic unigrams and bigrams (i.e., individual words and pairs of consecutive words, respectively, excluding common "stop words") in (i) a sample of 86,624 10-K reports filed between 1994 and 2021, and (ii) a sample of 22,993 *Wall Street Journal* "Economic News" articles published between 1994 and 2021. The 10-K reports are downloaded from SEC EDGAR while the news articles from *Dow Jones Factiva* and exclude documents with fewer than 5 sentences and 100 words. Exact matching is performed for all the listed terms except for "Inflation", "Deflation", "Recession", and "Currency" that are matched as substrings (to capture words such as "Hyperinflation" or "Recessionary"). While not listed, plural tenses are searched for when relevant. 10-K reports, *WSJ* articles, and macro-related terms are all converted into lower case before matching.

Appendix C

Examples of Macroeconomic Disclosures

Caterpillar Inc – CIK 0000018230
Report year: 2018, Item 7 – Management Discussion and Analysis

Retail revenue for 2018 was $1.31 billion, an increase of $73 million from 2017. The increase was due to a $73 million favorable impact from higher **interest rates** on retail finance receivables. For the year ended December 31, 2018, retail average earning assets were $23.10 billion, an increase of $9 million from 2017.

The average yield was 5.66 percent for 2018, compared with 5.35 percent in 2017. Operating lease revenue for 2018 was $1.01 billion, an increase of $26 million from 2017. The increase was due to a $27 million favorable impact from higher average rental rates on operating leases, partially offset by a $1 million unfavorable impact from lower average earning assets.

Wholesale revenue for 2018 was $415 million, an increase of $108 million from 2017. The increase was due to an $83 million favorable impact from higher average earning assets and a $25 million favorable impact from higher **interest rates** on wholesale finance receivables. For the year ended December 31, 2018, wholesale average earning assets were $4.85 billion, an increase of $1.04 billion from 2017. The average yield was 8.55 percent for 2018, compared with 8.04 percent in 2017.

Apple Inc. – CIK 0000320193
Report year: 2019, Item 1A – Risk Factors

Global and regional economic conditions could materially adversely affect the Company's business, results of operations, financial condition and growth.

The Company has international operations with sales outside the U.S. representing a majority of the Company's total net sales. In addition, a majority of the Company's supply chain, and its manufacturing and assembly activities, are located outside the U.S. As a result, the Company's operations and performance depend significantly on global and regional **economic conditions**.

Adverse **macroeconomic** conditions, including **inflation**, slower growth or **recession**, new or increased tariffs, changes to fiscal and **monetary policy**, tighter credit, higher **interest rates**, high unemployment and **currency** fluctuations could materially adversely affect demand for the Company's products and services. In addition, consumer confidence and spending could be adversely affected in response to financial market volatility, negative financial news, conditions in the real estate and mortgage markets, declines in income or asset values, changes to fuel and other energy costs, labor and healthcare costs and other **economic factors**.

In addition to an adverse impact on demand for the Company's products, uncertainty about, or a decline in, global or regional **economic conditions** could have a significant impact on the Company's suppliers, contract manufacturers, logistics providers, distributors, cellular network carriers and other channel partners. Potential effects include financial instability; inability to obtain credit to finance operations and purchases of the Company's products; and insolvency.

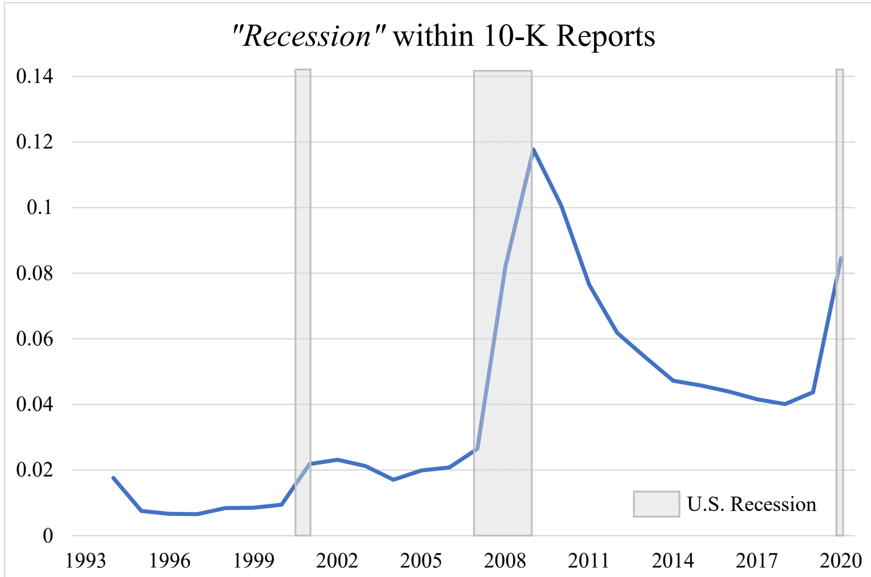
A downturn in the **economic environment** could also lead to increased credit and collectibility risk on the Company's trade receivables; the failure of derivative counterparties and other financial institutions; limitations on the Company's ability to issue new debt; reduced liquidity; and declines in the fair value of the Company's financial instruments. These and other **economic factors** could materially adversely affect the Company's business, results of operations, financial condition and growth.

The Walt Disney Company – CIK 0001744489
Report year: 2020, Item 7 – Management Discussion and Analysis

Operating expenses include operating labor, which decreased $1,304 million from $6,174 million to $4,870 million, cost of sales and distribution costs, which decreased $716 million from $2,918 million to $2,202 million, and infrastructure costs, which decreased $47 million from $2,469 million to $2,422 million. The decrease in operating labor was due to furloughs in response to lower volumes and the benefit of government credits for certain employee costs, partially offset by **inflation** and new guest offerings. Lower cost of goods sold and distribution costs were due to lower volumes. The decrease in infrastructure costs was due to lower operations support costs reflecting reduced volumes, partially offset by the write-down of assets at our retail stores and higher costs for new guest offerings. Other operating expenses, which include costs for such items as supplies, commissions/fees and entertainment offerings, decreased $463 million, from $2,454 million to $1,991 million, due to lower volumes, partially offset by higher charges for capital project abandonments.

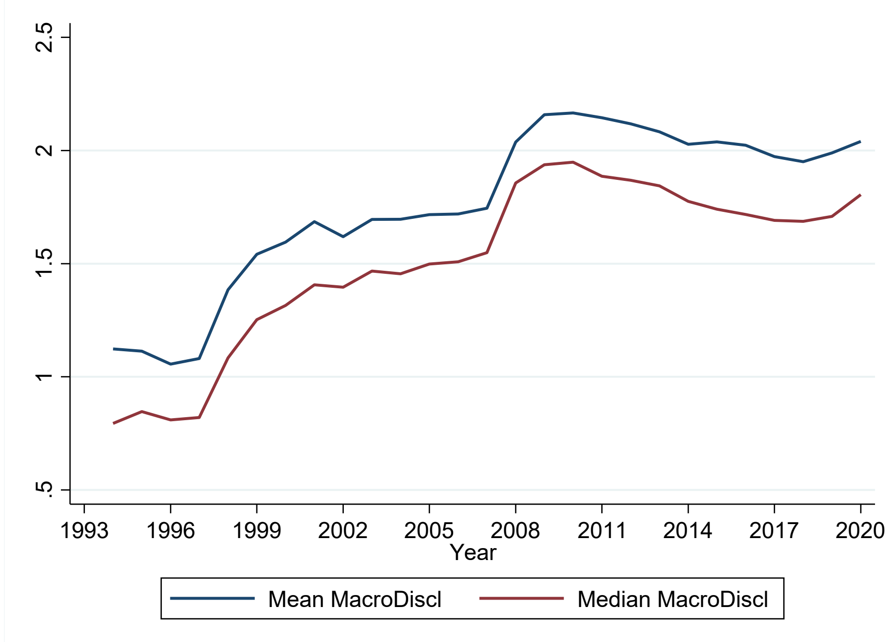
Appendix D

Time-series Variation of Recessionary Terms



This figure reports the time-trend of macroeconomic "recessionary" terms included in the computation of *MacroDiscl* (i.e., it reports average scaled word counts for words such as "recession" or "recessionary") within 10-K reports. The sample includes 86,624 firm-year observations, ranging from reporting years 1994-2020. The word counts are expressed per 1,000 words within the regulatory filing. The light-gray rectangles cover areas on the graph corresponding to economic recessions in the U.S.

Panel A: Time-trend of macroeconomic disclosures within 10-K reports



Panel B: Time-trend of macroeconomic disclosures within 10-K reports by quartile

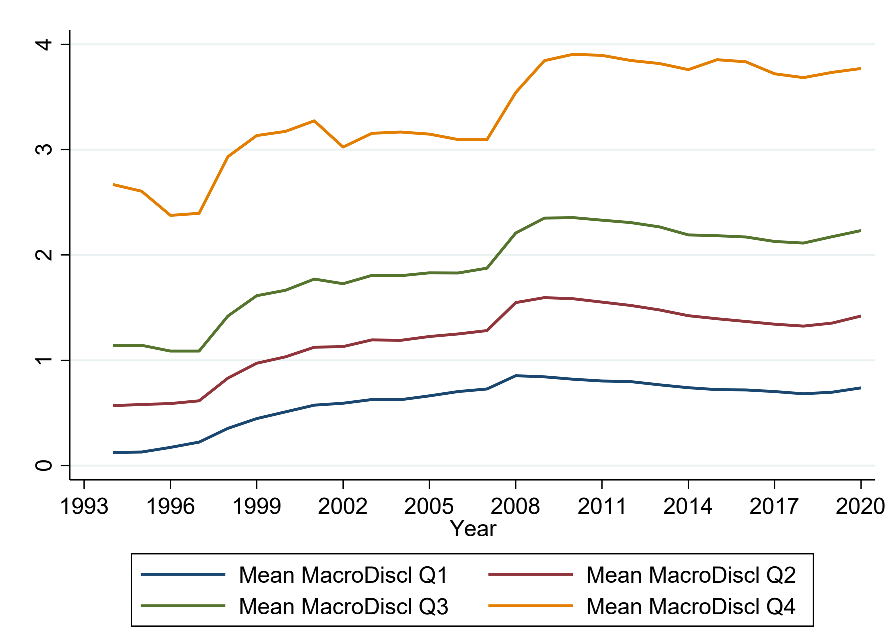
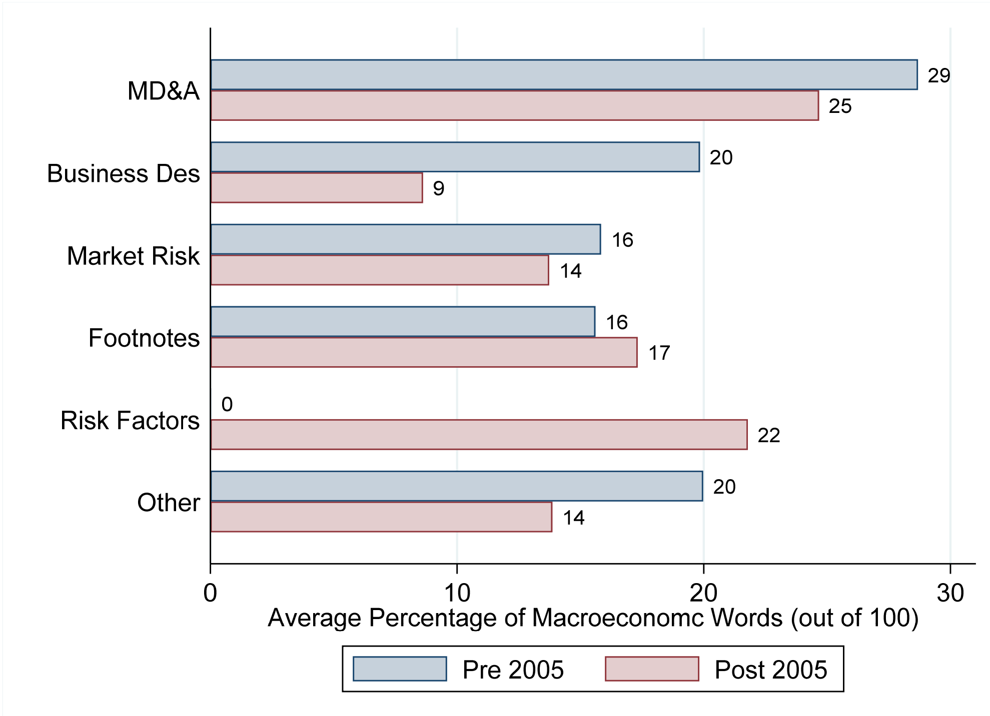


Figure 1: This figure reports the time-trend of macroeconomic disclosures within 10-K reports. The sample includes 86,624 firm-year observations, ranging from reporting years 1994-2020. *MacroDiscl* is defined as the total number of macroeconomic words per thousand words in firm *i*'s 10-K filing in year *t*. Panel A reports aggregate means and medians for each year. Panel B shows means for each year by quartile of *MacroDiscl*.

Panel A: Location of macroeconomic disclosures within 10-K reports



Panel B: Location of macroeconomic disclosures within 10-K reports over time

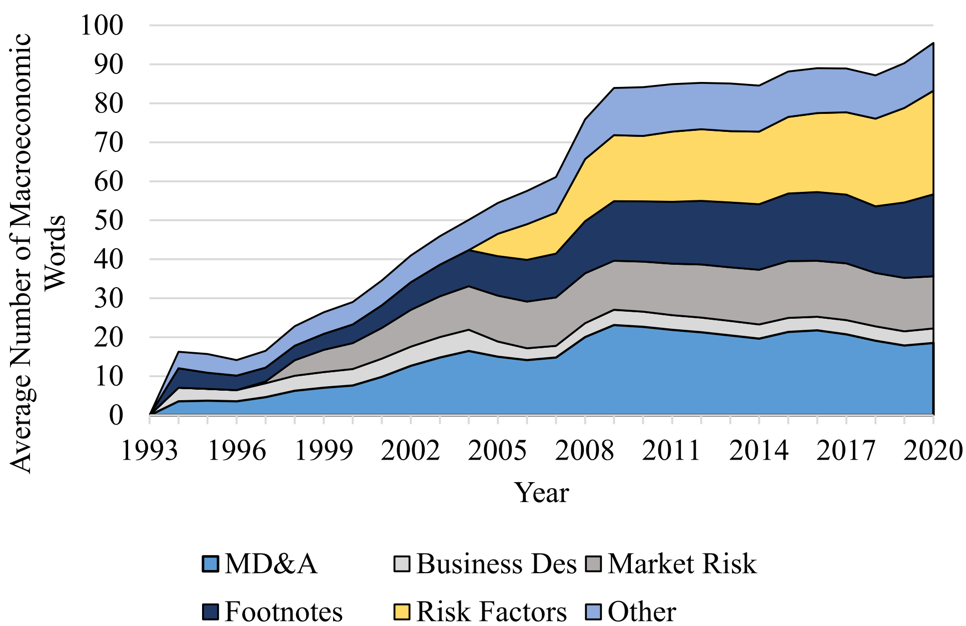


Figure 2: This figure reports the location of macro disclosures within specific sections of the 10-K. The sample includes 86,624 firm-year observations, during reporting years 1994-2020. Panel A shows the average percentages of macroeconomic words in each section, for the top five sections based on the frequency of macroeconomic terms. Light-blue bars report averages prior to the introduction of the "Risk Factor" section by the SEC (i.e., before 2005), while light-red bars show averages after 2005. Panel B displays the time trend of the average number of macroeconomic words in each section. "Other" includes all other 10-K sections.

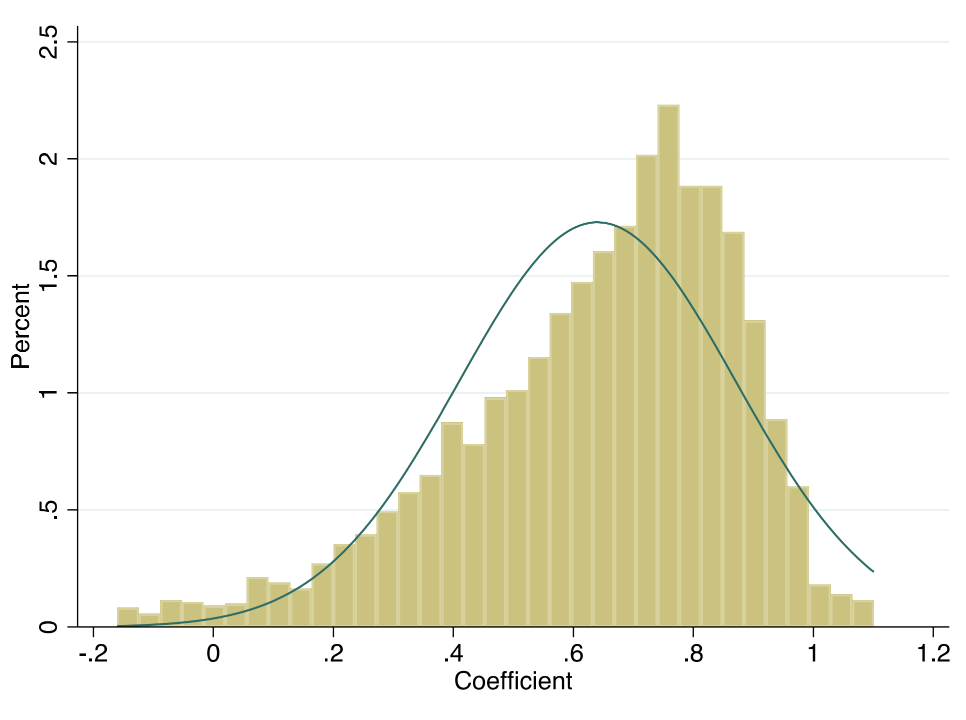


Figure 3: This figure plots the coefficients from the following firm-level time-series regressions:

$$MacroDiscl_{i,t} = \beta_0 + \beta_1 MacroDiscl_{i,t-1} + \varepsilon_{i,t}$$

MacroDiscl is the total number of macro-related words per 1,000 total words in firm *i's* 10-K in year *t* (*t-1)*. We limit this analysis to firms that have at least 10 firm-year observations thus reducing our sample to 58,913 firm-year observations between reporting years 1994-2020.

Table 1: Sample

Panel A: Selection Criteria

	Number
EDGAR 10-K filings by companies reporting between 1994 and 2020, with valid CIK, GVKEY, and PERMNO, and minimum 500 words	143,367
Less: 10-K reports:	
- filed by financial institutions (SIC codes 6000-6999)	(32,071)
Total EDGAR 10-K filings with available macroeconomic disclosures	111,296
Less: observations with missing:	
- CRSP or Compustat items	(17,195)
- lagged disclosures to compute $MacroDiscl_{t-1}$	(7,477)
Total firm-years included in the primary sample	**86,624**

Panel B: Summary Statistics

	N	Mean	SD	P25	P50	P75
MacroDiscl	86,624	1.770	1.170	0.890	1.507	2.376
Size	86,624	5.760	2.313	4.093	5.771	7.363
Beta	86,624	0.916	0.528	0.601	0.909	1.213
IVol	86,624	0.034	0.021	0.019	0.029	0.043
CFVol	86,624	0.816	2.177	0.048	0.154	0.561
BM	86,624	0.465	2.083	0.225	0.455	0.791
Leverage	86,624	0.233	0.272	0.007	0.172	0.351
ROA	86,624	-0.139	0.688	-0.088	0.023	0.066
Segments	86,624	1.112	0.477	0.693	1.099	1.386
InstOwn	86,624	0.390	0.363	0.000	0.334	0.726
HiMacro	86,624	2.167	1.323	1.000	2.000	3.000
SPI	86,624	-0.044	0.199	-0.024	0.000	0.000
Tone	86,624	-0.008	0.005	-0.012	-0.008	-0.005
$RFDiscl_{CEA}$	86,624	47.817	9.778	41.299	47.752	53.892

Table 1 presents the sample formation process and descriptive statistics for the primary sample of 86,624 firm-year observations, ranging from reporting years 1994-2020. Panel A reports the sample formation criteria. Panel B presents summary statistics. All variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles of their yearly distribution.

Table 2: Within-Firm Correlation Among Selected Macroeconomic Terms

	Relevant Keywords	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	*Interest Rates*	**1.00**	**0.13**	**0.13**	**0.17**	**0.18**	**0.15**	**0.17**	**0.31**	**0.26**	**-0.07**
(2)	*Federal Reserve*	**0.17**	**1.00**	0.00	**0.10**	**0.08**	**-0.02**	**0.10**	**0.07**	**0.02**	**-0.01**
(3)	*Inflation*	**0.12**	**0.09**	**1.00**	**0.05**	**0.12**	**0.02**	**0.02**	**0.16**	**0.10**	**0.03**
(4)	*Macroeconomic*	**0.18**	**0.22**	**0.11**	**1.00**	**0.27**	**0.20**	**0.21**	**0.21**	**0.14**	**0.05**
(5)	*Economic Conditions*	**0.16**	**0.12**	**0.12**	**0.27**	**1.00**	**0.30**	**0.23**	**0.26**	**0.17**	**0.07**
(6)	*Economic Environment*	**0.15**	**0.15**	**0.08**	**0.25**	**0.28**	**1.00**	**0.17**	**0.15**	**0.10**	**-0.03**
(7)	*Economic Trends*	**0.18**	**0.21**	**0.08**	**0.24**	**0.22**	**0.22**	**1.00**	**0.17**	**0.13**	0.00
(8)	*Currency*	**0.26**	**0.12**	**0.16**	**0.21**	**0.21**	**0.17**	**0.17**	**1.00**	**0.52**	**0.09**
(9)	*Foreign Exchange*	**0.22**	**0.13**	**0.12**	**0.17**	**0.16**	**0.14**	**0.17**	**0.44**	**1.00**	**0.06**
(10)	*Import and Export*	**-0.03**	**0.11**	**0.06**	**0.11**	**0.08**	**0.04**	**0.05**	**0.10**	**0.09**	**1.00**

Table 2 presents within-firm Pearson univariate correlations among selected macroeconomic terms counts scaled by the total number of words within the 10-K report. The lower triangle presents average correlations while the upper triangle shows median correlations. We limit this analysis to firms that have at least 10 firm-year observations thus reducing our sample to 58,913 firm-year observations between reporting years 1994-2020. *Relevant Keywords* includes counts for the respective keywords, both singular and plural when applicable (e.g., *Inflation* includes the counts for the word "inflation"); the only exceptions are *Interest Rates* that includes counts for "interest rate" and "discount rate" and *Import and Export* that includes counts for "import", "importing", "imported", "export", "exporting", "exported". All variables are winsorized at the 1st and 99th percentiles of their respective distribution. Correlations with a *p*-value <0.01 are presented in bold.

Table 3: Across-Firms Correlation Table

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	*MacroDiscl*	**1.00**													
(2)	*Size*	**0.35**	**1.00**												
(3)	*Beta*	**0.07**	**0.24**	**1.00**											
(4)	*IVol*	**-0.26**	**-0.55**	**0.04**	**1.00**										
(5)	*CFVol*	**0.20**	**0.52**	**0.09**	**-0.22**	**1.00**									
(6)	*BM*	**0.04**	**0.03**	**-0.04**	**0.01**	**-0.01**	**1.00**								
(7)	*Leverage*	**0.03**	**0.01**	**0.02**	**-0.02**	**0.07**	**-0.19**	**1.00**							
(8)	*ROA*	**0.19**	**0.30**	**0.00**	**-0.24**	**0.09**	**0.14**	**-0.17**	**1.00**						
(9)	*Segments*	**0.36**	**0.20**	**0.14**	**-0.11**	**0.09**	0.00	**-0.10**	**0.12**	**1.00**					
(10)	*InstOwn*	**0.31**	**0.53**	**0.17**	**-0.38**	**0.17**	**0.03**	**-0.02**	**0.21**	**0.16**	**1.00**				
(11)	*HiMacro*	**0.10**	**0.26**	**0.07**	**-0.13**	**0.08**	-0.01	**-0.05**	**0.13**	**0.10**	**0.20**	**1.00**			
(12)	*SPI*	**-0.11**	**-0.17**	**-0.07**	**0.02**	**-0.38**	**0.17**	**-0.11**	**0.03**	**-0.06**	**-0.06**	**-0.02**	**1.00**		
(13)	*Tone*	**-0.07**	**-0.05**	**-0.08**	**-0.05**	**-0.11**	**0.06**	**-0.05**	**0.07**	**-0.05**	**-0.13**	**-0.02**	**0.13**	**1.00**	
(14)	*RFDiscl*$_{CEA}$	**0.34**	**0.25**	**0.13**	**-0.13**	**0.14**	**0.04**	**-0.02**	**0.12**	**0.15**	**0.24**	**-0.02**	**-0.06**	**-0.23**	**1.00**

Table 3 presents Pearson univariate correlation for the primary sample of 86,624 firm-year observations, ranging from reporting years 1994-2020. All variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles of their yearly distribution. All correlations with a *p*-value <0.01 are presented in bold.

Table 4: Determinants of Macroeconomic Disclosures

	Dependent Variable: ***MacroDiscl***			
	(1)	(2)	(3)	(4)
Size	0.156 ***	0.103 ***	0.102 ***	0.087 ***
	(13.72)	(9.79)	(10.09)	(9.59)
Beta	-0.026	-0.053 ***	-0.055 ***	-0.078 ***
	(-1.38)	(-3.16)	(-3.23)	(-4.96)
IVol	-2.744 ***	-1.985 ***	-2.105 ***	-2.734 ***
	(-4.51)	(-3.93)	(-4.24)	(-5.52)
CFVol	0.014 **	0.018 ***	0.011 *	0.015 **
	(2.26)	(3.06)	(1.75)	(2.48)
BM		0.014 *	0.017 **	0.014 **
		(1.97)	(2.43)	(2.37)
Leverage		0.329 ***	0.324 ***	0.328 ***
		(11.88)	(11.91)	(12.45)
ROA		0.112 ***	0.114 ***	0.074 ***
		(7.67)	(7.48)	(5.54)
Segments		0.590 ***	0.588 ***	0.549 ***
		(19.67)	(19.58)	(19.07)
InstOwn		0.206 ***	0.204 ***	0.148 ***
		(6.26)	(6.24)	(4.71)
HiMacro			0.024	0.039
			(0.91)	(1.47)
SPI			-0.219 ***	-0.219 ***
			(-6.35)	(-6.11)
Tone				9.810 ***
				(3.62)
$RFDiscl_{CEA}$				0.029 ***
				(22.67)
Observations	86,624	86,624	86,624	86,624
FE	Year & Industry	Year & Industry	Year & Industry	Year & Industry
Adjusted R^2	0.33	0.39	0.39	0.42

Table 4 presents the results of estimating the following equation:

$$Macro\_Disc_{i,t} = \beta_0 + \beta_1 Size_{i,t} + \beta_2 Beta_{i,t} + \beta_3 IVol_{i,t} + \beta_4 CFVol_{i,t} + \beta_5 BM_{i,t} + \beta_6 Leverage_{i,t} + \beta_7 ROA_{i,t} + \beta_8 Segments_{i,t} + \beta_9 InstOwn_{i,t} + \beta_{10} HighMacro_{i,t} + \beta_{11} SPI_{i,t} + \beta_{12} Tone_{i,t} + \beta_{13} RFDiscl_{CEA\,i,t} + \varepsilon_{i,t}$$

where $Macro\_Disc_{i,t}$ is the total number of macroeconomic words per 1,000 total words in firm *i's* 10-K filing for year *t*. All other variable definitions are presented in Appendix A. The sample consists of 86,624 firm-year observations, ranging from reporting years 1994-2020. Continuous variables are winsorized at the 1st and 99th percentiles of their yearly distribution. All regressions are estimated with an intercept (not reported). "Industry" fixed effects are based on the Fama-French 48 classification. Cluster-robust-to-heteroskedasticity *t*-statistics are reported in parentheses; standard-errors are clustered by both firm and date. ***, **, * indicate significance at <0.01, <0.05, <0.10 (two-tailed tests).

Table 5: Macroeconomic Disclosure Levels and Aggregate Economic Activity

Aggregate Economic Activity	Dependent Variable: Δ *OI*				
	(1)	(2)	(3)	(4)	(5)
	MacroDiscl $_{t-1}$ *Quartile 1*	*MacroDiscl* $_{t-1}$ *Quartile 2*	*MacroDiscl* $_{t-1}$ *Quartile 3*	*MacroDiscl* $_{t-1}$ *Quartile 4*	*p-value Q4-Q1*
Δ *nGDP*					
Coeff	0.02	0.03	0.07	0.12	0.00 ***
t-stat	1.48	2.48 **	3.03 ***	3.64 ***	
R^2	0.08	0.19	0.27	0.35	0.02 **
Obs	27	27	27	27	
Δ *rGDP*					
Coeff	0.03	0.04	0.08	0.12	0.02 **
t-stat	1.46	2.27 **	2.77 ***	3.10 ***	
R^2	0.08	0.17	0.24	0.29	0.06 *
Obs	27	27	27	27	
Δ *Inflation*					
Coeff	0.05	0.08	0.17	0.32	0.03 **
t-stat	0.74	1.59	1.90 *	2.65 ***	
R^2	0.02	0.09	0.12	0.21	0.08 *
Obs	27	27	27	27	
Δ *IndProd*					
Coeff	0.01	0.02	0.05	0.07	0.00 ***
t-stat	1.55	2.86 ***	4.20 ***	4.14 ***	
R^2	0.09	0.25	0.40	0.41	0.00 ***
Obs	27	27	27	27	

Table 5 presents results of estimating the following equation for different levels of $MacroDiscl_{i,t-1}$

$$\frac{\Delta OI_t}{P_{t-1}} = \beta_0 + \beta_1 Aggregate\ Economic\ Activity_t + \varepsilon_{i,t}$$

where $\Delta OI_t/P_{t-1}$ is the value-weighted cross-sectional average of all firm-level changes in operating income for year *t*, scaled by beginning of the year stock price. *Aggregate Economic Activity* is alternatively (i) $\Delta\ nGDP_t$, the annual nominal GDP growth rate for year *t,* (ii) $\Delta\ rGDP_t$, the annual real GDP growth rate for year *t*, (iii) $\Delta\ Inflation_t$, the annual inflation growth rate for year *t*, and (iv) $\Delta\ IndProd_t$, the annual growth rate in industrial production for year *t*. Observations are sorted into quartiles each year based on the level of *MacroDiscl* in year *t-1*. $MacroDiscl_{i,t}$ is the total number of macro-related words per 1,000 words in firm *i's* 10-K filing in year *t-1*. Column (5) reports *t*-tests for statistical differences in coefficient and R^2 means between Quartile 4 and Quartile 1 of *MacroDiscl* in year *t-1*. Differences in R^2 are tested using bootstrapping with 500 iterations. ***, **, * indicate significance at <0.01, <0.05, <0.10 (two-tailed tests).

Table 6: Disclosure Levels for Varying Horizons and Aggregate Economic Activity

	Dependent Variable: Δ *OI*											
Aggregate Economic Activity	*MacroDiscl* $_t$				*MacroDiscl* $_{t-1}$				*MacroDiscl* $_{t-2}$			
	Q1	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
Δ *nGDP*												
Coeff	0.03	0.03	0.06	0.13	0.02	0.03	0.07	0.12	0.03	0.03	0.06	0.11
R^2	0.06	0.09	0.23	0.40	0.08	0.19	0.27	0.35	0.33	0.30	0.17	0.40
Δ *rGDP*												
Coeff	0.03	0.03	0.07	0.14	0.03	0.04	0.08	0.12	0.04	0.03	0.06	0.12
R^2	0.06	0.08	0.18	0.33	0.08	0.17	0.24	0.29	0.39	0.32	0.14	0.32
Δ *Inflation*												
Coeff	0.05	0.06	0.18	0.33	0.05	0.08	0.17	0.32	0.02	0.04	0.15	0.29
R^2	0.01	0.04	0.14	0.21	0.08	0.17	0.24	0.29	0.01	0.05	0.09	0.22
Δ *IndProd*												
Coeff	0.01	0.01	0.04	0.07	0.01	0.02	0.05	0.07	0.01	0.01	0.05	0.07
R^2	0.07	0.10	0.37	0.48	0.09	0.25	0.40	0.41	0.27	0.34	0.38	0.50

Table 6 presents results of estimating the following equation for levels of $MacroDisc_i$ computed for different horizons; namely, year *t*, *t-1*, and *t-2*.

$$\frac{\Delta OI_t}{P_{t-1}} = \beta_0 + \beta_1 Aggregate\ Economic\ Activity_t + \varepsilon_{i,t}$$

where $\Delta OI_t/P_{t-1}$ is the value-weighted cross-sectional average of all firm-level changes in operating income for year *t*, scaled by beginning of the year stock price. *Aggregate Economic Activity* is alternatively (i) $\Delta\ nGDP_t$, the annual nominal GDP growth rate for year *t,* (ii) $\Delta\ rGDP_t$, the annual real GDP growth rate for year *t*, (iii) $\Delta\ Inflation_t$, the annual inflation growth rate for year *t*, and (iv) $\Delta\ IndProd_t$, the annual growth rate in industrial production for year *t*. Observations are sorted into quartiles each year based on the level of $MacroDisc_i$ in year *t*, *t-1*, *t-2*. $MacroDisc_{i,t}$ is the total number of macro-related words per 1,000 words in firm i*'s* 10-K filing in year *t*. The sample includes firms with available disclosures for years *t*, *t-1*, and *t-2*.

Table 7: Alternative Macroeconomic Proxies

	Dependent Variable: Δ *OI*							
Aggregate Economic Activity								
Δ *nGDP*	*Coefficient*				R^2			
	Q1	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
Sorting variable $_{t-1}$								
MacroDiscl	*0.02*	*0.03*	*0.07*	*0.12*	*0.08*	*0.19*	*0.27*	*0.35*
HiMacro	0.09	0.04	0.06	0.10	0.39	0.14	0.34	0.23
Size	0.00	0.00	0.00	0.25	0.06	0.01	0.08	0.32
Beta	0.01	0.06	0.09	0.08	0.00	0.27	0.33	0.23
RFDiscl$_{CEA}$	0.05	0.06	0.05	0.09	0.33	0.23	0.14	0.29
RFDiscl$_{KM}$	0.10	0.05	0.05	0.06	0.44	0.26	0.14	0.07
RFDiscl$_{LM}$	0.11	0.07	0.03	0.04	0.50	0.23	0.11	0.12
PRDiscl	0.04	0.04	0.08	0.09	0.17	0.23	0.40	0.13
Δ *rGDP*	*Coefficient*				R^2			
	Q1	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
Sorting variable $_{t-1}$								
MacroDiscl	*0.03*	*0.04*	*0.08*	*0.12*	*0.08*	*0.17*	*0.24*	*0.29*
HiMacro	0.09	0.04	0.06	0.11	0.34	0.12	0.31	0.19
Size	0.00	0.00	0.01	0.27	0.04	0.03	0.08	0.27
Beta	0.01	0.07	0.11	0.09	0.02	0.24	0.28	0.18
RFDiscl$_{CEA}$	0.05	0.07	0.06	0.09	0.32	0.20	0.14	0.21
RFDiscl$_{KM}$	0.10	0.05	0.06	0.06	0.38	0.22	0.11	0.05
RFDiscl$_{LM}$	0.13	0.08	0.03	0.04	0.45	0.19	0.09	0.09
PRDiscl	0.04	0.04	0.09	010	0.14	0.17	0.37	0.11
Δ *Inflation*	*Coefficient*				R^2			
	Q1	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
Sorting variable $_{t-1}$								
MacroDiscl	*0.05*	*0.08*	*0.17*	*0.32*	*0.02*	*0.09*	*0.12*	*0.21*
HiMacro	0.21	0.08	0.11	0.25	0.19	0.06	0.11	0.11
Size	0.00	0.00	0.01	0.62	0.08	0.02	0.02	0.16
Beta	-0.01	0.13	0.25	0.25	0.00	0.10	0.17	0.17
RFDiscl$_{CEA}$	0.09	0.16	0.10	0.28	0.10	0.12	0.04	0.22
RFDiscl$_{KM}$	0.23	0.11	0.14	0.14	0.18	0.10	0.06	0.01
RFDiscl$_{LM}$	0.25	0.18	0.08	0.12	0.19	0.12	0.05	0.10
PRDiscl	0.11	0.13	0.17	0.21	0.10	0.18	0.14	0.10

Δ *IndProd*	*Coefficient*				R^2			
	Q1	*Q2*	*Q3*	*Q4*	*Q1*	*Q2*	*Q3*	*Q4*
Sorting variable $_{t-1}$								
MacroDiscl	*0.01*	*0.02*	*0.05*	*0.07*	*0.09*	*0.25*	*0.40*	*0.41*
HiMacro	0.05	0.02	0.03	0.06	0.44	0.25	0.38	0.29
Size	0.00	0.00	0.00	0.14	0.05	0.09	0.10	0.39
Beta	0.00	0.03	0.06	0.05	0.02	0.23	0.46	0.34
$RFDiscl_{CEA}$	0.02	0.03	0.03	0.06	0.32	0.27	0.19	0.43
$RFDiscl_{KM}$	0.05	0.03	0.04	0.03	0.46	0.27	0.22	0.13
$RFDiscl_{LM}$	0.06	0.04	0.02	0.02	0.55	0.29	0.21	0.17
PRDiscl	0.03	0.03	0.04	0.05	0.25	0.38	0.42	0.16

Table 7 presents results of estimating the following equation for different levels of alternative macroeconomic information proxies; *HiMacro*, *Size*, *Beta*, $RFDiscl_{CEA}$, $RFDiscl_{KM}$, $RFDiscl_{LM}$, and *PRDiscl*

$$\frac{\Delta OI_t}{P_{t-1}} = \beta_0 + \beta_1 Aggregate\ Economic\ Activity_t + \varepsilon_{i,t}$$

where $\Delta OI_t/P_{t-1}$ is the value-weighted cross-sectional average of all firm-level changes in operating income for year *t*, scaled by beginning of the year stock price. *Aggregate Economic Activity* is alternatively (i) $\Delta\, nGDP_t$, the annual nominal GDP growth rate for year *t,* (ii) $\Delta\, rGDP_t$, the annual real GDP growth rate for year *t*, (iii) $\Delta\, Inflation_t$, the annual inflation growth rate for year *t*, and (iv) $\Delta\, IndProd_t$, the annual growth rate in industrial production for year *t*. Observations are sorted into quartiles each year based on the lagged level of the previous six macroeconomic information proxies; the total number of observations in each regression is equal to 27. *HiMacro* is a categorical variable equal to one, two, three, or four if firm *i's* *R*-squared calculated from the following equation is in the first, second, third, or fourth quartile respectively: $e = \mu_e + B'M + m$, where *e* is the firm's earnings realization, μ_e is the constant, B' is the estimated sensitivity of the firm's earnings to the macroeconomic factor, *M,* which is a vector of macroeconomic factor realizations, and *m* is the firm-specific shocks on earnings (see Bonsall et al., 2013). *Size* is the natural logarithm of a firm's market capitalization. *Beta* is the CAPM beta using monthly returns over the past 12 months. $RFDiscl_{CEA}$ is the total number of Campbell et al. (2014) risk words per 1,000 words in firm *i's* 10-K filing in year *t-1*, $RFDiscl_{KM}$ is the total number of Kravet and Muslu (2013) risk words per 1,000 words in firm *i's* 10-K filing in year *t-1*, $RFDiscl_{LM}$ is the total number of Loughran and McDonald (2011) uncertainty words per 1,000 words in firm *i's* 10-K filing in year *t-1*. *PRDiscl* is the total number of top 120 political risk bigrams identified by Hassan et al. (2019) per 1,000 words in firm *i's* 10-K filing in year *t-1*. $MacroDiscl_{i,t-1}$ is the total number of target macro-related words per 1,000 words in firm *i's* 10-K filing in year *t-1* and is reported for benchmarking purposes.

Table 8: Sensitivity Analysis Excluding Risk Factor Disclosures

Aggregate Economic Activity	Dependent Variable: Δ ***OI*** (1)	(2)	(3)	(4)	(5)
	MacroDiscl t-1 wo RF Quartile 1	*MacroDiscl t-1 wo RF Quartile 2*	*MacroDiscl t-1 wo RF Quartile 3*	*MacroDiscl t-1 wo RF Quartile 4*	*p-value Q4-Q1*
Δ *nGDP*					
Coeff	0.03	0.03	0.07	0.11	0.01 **
t-stat	1.76 *	2.54 **	2.86 ***	3.67 ***	
R^2	0.11	0.20	0.25	0.34	0.02 **
Obs	27	27	27	27	
Δ *rGDP*					
Coeff	0.03	0.03	0.08	0.12	0.04 **
t-stat	1.75 *	2.16 **	2.70 ***	3.09 ***	
R^2	0.11	0.16	0.23	0.28	0.06 *
Obs	27	27	27	27	
Δ *Inflation*					
Coeff	0.06	0.10	0.16	0.31	0.04 **
t-stat	0.88	2.07 **	1.71 *	2.56 **	
R^2	0.03	0.12	0.11	0.20	0.17
Obs	27	27	27	27	
Δ *IndProd*					
Coeff	0.02	0.02	0.04	0.07	0.00 ***
t-stat	2.14 **	3.53 ***	3.91 ***	4.13 ***	
R^2	0.16	0.20	0.38	0.41	0.02 **
Obs	27	27	27	27	

Table 8 presents results of estimating the following equation for different levels of $MacroDiscl_{i,t-1}$ *wo RF*.

$$\frac{\Delta OI_t}{P_{t-1}} = \beta_0 + \beta_1 Aggregate\ Economic\ Activity_t + \varepsilon_{i,t}$$

where $\Delta OI_t/P_{t-1}$ is the value-weighted cross-sectional average of all firm-level changes in operating income for year *t*, scaled by beginning of the year stock price. *Aggregate Economic Activity* is alternatively (i) $\Delta\, nGDP_t$, the annual nominal GDP growth rate for year *t,* (ii) $\Delta\, rGDP_t$, the annual real GDP growth rate for year *t*, (iii) $\Delta\, Inflation_t$, the annual inflation growth rate for year *t*, and (iv) $\Delta\, IndProd_t$, the annual growth rate in industrial production for year *t*. Observations are sorted into quartiles each year based on the level of *MacroDiscl wo RF* in year *t-1*. $MacroDiscl_{i,t-1}$ *wo RF* is the total number of target macro-related words per 1,000 words in firm *i's* 10-K filing in year *t-1*, excluding "Item 1A" (i.e., "Risk Factors" section) from the count. Column (5) reports *t*-tests for statistical differences in coefficient and R^2 means between Quartile 4 and Quartile 1 of *MacroDiscl* in year *t-1*. Differences in R^2 are tested using bootstrapping with 500 iterations. ***, **, * indicate significance at <0.01, <0.05, <0.10 (two-tailed tests).

Table 9: "Bellwether" Prediction Tests

	Dependent Variable: ***Aggregate Economic Activity*** $_{t+1}$											
Sorting Variable $_t$	*Δ nGDP*			*Δ rGDP*			*Δ Inflation*			*Δ IndProd*		
Predictor $_t$	*R-squared*			*R-squared*			*R-squared*			*R-squared*		
	T1	*T2*	*T3*	*T1*	*T2*	*T3*	*T1*	*T2*	*T3*	*T1*	*T2*	*T3*
MacroDiscl												
Special Items	0.25	0.51	0.60	0.23	0.45	0.50	0.10	0.21	0.31	0.27	0.51	0.54
Forecasted Earnings Growth	0.13	0.37	0.58	0.08	0.31	0.49	0.16	0.17	0.27	0.13	0.38	0.59
HiMacro												
Special Items	0.54	0.57	0.52	0.45	0.48	0.45	0.27	0.30	0.22	0.49	0.56	0.48
Forecasted Earnings Growth	0.50	0.56	0.37	0.44	0.46	0.32	0.20	0.29	0.21	0.51	0.58	0.41
Size												
Special Items	0.35	0.65	0.45	0.31	0.57	0.38	0.14	0.28	0.24	0.41	0.61	0.40
Forecasted Earnings Growth	0.00	0.52	0.44	0.00	0.46	0.36	0.00	0.22	0.24	0.03	0.56	0.48
Beta												
Special Items	0.38	0.61	0.49	0.33	0.55	0.40	0.18	0.23	0.27	0.31	0.58	0.49
Forecasted Earnings Growth	0.12	0.50	0.47	0.09	0.46	0.38	0.09	0.18	0.38	0.09	0.57	0.55
$RFDiscl_{CEA}$												
Special Items	0.53	0.55	0.49	0.48	0.49	0.39	0.20	0.21	0.30	0.51	0.54	0.44
Forecasted Earnings Growth	0.31	0.47	0.49	0.28	0.41	0.39	0.11	0.20	0.27	0.27	0.52	0.52
$RFDiscl_{KM}$												
Special Items	0.68	0.46	0.24	0.61	0.40	0.17	0.28	0.21	0.21	0.62	0.46	0.23
Forecasted Earnings Growth	0.44	0.46	0.43	0.39	0.41	0.31	0.18	0.18	0.35	0.46	0.44	0.51
$RFDiscl_{LM}$												
Special Items	0.66	0.45	0.44	0.58	0.38	0.37	0.29	0.21	0.25	0.58	0.45	0.36
Forecasted Earnings Growth	0.44	0.49	0.47	0.38	0.42	0.36	0.19	0.24	0.30	0.45	0.50	0.54
PRDiscl												
Special Items	0.52	0.58	0.47	0.43	0.50	0.41	0.27	0.25	0.22	0.53	0.50	0.45
Forecasted Earnings Growth	0.42	0.49	0.51	0.35	0.42	0.40	0.21	0.22	0.33	0.43	0.53	0.53

Table 9 presents results of estimating the following equation for terciles of alternative macroeconomic information proxies

$$Aggregate\ Economic\ Activity_{t+1} = \beta_0 + \beta_1 Predictor_t + \varepsilon_{i,t}$$

where *Aggregate Economic Activity*, computed for year *t+1*, is alternatively (i) $\Delta\, nGDP_{t+1}$, the annual nominal GDP growth rate, (ii) $\Delta\, rGDP_{t+1}$, the annual real GDP growth rate, (iii) $\Delta\, Inflation_{t+1}$, the annual inflation growth rate, and (iv) $\Delta\, IndProd_{t+1}$, the annual growth rate in industrial production. *Predictor*, computed in year *t*, is aggregate *Special Items*, the cross-sectional average of special items scaled by market capitalization, or aggregate *Forecasted Earnings Growth,* the cross-sectional average of all firm-level differences between the consensus analyst forecast of annual EPS for year *t+1,* and realized EPS for year t+1. Observations are sorted into terciles each year based on the year *t* level of (a) *MacroDiscl*, (b) *Size*, (c) *HiMacro*, (d) *Beta*, (e) $RFDiscl_{CEA}$, (f) $RFDiscl_{KM}$, (g) $RFDiscl_{LM}$, (h) *PRDiscl*. *MacroDiscl* is the total number of target macro-related words per 1,000 words in firm *i's* 10-K filing in year *t*. All other variables are defined in Appendix A.

Table 10: Information Transfers at Earnings Announcement Dates

	Sorting variable: ***MacroDiscl*** $_{t-1}$				Sorting variable: ***MacroDiscl*** $_{t-1}$ ***Residual***			
	Quartile 4 Sample Ret [0,1]		*Quartiles 1-3 Sample* Ret [0,1]		*Quartile 4 Sample* Ret [0,1]		*Quartiles 1-3 Sample* Ret [0,1]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RM	1.179 ***	1.173 ***	1.103 ***	1.110 ***	1.114 ***	1.108 ***	1.129 ***	1.137 ***
	(26.70)	(26.07)	(20.16)	(20.55)	(18.20)	(20.20)	(20.88)	(21.12)
dUX	0.539 ***	0.577 ***	0.448 ***	0.469 ***	0.554 ***	0.589 ***	0.443 ***	0.447 ***
	(17.13)	(17.37)	(21.02)	(24.17)	(19.67)	(23.69)	(19.33)	(21.75)
dUX_Agg	0.016 *	0.001 *	0.000	-0.010	0.021 ***	0.001	0.001	-0.001
	(1.70)	(1.66)	(0.77)	(-1.15)	(4.60)	(1.42)	(0.27)	(-1.45)
dUX x dUX_Agg	**-0.001 *****	**-0.001 *****	**-0.000**	**0.000**	**-0.001 ****	**-0.001 ****	**-0.000**	**-0.000**
	(-5.54)	**(-3.52)**	**(-0.66)**	**(0.67)**	**(-2.56)**	**(-1.99)**	**(-0.83)**	**(-0.13)**
p-value *dUX x dUX_Agg*:								
(1) < (3)	0.00 ***							
(2) < (4)		0.00 ***						
(5) < (7)					0.02 **			
(6) < (8)						0.04 **		
Observations	48,714	48,669	110,592	110,502	41,222	41,174	118,084	117,997
FE	Date, Industry	Date, Firm	Date, Industry	Date, Firm	Date, Industry	Date, Firm	Date, Industry	Date, Firm
Adjusted R^2	0.15	0.17	0.10	0.12	0.14	0.17	0.10	0.12

Table 10 presents results from estimating the following equation separately for companies belonging to quartile 4 (i.e., high macro exposure) and quartiles 1-3 (i.e., lower macro exposure) of *MacroDiscl* $_{t-1}$

$$R_{i,t} = \beta_0 + \beta_1 RM_t + \beta_2 dUX_{i,t} + \beta_3 dUX\_Agg_{j,t} + \beta_4 dUX_{i,t}\ x\ dUX\_Agg_{j,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is firm's *i* stock return for days 0 to 1 around its quarterly earnings announcement (with day 0 being the announcement date), RM_t is the buy-and-hold return on the CRSP value-weighted index (including dividends) for the same 2-day interval, $dUX_{i,t}$ is firm's *i* decile of earnings surprise, computed as the difference between the announced EPS and the most recent analyst EPS consensus for that quarter scaled by the end-of-quarter price (we compute the consensus using the median forecast), $dUX\_Agg_{j,t}$ is the decile of the sum of earnings surprises for all the *j* companies that (i) belong to quartile 4 of *MacroDiscl* $_{t-1}$ and (ii) announce their earnings on the same announcement date (i.e., on days [-1,0] where day 0 is the announcement date) as firm *i*, $dUX_{i,t}$ *x* $dUX\_Agg_{j,t}$ is the interaction between the prior two variables. The decile breakpoints are generated each year by size decile. Decile variables take values 0-9 to enhance interpretability. Columns 1-4 report results using *MacroDiscl* $_{t-1}$ as the sorting variable. *MacroDiscl* $_{t-1}$ is the total number of target macro-related words per 1,000 words in firm *i's* 10-K filing in year *t-1*. Columns 5-8 show results using *MacroDiscl* $_{t-1}$ *Residual* as the sorting variable. *MacroDiscl* $_{t-1}$ *Residual* is the residual obtained from regressing *MacroDiscl* $_{t-1}$ on the determinants reported within Table 4 (excluding fixed effects). Columns 1,3,5,7 display results for regressions that include industry fixed effects. Columns 2,4,6,8 display results for regressions that include firm fixed effects. All regressions include year, month, and day fixed effects. All regressions are estimated with an intercept (not reported). "Industry" fixed effects are based on the Fama-French 48 classification. Cluster-robust-to-heteroskedasticity *t*-statistics are reported in parentheses; standard-errors are clustered by both firm and date. ***, **, * indicate significance at <0.01, <0.05, <0.10 (two-tailed tests). One-sided *p*-values for $dUX_{i,t}$ *x* $dUX\_Agg_{j,t}$ compare interaction terms across the sample partitions. In particular, these *p*-values are obtained by estimating fully interacted models which interact an indicator variable taking the value of "1" for firms in the fourth quartile and "0" for firms in the first quartile of macroeconomic disclosures with all the other variables included in each regression (including fixed effects). The resulting *t*-statistics for the interaction term are used to compute the one-sided *p*-value for the signed difference in coefficients.