Does Partisanship Affect Mutual Fund Information Processing? Evidence from Textual Analysis on Earnings Calls

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Abstract

This paper studies how partisanship affects mutual fund information processing at the firm level. Using textual analysis of earnings call transcripts, I identify discussions on partisan-sensitive topics, such as climate change, pandemic, and healthcare. I find that partisan funds react more strongly to topics aligned with their ideological beliefs and trade more after firms increase discussions on these topics. The effect is stronger for funds with higher polarization levels and for firms with larger weights in fund portfolios. Moreover, the observed pattern does not add value to fund performance, suggesting that the effect is not driven by rational expectations about future stock returns. Overall, these findings indicate that partisanship plays a role in mutual fund firm-level information processing.

Keywords: Partisanship, Political polarization, Mutual fund, Information processing, Textual analysis, Machine learning, Earnings calls.

JEL classification: G11, G23, G41.

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1 Introduction

What influences investors' information processing? This is a central question in finance. Traditionally, researchers have focused on financial metrics like attention, but recent studies have broadened the scope to include non-financial factors, offering a more comprehensive view of the societal context shaping financial decisions. Among them, one key factor is political beliefs, particularly in light of the growing political polarization between Democrats and Republicans on a wide range of issues, such as climate change, pandemic, and healthcare. Emerging evidence suggests that investors' political beliefs affect their investment decisions (Kaustia and Torstila, 2011; Sheng, Sun and Wang, 2024). While prior studies have examined how partisanship affects investor *preferences* at the *portfolio* level (Hong and Kostovetsky, 2012; Cassidy and Vorsatz, 2024), it remains unclear how partisanship shapes investor *information processing* at the *firm* level. Therefore, this paper studies whether political beliefs affect investors' firm-level information processing.

Among various investor groups, mutual funds provide an ideal setting. First, mutual funds pool money from individual investors and invest on their behalf, making them significant players in the market. Second, by matching fund manager names with their political donation records, I can infer the political leaning of fund managers at the individual level, allowing me to perform a granular and detailed analysis. Finally, mutual fund holdings are publicly available, providing the opportunity for a thorough analysis of their trading decisions. Therefore, this paper studies the relationship between partisanship and mutual fund firm-level information processing. Specifically, I examine whether Democratic and Republican funds respond differently to discussions of partisan-sensitive issues in portfolio companies' earning calls, and find that partisan funds react more strongly to topics aligned with their ideological beliefs.

To measure mutual fund partisanship, I infer fund managers' political leaning from individual-level political donation records. Using comprehensive data from the Federal Election Commission (FEC), I identify donations made by fund managers and classify each manager as a Democrat or a Republican based on whether their donations favor one party over the other. The political leaning of a mutual fund team is then determined by the composition of Democratic and Republican managers within the team.

To examine how partisanship affects mutual fund information processing, it is crucial to identify the specific *information* that may trigger different responses among funds with varying political leanings. This requires two steps: 1) identifying issues typically associated with partisan disagreements; and 2) quantifying firms' exposure to these issues. However, there are two measurement challenges. First, political disagreements span a wide range of topics, making it difficult to determine partisan-sensitive issues ex-ante. Second, there is no comprehensive data on firm-level exposures to these issues. To address these challenges, I take a data-driven approach and conduct textual analysis on earnings call transcripts.[2] Specifically, I apply Latent Dirichlet Allocation (LDA), an unsupervised machine learning method well-suited to tackle both measurement challenges. First, without prior knowledge about which partisan-sensitive topics are frequently discussed in earnings calls, LDA can extract latent topics from earnings calls, which solves the first challenge by identifying issues that concern investors most. Second, LDA quantifies a firm's exposure to partisan-sensitive topics based on the weight given to these issues in earnings calls, which addresses the second challenge by measuring the attention allocated to these topics.[3]

Using over 80,000 earnings calls transcripts between January 2008 and June 2022, I train an LDA model with 70 topics.[4] It summarizes earnings calls into a distribution of topics, where topic weights represents the relative importance of each topic. I label the 70 LDA topics using keywords and apply two additional machine learning techniques to construct a taxonomy and a visualization of the topic structure, providing a complete characterization of the topic model and facilitating the exploration of relationships between topics.

To identify partisan-sensitive topics in earnings calls, I combine LDA topics with survey data from the American Trends Panel survey (2020). I rank issues based on the degree of partisan disagreement in the U.S. and overlay these issues with LDA topics. The overlap covers the following partisan-sensitive topics frequently discussed in earnings calls: "pandemic" (related to Covid severity), "climate change" (linked to climate issues), and "healthcare" and "pharmaceuticals" (connected to healthcare affordability). I then define

[2] This approach follows recent studies that utilize earnings calls as a source to identify firms' exposures to difficult-to-measure issues (Hassan et al., 2019; Sautner et al., 2023).

[3] If a firm is increasingly exposed to a particular issue, it is reasonable to expect that participants will pay more attention to it during earnings calls.

[4] A 70-topic model is the model that yields the most coherent topic modelling output. I explain in detail on how the optimal number of topics is determined in section 3.2.

the Partisan-Sensitive Topics (PST) index as the sum of weights on these topics to measure overall attention to partisan-sensitive topics in earnings calls, and validate the PST index through a series of tests. First, I show that the measure demonstrates meaningful variation across industries. I also compare the measure with firm fundamentals and external measures, and find consistent patterns that validate the PST index in quantifying firms' exposure to partisan-sensitive issues.

Building on previous analyses of partisan-sensitive issues, I now explore the relationship between mutual fund partisanship and firm-level information processing. Specifically, I analyze whether Democratic and Republican funds trade differently, as reflected in their holding changes, in response to changes in portfolio firms' exposure to partisan-sensitive issues. The results show that partisan funds react more strongly to topics aligned with their ideological beliefs, trading more after firms increase discussions on these topics. In particular, because the Democratic party is more concerned with issues like the pandemic, climate change, and healthcare, and because the overall tone of earnings calls becomes more negative as firms discuss these topics more, I find that Democratic funds tend to sell more shares when firms increase discussions on these topics compared to Republican funds. The economic magnitude of this effect is substantial: for an all-Democrat mutual fund, a 1% rise in partisan-sensitive topic weights is associated with a 14% decrease in the fund's ownership of the stock compared to the average fund ownership change. This relationship holds after accounting for fully-saturated fixed effects (FE), including fund-by-quarter, firm-by-quarter, and fund-by-firm FEs, which absorb any time-varying unobserved fund characteristics and firm characteristics, as well as potential fund-firm pairing effects.

I then examine whether the partisan effect varies across different mutual funds and portfolio companies. First, I analyze whether the differential trading responses between Democratic and Republican funds are more pronounced among funds with greater political polarization. Using the proportion of donations made to a single party as a measure of polarization, I find that funds with higher polarization levels show a stronger reaction to partisan-sensitive topics, supporting the hypothesis that the effect is driven by partisanship. Next, I explore if the partisan effect varies with the importance of individual stocks in fund portfolios. As funds hold numerous stocks, their attention to any one company's earnings calls may be limited. Thus, I expect stronger effects for companies with higher weights in fund portfolios, as these companies might attract might more attention from fund managers.

Empirical tests also confirm this prediction. Taken together, these analyses support the argument that partisanship plays a role in mutual fund firm-level information processing.

While I have already documented a negative relationship between partisan-sensitive topic weights and the overall sentiment of earnings calls, one might be concerned that the overall sentiment does not capture the sentiment specific to each topic. To address this, I develop a topic-level sentiment measure. First, I identify distinctive keywords for each topic, and then assess the sentiment of each topic by analyzing the context surrounding these keywords in earnings calls. Using this measure, I construct a sentiment-augmented Partisan-Sensitive Topics (PST) index, which incorporates the tone associated with each partisan-sensitive issue. The relationship between mutual fund partisanship and firm-level information processing continues to hold after including topic-level sentiment into the PST index, confirming that partisan funds process firm-level information in a way that aligns with their ideological beliefs.

After documenting the partisan effect in mutual fund trading responses to partisan-sensitive issues, a natural follow-up question is whether the effect is due to rational expectations about future stock returns or behavioral considerations. The *rational expectation* explanation states that Democratic funds trade more because they accurately foresee that firms with heightened exposure to partisan-sensitive issues will underperform in the future. In this case, such trades should add value to the fund. In contrast, the *behavioral consideration* explanation suggests that Democratic funds' responses are either not based on beliefs about future stock returns or are driven by mistaken beliefs about them. Under this scenario, these trades should not add value to fund performance. To differentiate between the two explanations, I construct a measure to capture whether a trade adds value to a fund by multiplying a mutual fund's trading of a stock in quarter t by the stock's return in quarter $t+1$. I then rerun the main regression using the new measure, and the results show that Democratic funds do not profit from trading in response to firm exposure to partisan-sensitive issues. This finding confirms the behavioral consideration explanation, but contradicts the rational expectation story.

Next, I examine a number of alternative explanations. The first concern is that fund characteristics associated with partisanship might confound how funds react to earnings call contents. To address this, I control for additional interaction terms and show that they do not account for the main finding. The second explanation is that the result could be due to mutual funds catering to their investors' preferences. For instance, Democratic funds may react more strongly to partisan-sensitive topics to curb potential outflows from Democratic investors. To rule this out, I control for mutual fund investor partisanship using the political leaning of the state where the fund is headquartered, following Hong and Kostovetsky (2012). The main result remains robust. The third concern is related to strategic disclosure by firms, where CEOs may adjust their discussions of partisan-sensitive issues during earnings calls based on their shareholders' political preferences or their own political leanings. Such adjustments could introduce measurement errors in weights assigned to partisan-sensitive topics. To address this, I focus on firms with a balanced mix of investors representing both political sides, as well as companies led by non-partisan CEOs. The main result holds on both samples. The last explanation is that the text-based measure from earnings calls might capture not only firms' actual exposure to partisan-sensitive issues, but also investors' pre-existing concerns, as call participants may raise more questions about these issues during Q&A sessions. To address this, I repeat the analysis using only the presentation session of earnings calls, and show that the result continues to hold. Taken together, these results confirm the robustness of the main findings.

Finally, I perform several robustness checks. First, I perform a placebo test on typical LDA topics without partisan disagreement. The intuition is that if the differential response of partisan funds is indeed due to partisanship, there should be no effect on topics without partisan disagreement. Empirical tests support this hypothesis. Second, I exclude non-partisan funds from the sample to provide a more direct comparison between Democratic- and Republican leaning funds, and show that the main finding remains robust. Third, to address concerns that the results might be influenced by a fund's ESG classification, I exclude ESG funds using the sustainable fund list from the Morningstar Sustainable Fund Landscape Report. I find that the main finding continues to hold, suggesting that the results are not driven by funds' ESG focus. Finally, I use an alternative measure that does not separate the "pandemic/crisis" topic in the LDA model and show that the result remains robust.

This paper makes several important contributions to the literature. First, it extends the research on how fund managers' backgrounds and personal experiences influence their investment decisions. Prior studies have highlighted various determinants, including local bias and hometown familiarity (Coval and Moskowitz, 1999, 2001; Teo, 2009; Pool, Stoffman and Yonker, 2012; Sialm, Sun and Zheng, 2020), birth month (Bai et al., 2019), marital status (Lu, Ray and Teo, 2016), religiosity (Shu, Sulaeman and Yeung, 2012), climate experience (Huynh, Li and Xia, 2021), and team background diversity (Bär, Niessen-Ruenzi and Ruenzi, 2009; Lu, Naik and Teo, 2024). Building on this body of work, this paper introduces political leanings as a novel behavioral determinant of mutual fund investment, illustrating how partisanship affects firm-level information processing beyond economic fundamentals.

This paper also contributes to the literature on how partisanship affects the behavior of financial market participants.[5] Focusing on mutual funds, Hong and Kostovetsky (2012) find that Democratic fund managers hold less of their portfolios in socially irresponsible companies. Wintoki and Xi (2019) document that fund managers are more likely to allocate assets to firms managed by executives and directors with whom they share a similar political partisan affiliation. Cassidy and Vorsatz (2024) show that Republican mutual fund teams actively purchase more equity, especially in high beta industries, before and after the 2016 Presidential election. Evans et al. (2024) document that politically diverse teams outperform politically homogeneous teams. Different from the above papers' focus on fund *preference* at the *portfolio* level, this paper contributes to the literature by studying how partisanship affects fund *information processing* at the *firm* level, documenting that funds respond more strongly to information that aligns with their political beliefs.

Moreover, this paper contributes to the literature applying textual analysis and machine learning methods in finance. Several studies have developed text-based measures from earnings call transcripts to capture firm characteristics that are otherwise hard to measure, such as political risk (Hassan et al., 2019), corporate culture (Li et al., 2021a; Li et al., 2021b), epidemic exposure (Hassan et al., 2023), and climate exposure (Sautner et al., 2020; Chava, Du and Malakar, 2021; Dzieliński et al., 2022; Jaunin and Terracciano, 2022; Li et al., 2024). Adding to this research, this paper provides a *complete characterization* of topics of interest to investors, analysts, and other market participants. As noted in Hassan et al. (2019), "any issue raised during an earnings call will tend to be of some concern either for

[5] See Kaustia and Torstila (2011); Hutton, Jiang and Kumar (2014); Giuli and Kostovetsky (2014); Jiang, Kumar and Law (2016); Cookson, Engelberg and Mullins (2020); Kempf and Tsoutsoura (2021); Meeuwis et al. (2022); Zhang (2022); Kempf et al. (2023); Dagostino, Gao and Ma (2023); Sheng, Sun and Wang (2024); Wu and Zechner (2024); Wang and Zeng (2024).

the firm's management or its analysts, such that quantifying the allocation of attention between different topics is interesting in its own right". While this paper only focuses on partisan-sensitive topics, other topics can be explored for future research questions.

The rest of the paper is organized as follows. Section 2 details the data and measures used. Section 3 describes how partisan-sensitive topics are identified in earnings calls. Section 4 presents the empirical results. Section 5 concludes.

2 Data and Measurement

This section provides an overview of the data and measures used in the empirical analyses. Section 2.1 describes data sources. Section 2.2 explains how I use political contributions to infer mutual fund partisanship. Section 2.3 presents summary statistics for key variables.

2.1 Data

To construct the main dataset, I combine data from various sources. I begin with mutual fund portfolio holdings from CRSP survivorship-bias-free mutual fund database from 2008 to 2022. To align with the quarterly frequency of earnings calls, I retain the most recent snapshot within each calendar quarter. I then calculate fund ownership of a stock as the number of shares held by the fund divided by the total shares outstanding of the stock. To complement fund holdings, I collect mutual fund characteristics from CRSP mutual fund summary file, such as fund assets under management (AUM), inception date, fee structure, and turnover. Since fund characteristics are provided at the share-class level, I aggregate all variables to the fund level. Fund size is calculated as the sum of total net assets (TNA) across all share classes. The inception date is the start date of the oldest share class. Returns, fee structures, and turnover are the share-class-size weighted averages within each fund. I restrict the sample to domestic equity funds, given that the paper focuses on earnings calls conducted by U.S. public companies. Further, index funds are excluded from the sample, as this paper examines the impact of fund managers' political beliefs on their trading.

Next, I manually compile a dataset of political donations made by fund managers to infer mutual fund partisanship. I begin with a list of U.S. open-end mutual funds from Morningstar. It provides a complete history of managers, including each manager's full name and their start and end date at the fund. I then match the list of fund manager names with individual political donation records from the Federal Election Commission (FEC). Section

2.2 details the matching process. I successfully identify 1,630 fund managers with at least one donation record between 1980 and 2021. The sample is at least comparable to, if not larger than, similar datasets in the literature (Hong and Kostovetsky, 2012; Vorsatz, 2022).

Further, I supplement the main dataset with firm characteristics from Compustat/CRSP merged database. I restrict my sample to common stocks listed on NYSE, Nasdaq, and AMEX, and exclude stocks whose headquarters are outside the United States. I also exclude penny stocks whose lowest price is below $1 during the sample period.

Finally, to construct the text-based measure of partisan-sensitive topics, I download full earnings call transcripts from Capital IQ Transcripts Dataset. Although the earliest date available in this dataset is from 2004, transcripts between 2004 and 2008 were created retrospectively, resulting in limited coverage prior to 2008. Thus, I focus on the period after 2008. The final sample consists of 2,619 funds, 2,806 companies, and 88,170 earnings calls held by these companies between January 2008 and June 2022.

2.2 Measuring mutual fund partisanship

To identify political donations made by mutual fund managers, I merge fund manager names from Morningstar with individual political donations from the Federal Election Commission (FEC).[6] The data include information on the contributing individual's name, employer, occupation, contribution date, amount, and the receiving committee. I first match by fund managers' first and last names, and then use middle names, employer names, and occupation to eliminate incorrect matches.[7]

To infer fund manager partisanship, I label the political leaning of each donation record. Since each donation is made to a political action committees (PAC) rather than individuals, I classify the political leaning of each donation based on the party affiliation of the receiving

[6] This data is publicly available on the FEC website. The threshold for including contributions in this dataset has varied over time. A contribution will be included if the reporting period amount is $500 or more during 1975–1988, $200 or more during 1989–2014, and if the contribution's election cycle-to-date amount exceeds $200 from 2015 to the present.

[7] Specifically, I first drop observations with inconsistent middle names, when this information is available in both datasets. Then, I perform textual analyses to match employer names. Given that employer information is self-reported in the FEC dataset, I preprocess employer names by removing punctuation, extra blank spaces, and common company suffixes. I then compare the similarity of firm names in both datasets and retain observations with a similarity score above 60%. Finally, I manually check all remaining matches based on occupation, zip code, and other information that helps infer the political contributor's identity, ensuring accurate matches between the datasets.

PAC. Specifically, if the money goes to a committee already registered with a party, I use that party affiliation to label the donation. Otherwise, I infer the committee's political leaning based on how the PAC allocates its funds. Following Vorsatz (2022), a committee is labeled as leaning Republican (Democrat) if it spends more than two-thirds on Republican (Democratic) candidates.

Next, I use fund managers' political donations from the past 10 years to infer their political leanings at any given point in time.[8] By focusing only on donations within the 10 years preceding the measurement, I avoid forward-looking bias and allow a fund manager's political leaning to vary over time. Accordingly, a fund manager is classified as a Democrat if they donated more to the Democratic party, a Republican is they donated more to the Republican party, and a non-partisan if they donated the same amount to both parties or to committees with no clear political leanings.

Lastly, I aggregate partisanship from the fund manager level to the fund level. I first calculate the proportion of Democratic- and Republican-leaning managers in a mutual fund team, then subtract the latter from the former. In other words, the net Democratic leaning of a mutual fund (*Net Dem*) is calculated as:

$$NetDem_{i,t} = \frac{\#Democrats_{i,t} - \#Republicans_{i,t}}{\#Total\ Managers_{i,t}} \tag{1}$$

where $\#Democrats_{i,t}$ is the number of Democratic-leaning managers at fund i in month t, $\#Republicans_{i,t}$ is the number of Republican-leaning managers at fund i in month t, and $\#Total\ Managers_{i,t}$ is the total number of current managers at fund i in month t. $Net\ Dem_{i,t}$ serves as the main measure of fund partisanship in the subsequent analyses.

2.3 Summary statistics

Table 1 presents the summary statistics for the main variables used in the empirical analysis. At the fund level, an average fund has a total net asset value of $2.19 billion, with a net asset value of $24.5 per share. The management fee and expense ratio are 0.65% and 1.1%, respectively, while the turnover ratio indicates an average portfolio turnover of 67%. On average, each fund is managed by 2.91 individuals, with 0.12 managers leaning toward

[8] For example, a fund manager's political leaning in September 2020 is inferred from her political donations made between September 2010 and August 2020.

the Republican party, 0.13 managers favoring the Democratic party, 0.07 managers identifying as non-partisans, and 2.60 managers being non-donors. At the firm level, the average portfolio company has a market size of $13 billion, a book-to-market ratio of 0.52, a return on assets (ROA) of 0.57%, and a profitability of 7.8%. At the fund-by-firm level, mutual funds on average hold 0.15% ownership of a stock, and a typical fund includes 311 assets in its portfolio.

3 Partisan-sensitive discussions in earnings calls

In this section, I describe how discussions on partisan-sensitive issues are identified in earnings calls. Earnings conference calls serve as an effective communication channel for firms to engage with their shareholders, analysts, and investors. To analyze the content of these calls, I perform textual analysis on earnings call transcripts. Specifically, I use an unsupervised machine learning method known as Latent Dirichlet Allocation (LDA), introduced by Blei, Ng, and Jordan (2003). The basic idea of LDA is to represent each document as a probability distribution over different topics, where each topic is a probability distribution over vocabulary terms. LDA has gained popularity in the finance and economic literature and has been successfully applied in various contexts. For instance, prior studies have employed LDA on FOMC transcripts (Hansen, McMahon and Prat, 2018), business news (Bybee et al., 2024), employee reviews (Sheng, 2024), and crypto whitepapers (Liu, Sheng and Wang, 2024).

LDA is particularly suitable in this setting for two reasons. First, its unsupervised nature means that one does not need to have extensive prior knowledge about the topics of interest. Since there is no predefined set of partisan-sensitive topics, LDA can automatically identify topics that concern investors based on word distributions in earnings calls. Second, LDA quantifies a firm's exposure to different issues based on weights assigned to these topics in earnings calls. If a firm is increasingly exposed to a particular issue, it is reasonable to expect participants to pay more attention to it during earnings calls. Thus, the attention allocated to each topic serves as a proxy for the firm's exposure to these issues, and analyzing the topic distribution in earnings calls offers a comprehensive understanding of issues that are of interest to analysts, investors, and other market participants.

3.1 Training an LDA model

As an unsupervised machine learning technique, LDA only requires researchers to provide two inputs: the document corpus and the desired number of topics. To construct the corpus, I transform transcripts into bag-of-words representations, applying standard preprocessing procedures beforehand. These includes tokenization, removing stop words, converting words to original forms (i.e. lemmatization), and forming bigrams (i.e. common two-word phrases). The bag-of-words representation is then created by counting word frequencies within each transcript. To determine the optimal number of topics, I train LDA models using different numbers of topics ranging from 10 to 100 in increments of 10. Given the large size of the transcript dataset, I train LDA models on a 20% random sample and evaluate their performance using the coherence value. Coherence measures the semantic consistency of words within a topic and indicates its interpretability (Röder et al., 2015), with higher values corresponding to clearer thematic interpretations. As shown in Figure 1, the model with 70 topics achieves the best performance and is therefore selected as the optimal model and applied to the full transcript dataset.

Next, I explore the output generated by the trained LDA topic model. The output has two components: the distribution of terms for each topic and the distribution of topics for each transcript. It is worth noting that LDA does not automatically label topics; researchers typically assign labels manually. Following this practice, I use the top keywords associated with each topic to assign labels by referring to relevant literature and conducting online searches (Bybee et al., 2024). Appendix B lists the labels and the top 15 keywords for each topic. The results indicate that LDA identifies coherent and interpretable topics.[9]

To provide a complete characterization of the topic model and better understand the relationships between topics, I use two machine learning techniques to build a taxonomy of LDA topics and a visualization of topic distances (see details of these methods in the Internet Appendix). First, I construct a topic taxonomy using hierarchical agglomerative clustering, as applied in prior studies (Bybee et al., 2024; Liu, Sheng, and Wang, 2024). As shown in Figure 2, semantically similar topics—such as finance-related topics like "losses",

[9] For instance, the "pandemic/crisis" topic includes keywords such as "pandemic, demand, environment, employee, recovery, challenge, decline, uncertainty", the "inflation" topic is characterized by keywords like "inflation, pricing, gross margin, basis point, inflationary, pressure", and the "debt" topic features keywords such as "facility, debt, cash flow, credit facility, balance sheet, liquidity".

"profits", and "debt"—are grouped into broader categories, demonstrating the topic model's quality. Second, I use multidimensional scaling to visualize topic distances.[10] As shown in Figure 3, topics are represented as circles, with closer circles indicating greater similarity. The visualization aligns with the taxonomy, further confirming the model's validity. These results validate the LDA model's robustness and its ability to identify diverse topics while revealing intuitive and economically meaningful relationships among them.

3.2 Identifying partisan-sensitive topics

To examine the impact of mutual fund partisanship on firm-level information processing, it is crucial to identify discussions in earnings calls where the two political parties may disagree. However, not all topics identified by LDA are sensitive to partisan interpretation. In order to identify partisan-sensitive topics, I use the American Trends Panel survey conducted by Pew Research Center in 2020. The survey asked participants: "How much of a problem do you think each of the following are in the country today?" Ten issues included in the survey are: minority treatment by the justice system, the coronavirus outbreak, the federal budget deficit, government ethics, terrorism, healthcare affordability, illegal immigration, unemployment, climate change, and violent crime.

To understand the extent of partisan disagreement on these issues, I manually aggregate survey responses based on the political leanings of survey participants and rank the issues accordingly. The results are shown in Figure 4. Among these issues, climate change shows the greatest partisan disagreement, with over 90% of Democrats viewing it a very big or moderately big problem, while only 32% of Republicans share the same perspective. Other issues that exhibit major partisan disagreements include minority treatment by the justice system, illegal immigration, Covid severity, and healthcare affordability. By overlaying these issues with topics identified through the LDA model, I am able to identify partisan-sensitive topics that are frequently discussed during earnings calls.

I identified four partisan-sensitive topics. The first topic is the "pandemic/crisis" topic, which is closely relates to Covid severity. As shown in Figure 5 Panel A, this topic includes keywords like "pandemic, demand, environment, employee, recovery", with discussions

[10] Multidimensional scaling (MDS, Torgerson, 1958) is a dimensionality reduction method that preserves the original high-dimensional distances between topics in a two-dimensional representation.

surging in 2020.[11] The second topic is the "climate change" topic, which aligns with partisan disagreement on the climate change issue. Figure 5 Panel B shows keywords such as "energy, utility, solar, power, renewable, gas, wind", which overlap significantly with climate change exposure terms in Sautner et al. (2023).[12] The third and fourth topics are "healthcare" and "pharmaceuticals", which are both closely related to healthcare affordability. Figure 5 Panel C and D show that the "healthcare" topic features keywords such as "health, care, health care, member, patient, hospital, medical", while the "pharmaceuticals" topic highlights "clinical, trial, development, program, FDA, drug". The time trends also indicate that these topics gained attention during Democratic administrations and health crises.[13]

To capture the overall attention paid to partisan-sensitive topics in earnings calls, I aggregate the weights of the previously identified topics and define the Partisan-Sensitive Topics (PST) index. It is calculated as the sum of the weights assigned to the individual topics, namely:

$$\text{PST} = \text{Pandemic} + \text{Climate change} + \text{Healthcare} + \text{Pharmaceuticals} \tag{2}$$

Th PST index captures the total attention directed towards partisan-sensitive topics during earnings calls.

Table 1 provides summary statistics for partisan-sensitive topics. On average, firms allocate approximately 2% of the weight to the pandemic topic, 2% to the climate change topic, 1% to the healthcare topic, and 0.9% to the pharmaceutical topic during earnings calls. Together, these partisan-sensitive topics account for about 6% of the aggregate attention in earnings calls. Besides, Table A1 in the online appendix provides short excerpts

[11] The inclusion of both "pandemic" and "crisis" in this topic reflects the shared terminology used to describe both events, such as "challenge, decline, uncertainty". To separate the two effects, I create two distinct topics based on the timing of the earnings call: one for discussions before 2020 (referred to as "crisis") and another for discussions after 2020 (referred to as "pandemic"). This separation allows for a more nuanced analysis; however, in the robustness section, I show that the finding remains robust without this separation.

[12] The top 10 bigrams are: renewable energy, electric vehicle, clean energy, new energy, climate change, wind power, wind energy, energy efficient, greenhouse gas, and solar energy.

[13] One caveat is that the current list of partisan-sensitive issues favors more recent sample periods, as it is based on the 2020 survey, which does not account for the time-series variation in partisan-sensitive issues. Unfortunately, earlier versions of the American Trends Panel Survey do not include the specific question needed to identify such issues.

from transcripts with highest weights for each partisan-sensitive topic, illustrating how firms discuss their exposure to these topics in earnings calls.[14]

To validate the effectiveness of the LDA-based measure in capturing firms' exposure to partisan-sensitive issues, I conduct a series of tests. First, I compare the LDA-based measures with external benchmarks, including firm fundamentals and measures from the literature. For example, the pandemic topic weight is negatively related to firm ROA and profitability, reflecting the adverse impact of Covid on businesses, and positively correlates with the epidemic exposure measure developed by Hassan et al. (2023), which quantifies Covid mentions in earnings calls. Similarly, the climate change topic weight strongly correlates with the measure developed by Sautner et al. (2023), which captures firm attention to climate change issues using a machine learning keyword discovery algorithm. These findings align with economic intuition. Next, since there are no existing measures in the literature to validate the healthcare and pharmaceutical topics, I examine the industry distribution of partisan-sensitive topics. The results are also intuitive and consistent with expectations: agriculture and restaurants/hotels/motels industries show highest weights on the pandemic topic; energy-related industries have the highest weight on the climate change topic; and the pharmaceutical products and the healthcare industry have highest weights on the pharmaceutical and healthcare topic. These results confirm the accuracy of the LDA-based partisan-sensitive topic (PST) index in quantifying firms' exposure to these issues. Further details on these validation tests are provided in the Internet Appendix.

Taken together, this section describes how I use LDA topic modeling to identify and quantify firms' exposure to partisan-sensitive issues in earnings calls, and introduces the Partisan-Sensitive Topic (PST) index to capture the aggregate attention firms allocate to these issues.

[14] For example, during its July 2020 conference call, UniFirst Corporation stated, "our revenues were mostly impacted by customer closures related to the Coronavirus pandemic as well as related reductions in workforce for customers who remained open," highlighting the tangible impact of the pandemic on the company. Similarly, Alliant Energy Corporation discussed that "EPS Clean Power Plan would require states to develop plans to reduce greenhouse gas emissions from existing power plants by 2030. [...] At the same time, we are focused on economically meeting the energy and capacity needs of our customers," emphasizing the challenge of balancing regulatory requirements with the company's financial goals.

4 Results

4.1 Baseline result

In this section, I analyze the relationship between mutual fund partisanship and firm-level information processing. Specifically, I examine whether Democratic and Republican funds respond differently, as reflected in their holding changes, to changes in firms' exposure to partisan-sensitive issues—such as climate change, healthcare affordability, and the Covid pandemic—measured by topic weights in earnings calls. I employ the following regression specification:

$$\begin{aligned} \mathit{\Delta FundOwn}_{f,i,t} = \alpha + \boldsymbol{\beta_1} \mathit{\Delta PST}_{i,t} \times \mathit{Net\ Dem}_{f,t} + \beta_2 \mathit{\Delta PST}_{i,t} + \beta_3 \mathit{Net\ Dem}_{f,t} \\ + \mathit{Controls}_{f,i,t} + \mathit{FEs} + \varepsilon_{f,i,t} \end{aligned} \tag{3}$$

where $\mathit{\Delta FundOwn}_{f,i,t}$ represents the change in fund *f*'s ownership of stock *i* in quarter *t*.[15] If fund holdings for quarter *t-1* are unavailable or fund *f* did not report stock *i* in quarter *t-1* holdings, I use the most recent non-zero holdings of the stock.[16] I prefer fund ownership over portfolio weights because it reflects the fund's active trading decisions for a particular stock (Chen, Jegadeesh, and Wermers, 2000), while portfolio weights are affected by stock price changes and the trading of other stocks in the portfolio. $\mathit{\Delta PST}_{i,t}$ captures the change in the weights of partisan-sensitive topics (PST) in firm *i*'s earnings calls during quarter t, relative to the PST weights when the firm was last held by the fund. I use the change rather than the level to capture the effect of new information on mutual fund trading decisions. $\mathit{Net\ Dem}_{f,t}$ measures the degree fund *f* leans toward the Democratic party in quarter t, as defined in equation (1). Control variables include firm characteristics (firm size, book-to-

[15] Specifically, it is calculated as the change in the number of stock *i* shares held by fund *f* from *t-1* to *t* divided by the total shares outstanding of stock *i* in *t-1*:

$$\Delta \mathit{Fund\ Own}_{f,i,t} = \frac{\#\mathit{Shares}_{f,i,t} - \#\mathit{Shares}_{f,i,t-1}}{\#\mathit{Shares\ outstanding}_{i,t-1}}$$

[16] To ensure robustness, I conduct two tests in Table A2 in the online appendix. First, I calculate $\mathit{\Delta FundOwn}_{f,i,t}$ and $\mathit{\Delta PST}_{i,t}$ by subtracting only the values of quarter t-1 from those in quarter t. Second, I examine a continuous holding sample, where a fund maintains ownership of a stock across consecutive quarters. In this setup, changes in fund ownership of a stock and partisan-sensitive topic weights are also calculated by subtracting the quarter t-1 values from those in quarter t. The main results remain robust in both settings.

market ratio, ROA, and profitability) and fund characteristics (fund size, fund age, expense ratio, management fee, and fund turnover). Standard errors are clustered at the fund level.

The key coefficient of interest in equation (3) is β_1, which captures the differences in how Democratic and Republican funds respond to changes in exposure to partisan-sensitive topics. Given that the Democratic party is more concerned about the pandemic, climate change, and healthcare affordability issues, it is reasonable to expect stronger trading responses from Democratic funds. However, one might be concerned about whether portfolio companies discuss these issues in a positive or negative context, which could, in turn, affect the trading behavior of mutual funds.[17]

To address this concern, I first examine the relationship between the weights of partisan-sensitive topics and the overall earnings call sentiment before running the main regression. I compute the net sentiment of an earnings call as the percentage of positive words minus the percentage of negative words in a transcript, using the Loughran and McDonald (2011) dictionary. The results, shown in Table A3, reveal that companies with higher weights on partisan-sensitive topics have a more negative overall tone during earnings calls, suggesting that firms generally take a pessimistic stance when discussing these topics. However, one might still question whether the overall sentiment of an earnings call truly reflects sentiment related to a specific topic. To address this more thoroughly, I introduce a more nuanced analysis in section 4.3 by developing a topic-level sentiment measure. I then supplement the Partisan Sensitive Topic (PST) Index with the sentiment of each individual topic, and show that the main finding remains robust when accounting for topic-level sentiment.

Since the overall tone of an earnings call becomes more negative as firms increase discussions on partisan-sensitive topics, one might expect Democratic funds to sell more stock shares when firms increase discussions on these topics compared to Republican funds. The regression results of equation (3) are presented in Table 2. The results show that partisan funds react more strongly to topics aligned with their ideological beliefs, trading more when firms increase discussions on these topics. Specifically, the coefficient on the interaction term ($\mathit{\Delta PST}_{i,t} \times \mathit{Net\ Dem}_{f,t}$) is negative and statistically significant at the 1% level, suggesting that when a firm's exposure to partisan-sensitive issues—those that the

[17] For example, Pfizer profited from the pandemic through vaccine development, so it would not make sense for Democratic funds to divest from Pfizer due to increased discussions of the pandemic in its earnings calls.

Democratic party is more concerned about—increases, Democratic funds are more likely to sell their stock shares compared to Republican funds. The economic impact of this effect is substantial. In column (1), the coefficient of the univariate regression is -0.0103 (with a t-statistic of 3.25), indicating that for an all-Democrat fund team (i.e., Net Dem = 1), a 1% rise in the weights of partisan-sensitive topics is associated with a 0.0001% reduction in the fund's ownership of the stock. While this percentage may seem small, it represents a considerable 14% decrease compared to the average fund ownership change of 0.00073%.[18]

In Table 2 column (2), I include firm and fund characteristics to examine whether these control variables explain the observed univariate result. I find that certain characteristics affect fund trading behavior. For example, larger and younger funds are linked to larger changes in holdings. However, the coefficient on the interaction term remains statistically significant, indicating that the partisan effect persists after including these control variables.

In Table 2 column (3), I further control for fund, firm and quarter fixed effects. Fund fixed effects account for any time-invariant factors specific to a fund, such as its headquarter location or investment category (e.g., ESG fund). Firm fixed effects capture time-invariant characteristics of the firm, such as industry. This is particularly relevant as the industry could affect the topics discussed during earnings calls. Lastly, quarter fixed effects absorb general economic trends that might affect funds' buying or selling behavior. Notably, even after controlling for these fixed effects, the coefficient on $\Delta PST_{i,t} \times Net\ Dem_{f,t}$ remains statistically significant, suggesting that the result is not driven by fund-, firm-, or time-level invariant factors.

In Table 2 column (4), I use a more stringent specification by including fund-by-quarter fixed effects in the regression. This approach absorbs all unobserved time-varying fund characteristics, addressing concerns that other fund characteristics related to partisanship might directly affect mutual fund trading behavior. Since the regression operates at the fund-firm-quarter level, the coefficient on the interaction term can still be identified. Importantly, the main result continues to hold, suggesting that the partisan effect on mutual fund trading is not driven by other fund characteristics linked to partisanship.

[18] The magnitude is comparable to other partisan effects documented in the literature. For example, Kempf and Tsoutsoura (2021) show that credit rating analysts who do not support the president's party are more likely to adjust ratings downward relative to analysts who are aligned with the president's party by 11.4%.

In Table 2 column (5), I further refine the analysis by including firm-by-quarter fixed effects to account for all time-varying firm characteristics. Even after controlling for these factors, the coefficient on the interaction term remains significant, addressing concerns that unobservable firm characteristics, which may be correlated with the topic distribution in earnings calls, could confound the main result.

Finally, in Table 2 column (6), I consider the strongest specification by incorporating fund-by-firm fixed effects in the regression. These fixed effects absorb potential fund-firm pairing effects, such as social connections between mutual funds and portfolio companies, fund-firm political alignment (Wintoki and Xi, 2019), or a fund's static preference for a certain stock. Once again, the main result remains statistically and economically significant, even after accounting for these factors.

Taken together, the results consistently show that partisan funds react more strongly to topics aligned with their ideological beliefs and trade more when firms increase discussions on these topics. This relationship remains robust even after controlling for various control variables and including a comprehensive set of fixed effects. These findings suggest that partisanship plays an important role in explaining how mutual funds process firm-level, partisan-sensitive information.

4.2 Subsample analysis

In this section, I explore heterogeneous partisan effects among subgroups of mutual fund managers and portfolio companies. First, if the differential trading responses to partisan-sensitive topics between Democratic and Republican funds are truly driven by partisanship, the effect should be stronger among funds managers with more polarized political beliefs. To measure polarization, I classify a fund manager as either a strong or weak partisan based on the proportion of contributions to a single party, following prior literature (Vorsatz, 2022). Specifically, a fund manager is labeled a "strong Republican (Democrat)" if at least 75% of donations go to the Republican (Democratic) party, and a "weak Republican (Democrat)" if the contributions to Republicans (Democrats) fall between 50% and 75%. For strong partisans, the net political leaning of a mutual fund is calculated as *(#Strong Dem - #Strong Rep)/#Total managers*. Similarly, for weak partisans, the net political leaning is computed as *(#Weak Dem - #Weak Rep)/#Total managers*.

The regression results, presented in Table 3 columns (1) - (2), show that the coefficient on the interaction term for the more polarized subgroup is -0.017 and statistically significant at the 1% level. In contrast, the coefficient for the less polarized subgroup is about half as large and statistically insignificant. These findings indicate that mutual fund managers with more polarized political beliefs exhibit a stronger reaction to partisan-sensitive topics than less polarized fund managers, supporting the argument that partisanship affects mutual fund firm-level information processing.

Next, I examine whether the partisan effect varies based on the importance of individual stocks within mutual fund portfolios. Given that mutual funds typically hold many stocks in their portfolios, managers may not have sufficient attention to analyze the earnings calls of each portfolio company. Thus, it is reasonable to expect stronger effects among firms with higher weights in fund portfolios, as these stocks likely receive greater attention from fund managers. To test this prediction, I split the sample based on the ranking of securities in fund portfolios, where securities are sorted by portfolio weights in descending order. The results, presented in Table 3 columns (3) - (4), show that the partisan effect is stronger for stocks ranked higher in the portfolio. Conversely, the coefficient for the lower-ranking group is about one-third as large and only marginally significant at 10% level, supporting the hypothesis that the partisan effect is stronger for firms with higher portfolio weights.

4.3 Sentiment-augmented PST index

While I have established a negative relationship between partisan-sensitive topic weights and the overall sentiment of earnings calls, one might still be concerned about whether the overall sentiment truly captures the sentiment of individual topics. To address this, in this section, I introduce a method to measure sentiment at the topic level. This approach refines the Partisan Sensitive Topic Index (PST) by integrating the sentiment of each specific topic into the index.

Developing a topic-level sentiment measure involves a two-step process. I first identify keywords associated with each topic, and then analyze the sentiment of the context around the keywords. However, a challenge arises due to the non-mutually-exclusive nature of LDA topic keywords—frequent terms often appear across multiple topics, making it difficult to map keywords to individual topics. To identify distinctive terms for each topic, I scale topic-term weights by total term frequency, following the methodology of Sievert and Shirley (2014) and Bybee et al. (2024):

$$\tilde{\phi}_{k,w} = \frac{\phi_{k,w}}{p_w}, \tag{5}$$

where $\phi_{k,w}$ represents the weight of term w in topic k, and p_w denotes the frequency of term k in the entire corpus. This scaling approach underweights common terms and overweights terms uniquely associated with a specific topic. Using the scaled weights ($\tilde{\phi}_{k,w}$), I rank terms and select the top 100 distinctive words for each topic.

The second step involves analyzing the sentiment of the context surrounding each distinctive term. Following Hassan et al. (2019), I define "context" as the ten words before and after each distinctive term. The net sentiment of this context is then calculated as the proportion of positive and negative words using the Loughran and McDonald (2011) dictionary.[19] This process is expressed as:

$$Topic\ Sentiment_{k,i,t} = \frac{I(b \in \mathbb{D}_k) \times \sum_{c=b-10}^{c=b+10} Sent(c)/21}{B_{k,i,t}}, \tag{6}$$

where $I(b \in \mathbb{D}_k)$ is an indicator function of whether the word b is in $\mathbb{D}_k$, the distinctive term set of topic k. $Sent(c)$ is a function that equals 1 (-1) if c is a positive (negative) word, and $B_{k,i,t}$ is the number of distinctive terms belonging to topic k in transcript i. Topic sentiment is derived as the average sentiment across all contexts for distinctive words of the topic. To account for firms' tendency to maintain a positive tone in earnings calls, I normalize the sentiment measure by subtracting the overall sentiment of an earnings call from the topic-level sentiment.

In the last step, I construct a sentiment-augmented PST index that incorporates topic-level sentiment. Specifically:

[19] As an illustrative example, consider the sentence: "…The impact of COVID-19 continued throughout the second quarter as closures and widespread uncertainty resulted in reduced customer demand and lower growth and…". Here, the term "widespread" is a distinctive term of the pandemic topic. The context of this term extends over a 21-word span, beginning from "COVID" and concluding with "growth". Within this context, "closure" is a negative word, and there is no positive word. Consequently, the net sentiment for this context is calculated as (% positive words - % negative words) / total words = (0 − 1) / 21 = –4.76%.

$$Sent\ PST = I(neg) \times Pandemic + I(neg) \times Climate\ change$$
$$+ I(neg) \times Pharmaceuticals + \ I(neg) \times Healthcare \qquad (7)$$

where I(neg) is a function that equals 1 if the normalized topic sentiment for a particular topic is negative, -1 if the sentiment is positive, and 0 if the sentiment is neutral or if no distinctive terms for the topic appear in the transcript. This method subtracts weights for positively discussed topics from topics discussed negatively, aligning the index with the expectation that Democratic funds should respond more negatively to firms' exposure to these issues.

I then repeat the main analysis with the sentiment-augmented PST index, and present the results in Table 4. The coefficient on *ΔSent PST × Net Dem* remains negative and statistically significant across all specifications, indicating that the main result continues to hold after taking the topic-level sentiment into account.

Taken together, the analyses in previous sections support the argument that partisan disagreements on sensitive issues contribute to the differential trading responses between Democratic and Republican funds. Specifically, partisan funds react more strongly to topics aligned with their ideological beliefs, trading more when firms increase discussions on these topics. This relationship is further supported by subsample analyses and remains robust even after accounting for the sentiment of discussions around each partisan-sensitive issue.[20]

4.4 Is the partisan effect rational?

The main finding shows that Democratic funds react more strongly to partisan-sensitive issues aligned with Democratic priorities and tend to sell more shares when firm increase discussions of these issues. Two potential explanations could account for this behavior. The first explanation is based on *rational expectations*, suggesting that Democratic funds sell more because they accurately foresee that firms with greater exposure to partisan-sensitive

[20] The different trading reactions can be attributed to differences in mutual fund belief updating regarding portfolio companies' future cash flow expectations or their risk exposure to these issues. For example, when a firm increases discussions on issues that Democrats consider significant (e.g. the Covid pandemic), Democratic funds may form more negative expectations about the firm's future cash flows. They may also perceive higher risk exposure for the firm to the pandemic, compared to Republican funds. These factors could lead to a lower stock valuation and more pronounced selling behavior. While the paper cannot distinguish between risk-based and cash flow-based explanations due to a lack of data on fund-stock-quarter-level risk assessments and cash flow expectations, it does explore whether the differential trading response is driven by rational decision-making or behavioral considerations.

issues will underperform in the near future. If so, these trades should add value to mutual fund performance. The second explanation focuses on *behavioral considerations*, suggesting that Democratic funds' responses may not be based on beliefs about future stock returns, or may be based on mistaken beliefs about future stock returns. If this is true, Democratic funds would not profit from these trades. To distinguish between the two explanations, it is crucial to determine whether Democratic funds profit from trading in response to firms' exposure to partisan-sensitive issues.

To quantify whether mutual funds profit from a trade, I construct a measure capturing the "value-add" of the trade based on its contribution to fund performance. It is calculated as the change in the portfolio weight of a stock in quarter t multiplied by the stock's return in quarter t+1 ($\Delta Weight_{f,i,t} \times R_{i,t+1}$).[21] If a fund sells a stock and the stock price decreases subsequently (i.e. both $\Delta Weight_{f,i,t}$ and $R_{i,t+1}$ are negative), or if a fund buys a stock and the stock price later increases (i.e. both $\Delta Weight_{f,i,t}$ and $R_{i,t+1}$ are positive), this measure will yield a positive value. I then use this measure as the dependent variable and run the following regression:

$$\begin{aligned} \Delta Weight_{f,i,t} \times R_{i,t+1} = \alpha + \boldsymbol{\beta_1} \mathit{\Delta PST}_{i,t} \times \mathit{Net\ Dem}_{f,t} + \beta_2 \mathit{\Delta PST}_{i,t} + \beta_3 \mathit{Net\ Dem}_{f,t} \\ + Controls_{f,i,t} + FEs + \varepsilon_{f,i,t} \qquad (4) \end{aligned}$$

where $\Delta Weight_{f,i,t}$ is the change in the weight of stock *i* in fund *f*'s portfolio at the end of quarter *t*, and $R_{i,t+1}$ is the return of stock *i* in quarter *t+1*. The coefficient of interest is β_1, which captures whether Democratic funds benefit more from trading in response to firms' exposure to partisan-sensitive issues. The regression results are shown in Table 5. The coefficient on the interaction term is negative across all specifications, although not always statistically significant. This suggests that Democratic funds do not gain and may even incur losses from trading based on firms' exposure to partisan-sensitive issues. As a result, this finding contradicts the rational expectation explanation and supports the behavioral consideration channel.

[21] For example, if a fund with \$1 million asset under management (AUM) reduces the holding of a stock from \$10,000 to \$5,000, and if the stock yields a -10% return in the following quarter, the "value-add" of this trade to fund performance is $\frac{(\$5000 - \$10000)\times(-10\%)}{\$1,000,000} =$ 0.05%.

Another approach to distinguish between the two explanations is to directly examine the performance of portfolio companies. By determining whether firms underperform after facing increased exposure to partisan-sensitive issues, we can also gain insights into whether the partisan effect is driven by rational expectations or behavioral considerations. To test this, I regress the return of stock i in quarter $t+1$ ($R_{i,t+1}$) on the change in partisan-sensitive topic weights in quarter t ($\Delta PST_{i,t}$). The results, reported in Table A4 in the Internet Appendix, show that the coefficient on ΔPST is statistically insignificant across all columns. This suggests that firms with increased exposure to partisan-sensitive topics do not generate lower returns in the following quarter. As a result, Democratic funds would not profit from selling these stocks more heavily than Republican funds. Again, this finding supports the behavioral consideration explanation, but contradicts the rational expectation hypothesis.

4.5 Alternative explanations

While control variables and a comprehensive set of fixed effects have been included in the main regression, there may still be concerns about other possible explanations for the main result. In this section, I explore four non-mutually exclusive alternative explanations.

4.5.1 Are the results explained by confounding fund characteristics?

The first alternative explanation is that the observed partisan effect may be due to other fund characteristics associated with mutual fund partisanship. While the direct impact of fund characteristics on mutual fund trading has been addressed through fund-by-quarter fixed effects, this does not control for fund characteristics' influence on how funds respond to earnings call discussions. For example, larger funds may believe that they can exert more influence on portfolio companies. If they disapprove of a firm's earnings calls, they may choose to express their opinions through proxy voting rather than selling off stock shares of the company. Thus, if Republican funds are generally larger funds, their weaker trading responses to partisan-sensitive topics may be due to size rather than political beliefs.

To address this concern, I include interaction terms between fund characteristics and ΔPST in the main regression. This controls for the potential influence of other fund characteristics on mutual fund responses to earnings call discussions. The regression results, shown in Table 6, suggest that fund size is related to how funds react to partisan-sensitive topics, as indicated by the significant coefficient of ΔPST × Ln(1+fundsize) in column (5).

However, the inclusion of these interaction terms does not affect the coefficient on the main variable of interest, ΔPST $\times$ Net Dem, indicating that the main result reflects the impact of partisanship, rather than the influence of other fund characteristics.

4.5.2 Are the results due to mutual funds catering to investor preferences?

A second alternative explanation is that Democratic funds' stronger reaction to partisan-sensitive topics may not reflect their inherent preferences, but rather because they cater to the preferences of fund investors. For instance, Democratic-leaning investors may be averse to increased exposure to issues that the Democratic party advocates as major concerns, such as climate change, healthcare affordability, and the pandemic. If these investors perceive that the fund is not adequately responding to these critical issues, they may withdraw their money. Given that investors often exhibit a preference for local funds due to local bias (Bailey et al., 2011), if Democratic funds are more likely to attract Democratic investors, these funds may reduce investments in firms with increased exposure to partisan-sensitive issues to prevent outflows. In this case, changes in fund holdings are not driven by the political attitudes of the fund managers, but rather by the preferences of fund investors.

To investigate this alternative explanation, I follow Hong and Kostovetsky (2012) and use the political leaning of the state where the mutual fund is headquartered as a proxy for the partisanship of fund investors. The underlying assumption is that if a fund's clients are primarily local, the headquarter state's political leaning can serve as a proxy for the political values of its clientele.[22] To measure state-level political leaning, I construct *state Dem vote*, the Democratic voting share in the headquarter state during the most recent presidential election before the earnings call. I then introduce an interaction term between *state Dem vote* and *ΔPST* in the main regression to account for the influence of local investors' preferences on mutual funds' responses to earnings calls. The regression results, presented in Table 7, show that this new variable does not explain differences in mutual fund trading responses. Moreover, the coefficient on *ΔPST × Net Dem* remains significant across all specifications, suggesting that the differential trading response between Democratic and Republican funds is not driven by mutual funds catering to their investor preferences.

[22] It is worth noting that this is an imperfect proxy for the political leaning of mutual fund investors. However, since the identity of mutual fund investors is unobservable, this is the best available proxy in the literature.

4.5.3 Are the results due to firms' strategic disclosure in earnings calls?

The third concern stems from the perspective of portfolio companies. So far, the paper assumes that text-based measures from earnings calls accurately reflect a firm's exposure to partisan-sensitive issues. However, potential bias may arise if CEOs strategically adjust the emphasis on these topics based on their shareholder base's political preferences or their personal political leanings. For example, if a company's investors predominantly lean Democratic during the pandemic, the CEO may carefully navigate discussions around the pandemic to manage investor sentiment. To prevent panic selling, they may downplay the pandemic's significance. Conversely, if shareholders express high concerns, the CEO might expand on the topic. Moreover, the political leanings of CEOs themselves can also influence the topics discussed in earnings calls. A Democratic CEO, for example, may be more likely to discuss climate change, even when their firm's exposure to the issue is similar to that of a firm led by a Republican CEO. The strategic adjustments by CEOs in earnings calls may introduce measurement errors when assessing firms' exposure to partisan-sensitive topics, leading to biased estimates of the actual partisan effect on mutual fund trading responses.[23]

To address the concern of strategic disclosure influenced by partisan shareholders, I identify a subset of companies with a balanced mix of mutual fund shareholders from both political sides.[24] This setting provides a controlled environment to examine the main finding, as these portfolio companies face fewer external pressures to selectively disclose information. To create this subset, I calculate the aggregate holdings of Democratic and Republican mutual funds for each stock each quarter. I then retain firm-by-quarter observations where there are no partisan holdings, or where the ratio of total Democratic to Republican holding falls between 0.8 and 1.2 (allowing for a 20% margin of error). The regression results are presented in Table 8. While this results in a much smaller sample compared to the full dataset, the coefficient on the interaction term remains significant at a level of at least at

[23] It is important to note that the text-based measure may not systematically bias the main findings, as it may simply serve as a noisy but unbiased proxy for firms' exposure to partisan-sensitive issues. In the Covid example above, since firm CEOs can either downplay or emphasize partisan-sensitive topics, the resulting coefficient may be underestimated, but remains unbiased. In this case, the main finding's interpretation still holds. Nonetheless, I take a conservative approach and run additional tests to examine the strategic disclosure concern more carefully.

[24] One caveat of the method is that the balanced sample is constructed solely from mutual funds holdings, so an implicit assumption is that the partisan distribution among mutual fund investors is representative of that among other types of investors.

the 5% level. These results address concerns about portfolio companies selectively disclosing information to cater to partisan shareholders.

Next, to mitigate the impact of CEO political leanings on firms' strategic disclosure, I identify another subset of companies led by non-partisan CEOs—those who either made no political donations or donated equally to both parties. I manually compile a dataset of CEO political donations by matching CEO information from ExecuComp, which covers firms in the S&P 1500 index, with individual political contribution records from the Federal Election Committee (FEC). To classify CEOs' political leanings, I adopt a method similar to the one used for mutual fund managers in Section 2.2. I first match based on CEOs' first and last names, and use other information to rule out incorrect matches. I then analyze political donations over the past ten years to determine a CEO's political leaning at any given time. A CEO is classified as a Democrat (Republican) if more donations go to the Democratic (Republican) party, and non-partisan if donations are equally distributed between two parties or to PACs without explicit party affiliations. I then exclude firms with CEOs classified as Democrats or Republicans, and retain only those led by non-partisan CEOs in any firm-year pair. This subset thus consists of CEOs who either made no political donations or donated equally to both parties.

Next, I repeat the main analysis, and the empirical results are presented in Table 9. Notably, the coefficient on ΔPST $\times$ Net Dem remains statistically significant across all specifications. This indicates that the main finding continues to hold within the non-partisan CEO sample, ruling out concerns about biased information disclosure due to the personal political beliefs of portfolio companies' CEOs.

4.5.4 Are the results due to investors' concerns expressed during Q&A?

The final concern is that the text-based measure from earnings calls may capture not only firms' actual exposure but also investors' pre-existing concerns about partisan-sensitive issues. For instance, if Democratic investors are more concerned about climate change, they may ask more questions on the topic during earnings calls. Consequently, the text-based measure could reflect both investors' concerns and the firm's actual exposure. In this case, the higher weights on climate change in earnings calls and stronger trading reactions from Democratic funds might both arise from investors' pre-existing concerns about the issue rather than the firm's exposure.

To address this concern, I focus on the presentation section of earnings calls, where call participants have limited influence over the content, providing a more controlled and relatively exogenous environment. After filtering out operator messages, I divide transcripts into the presentation and Q&A sections, and calculate LDA topic weights for each section independently. I then run the main regression separately for both sections, with the results reported in Table 10. In Panel A, the coefficient on $\Delta PST \times Net\ Dem$ remains statistically significant, suggesting that the main result continues to hold in the presentation section. This finding rules out the concern that the results are driven by investors' pre-existing concerns shaping the conversation.

In summary, the results in this section provide strong evidence that the relationship between partisanship and mutual fund trading responses to firms' exposure to partisan-sensitive issues is not explained by alternative explanations. These include confounding fund characteristics, mutual funds catering to investor preferences, firms' strategic disclosure in earnings calls, and investors' pre-existing concerns expressed during earnings calls. These findings further reinforce the reliability of the main finding that partisanship plays a role in explaining mutual fund firm-level information processing.

4.6 Robustness

In this section, I perform additional tests to evaluate the robustness of the main finding.

First, I conduct a placebo test on LDA topics that do not involve partisan disagreement. The rationale is that if the different trading responses of Democratic and Republican funds are driven by factors other than partisanship, we should observe the partisan effect on all topics, not just partisan-sensitive ones. Conversely, if the effect is truly due to partisanship, there should be no effect on topics without partisan disagreement. I examine several commonly discussed topics. The first topic is "profits", since earnings calls primarily provide updates on a company's financial performance, with profits serving as key indicators of its financial well-being. Another topic is "investment", which is also a critical aspect of operations that helps investors and analysts evaluate potential risks and returns. Additionally, I examine "supply chain" and "raw material", which are related to a firm's daily operations. Figure A1 visualizes of keywords and time trends for these topics. Importantly, these topics are not highly polarizing issues and are typically not associated with partisan disagreement. The regression results in Table 11 show that the coefficients on

$\Delta Topic \times Net\ Dem$ are both economically small and statistically insignificant for these non-partisan-sensitive topics. This finding mitigates the concern that the differential trading response of Democratic and Republican funds is driven by factors unrelated to political leanings, further supporting for the main finding.

Next, I explore several alternative specifications of the main result. In earlier analyses, the sample includes both partisan and non-partisan mutual funds. As Rice (2023) and Wang and Zeng (2024) suggest, including non-partisan funds creates a more continuous sample by incorporating fund-year observations without clear political leanings, thereby improving the precision of coefficient estimates. However, this method may complicate direct comparisons between Democratic- and Republican-leaning funds. To address this issue, I restrict the sample to partisan funds—those identified as leaning Democratic or Republican—allowing for a more straightforward comparison. As shown in Table 12 column (1), our main finding remains robust, providing a clearer picture of the partisan effect.

Further, one might be concerned whether the results are influenced by a fund's ESG classification. Since climate change is one of the partisan-sensitive issues, mutual fund trading responses to the PST index may differ between ESG vs. non-ESG funds. If Democratic-leaning funds are more likely to have an ESG focus, their stronger trading reactions could be driven by this focus rather than partisanship. In the main analysis, I already include stringent fixed effects, such as fund × firm fixed effects, which should account for fund preferences at the fund-firm level—for example, ESG funds avoiding "brown" stocks or specific industries. However, there remains a concern that these fund-firm preferences could vary over time. For instance, a fund might divest from a stock if its ESG rating worsens, a dynamic not fully captured by the current fixed effects. To address this concern, I conduct a test by excluding ESG funds from the sample. Using the sustainable fund list from the Morningstar Sustainable Fund Landscape Report, I remove ESG funds from the analysis. As shown in Table 12 column (2), the main finding remains robust, indicating that the result is not driven by whether mutual funds have an ESG focus.

Moreover, I examine an alternative measure of the pandemic topic. In the main analysis, I separate the "pandemic/crisis" topic identified by the LDA model into two distinct topics: "pandemic" and "crisis". However, one might be concerned about the subjectivity of this manual adjustment. To address this, I repeat the main analysis without separating the two topics. The results, presented in Table 12 Panel A column (1), show that the finding remains robust, indicating that the separation does not affect the main result.

5 Conclusion

This paper studies the relationship between partisanship and mutual fund firm-level information processing. Applying LDA topic modelling on earnings call transcripts, I identify partisan-sensitive topics, such as climate change, healthcare, and the Covid pandemic, which may trigger different responses among funds with varying political leanings.

The main finding is that partisan funds react more strongly to topics aligned with their ideological beliefs, trading more after firms increase discussions on these topics. Specifically, because the Democratic party is more concerned with the pandemic, climate change, and healthcare affordability issues, and because the overall tone of earnings calls becomes more negative as firms discuss these issues more, I find that Democratic funds tend to sell more stock shares when firms increase discussions on these topics compared to Republican funds. This relationship holds after controlling for fully-saturated fixed effects and accounting for the sentiment for each topic. The effect is stronger in more politically polarized funds and firms with higher portfolio weights.

Moreover, I find that the partisan effect does not add value to fund performance, suggesting that the pattern is driven by behavioral considerations rather than rational expectations about future stock returns. I also rule out several alternative explanations, including confounding fund characteristics, mutual funds catering to investor preferences, portfolio companies' strategic disclosure during earnings calls, and investors expressing pre-existing concerns in conference calls. I further conduct several robustness checks, including a placebo test on non-partisan topics, excluding non-partisan and ESG funds from the analysis, and using an alternative measure for the pandemic topic. All of these tests confirm the robustness of the main results.

In conclusion, this study provides compelling evidence that partisanship plays an important role in mutual fund information processing. While prior research has primarily focused on the impact of partisanship on investor preferences at the portfolio level, this paper extends the literature by examining how partisanship affects investor information processing at the firm level. The findings highlight the importance of considering political beliefs in investors' decision-making processes. These insights have practical implications for both investors and policymakers, offering a deeper understanding of how societal factors, such as partisanship, shape financial decisions. By recognizing the partisan effect on institutional investors' information processing, policymakers can take actions to promote a more objective, informed, and equitable investment environment for all investors.

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Figure 1. Model selection: choose the optimal number of topics

This figure plots the performance of LDA models trained with different topic numbers ranging from 10 to 100. The x-axis represents the number of topics, while the y-axis represents the coherence value, a metric indicating the semantic coherence of words within a given topic. A higher coherence value suggests a stronger correlation among the words, leading to clearer and more meaningful themes. The graph shows that the LDA model with 70 topics achieves the optimal performance based on the coherence value.

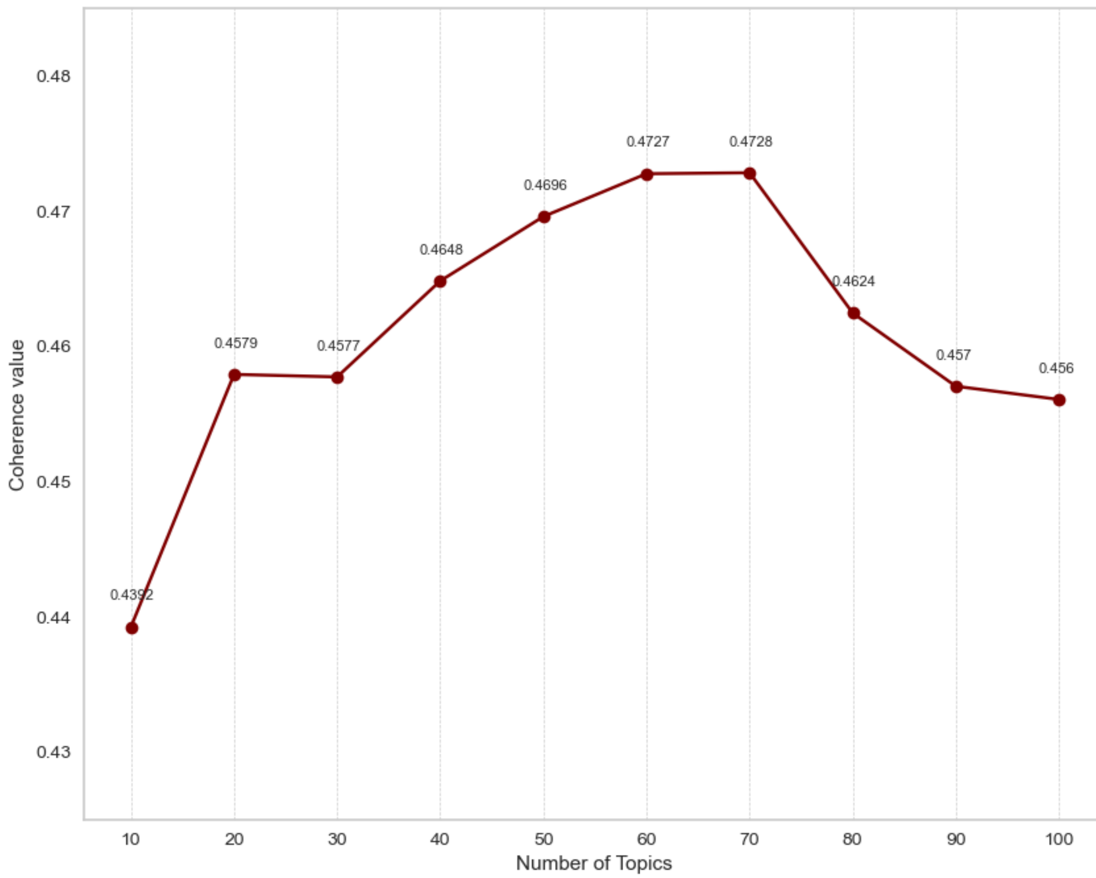


Figure 2. A taxonomy of earnings call topics

This figure illustrates a taxonomy of LDA topics derived from earnings call transcripts. The taxonomy is generated using hierarchical agglomerative clustering, a machine learning technique that groups topics by semantic similarities into broader categories. Please see Appendix B for a detailed list of keywords associated with each topic.

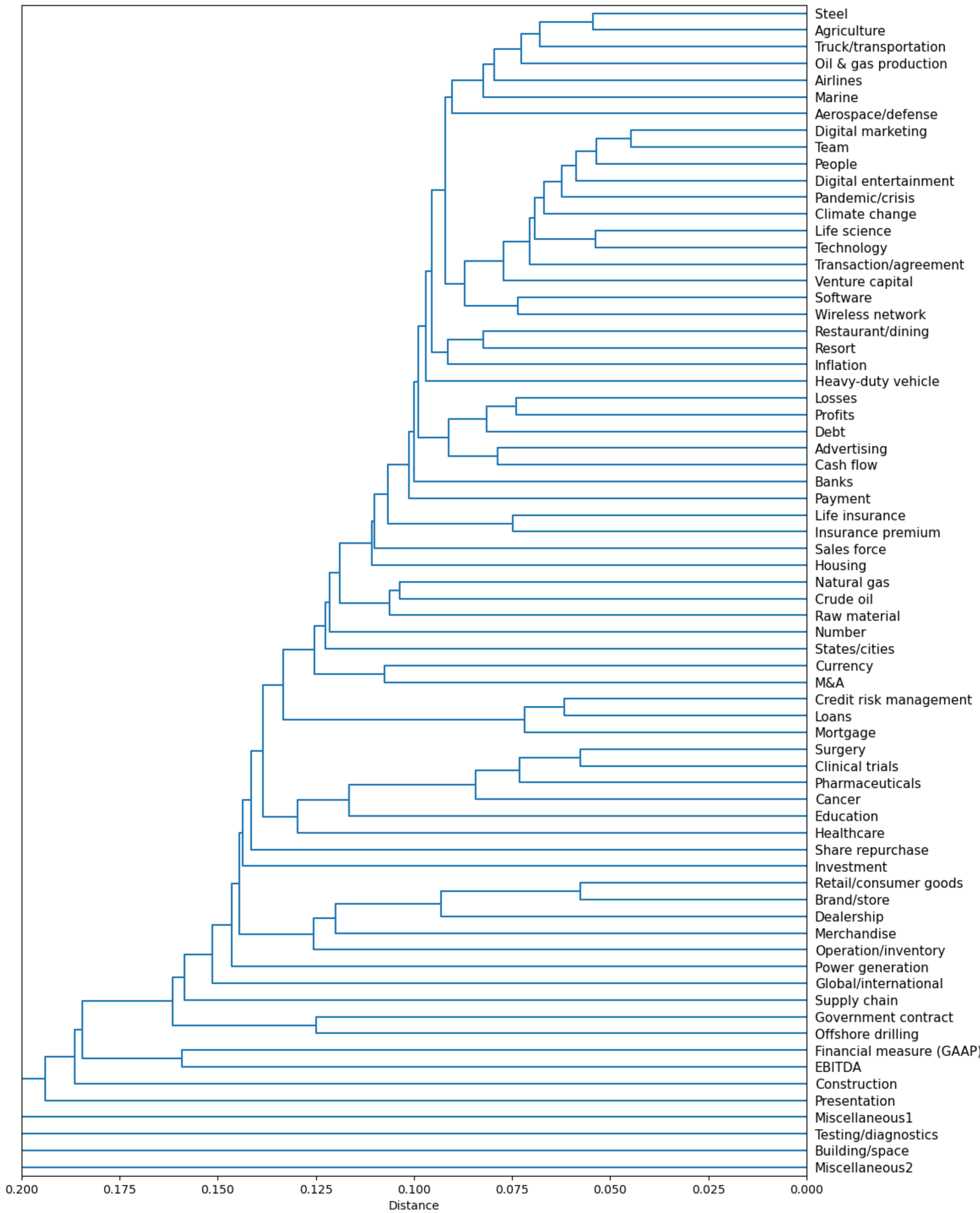
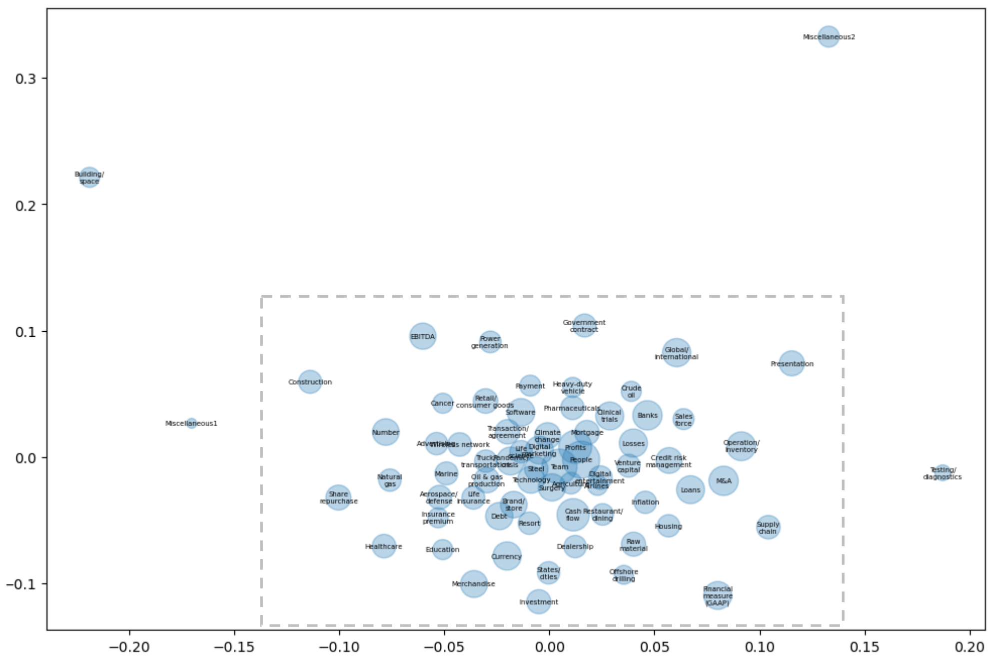


Figure 3. Topic Distance via Multi-Dimensional Scaling

This figure plots the semantic relationships between topics using multi-dimensional scaling, a dimensionality reduction technique that preserves the original high-dimensional distances between topics in a two-dimensional layout. Each circle represents a topic, with the circle size indicating the topic size and the distance between circles reflecting the semantic distance between topics. Panel A displays all 70 topics, while Panel B zooms in on the more concentrated area within the dashed box.

Panel A: 70 topics



Panel B: exclude outliers

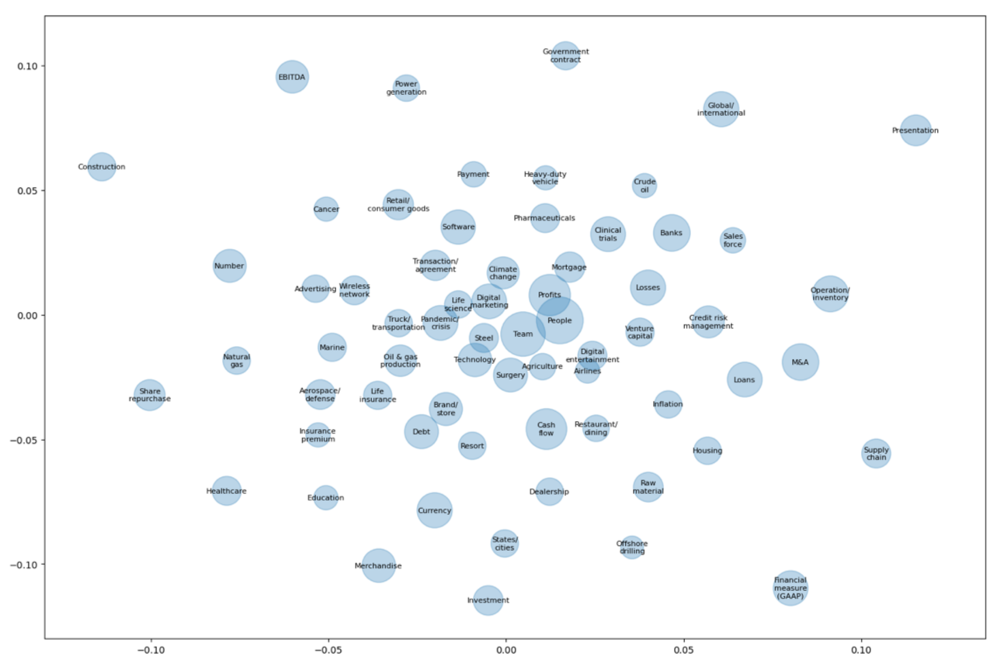


Figure 4. Partisan disagreement over certain issues

This figure shows the level of partisan disagreement across ten issues surveyed in the 2020 American Trends Panel survey by the Pew Research Center. The survey asked: “How much of a problem do you think each of the following are in the country today?” The ten issues include minority treatment by the justice system, the coronavirus outbreak, the federal budget deficit, government ethics, terrorism, healthcare affordability, illegal immigration, unemployment, climate change, and violent crime. Responses are aggregated and categorized by participants’ political leanings, and the figure ranks the issues by the degree of observed partisan disagreement.

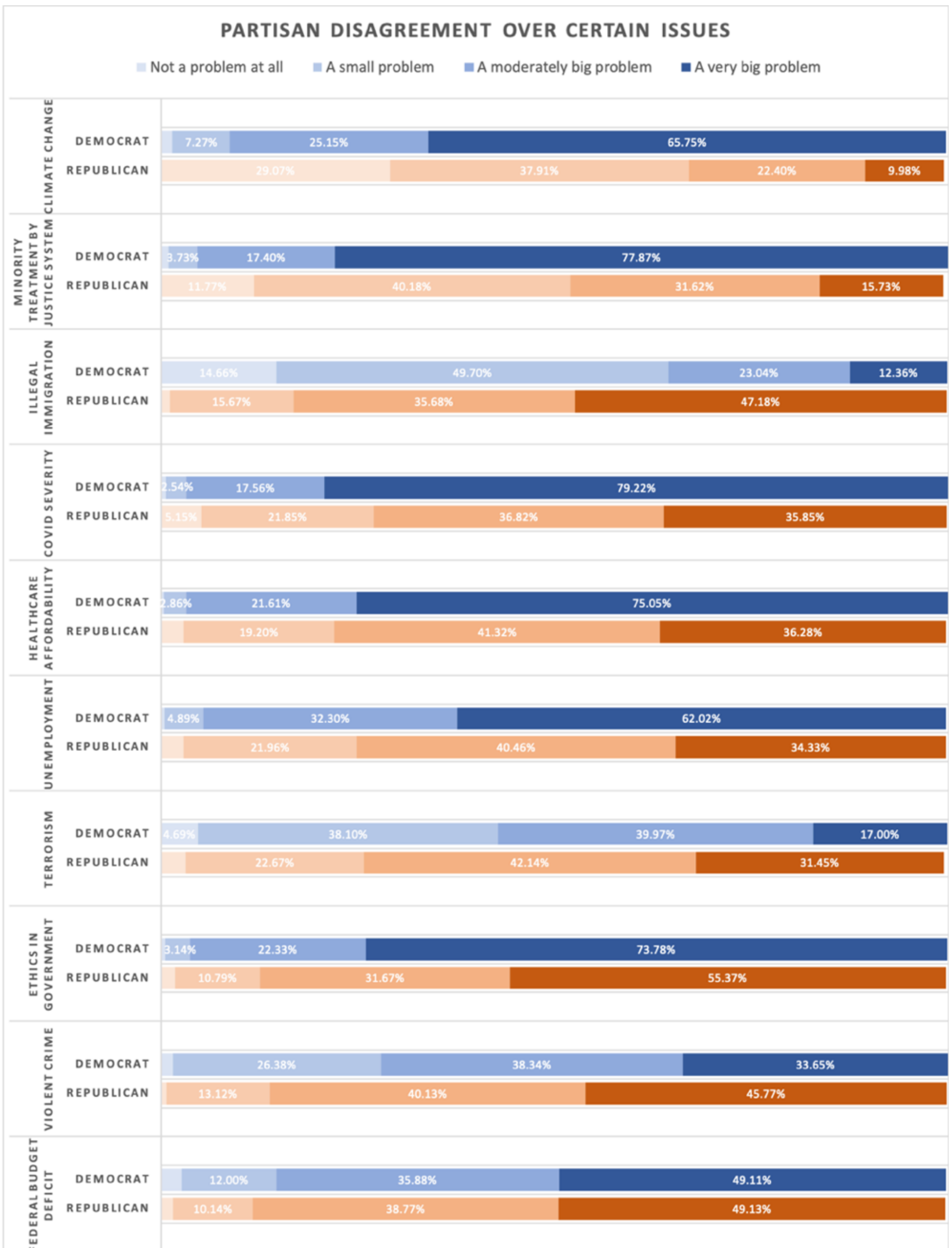
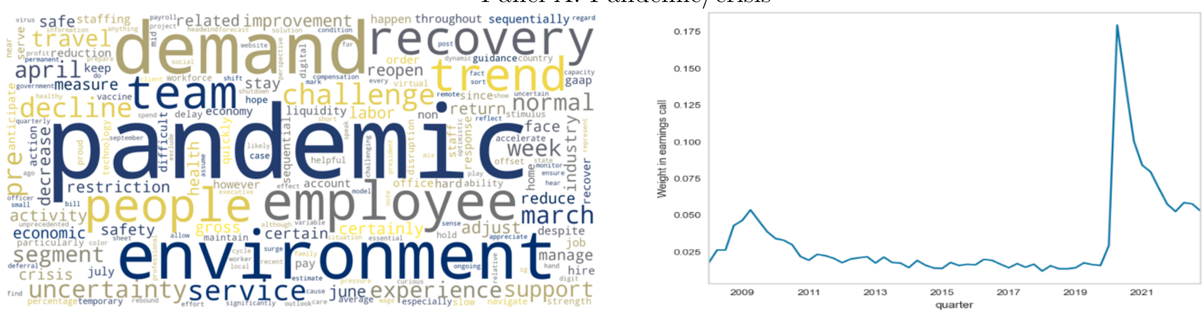


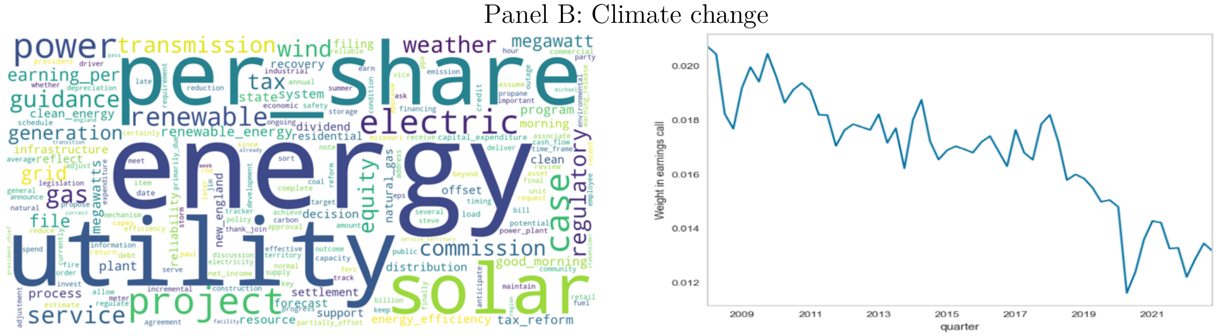
Figure 5. Keywords and time trends of partisan-sensitive topics

This figure shows the keywords and time trends for the average weight assigned to partisan-sensitive topics in earnings calls. Panel A illustrates the pandemic/crisis topic, Panel B shows the climate change topic, and Panels C and D highlight the healthcare and pharmaceuticals topics, respectively.

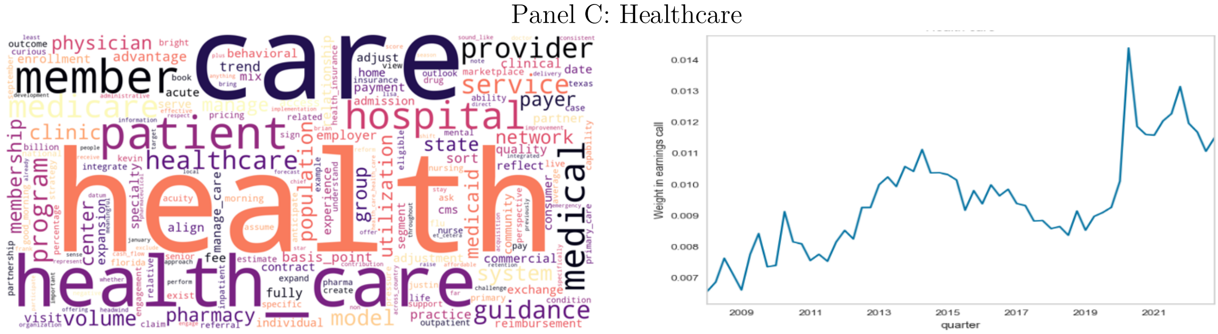
Panel A: Pandemic/crisis



Panel B: Climate change



Panel C: Healthcare



Panel D: Pharmaceuticals

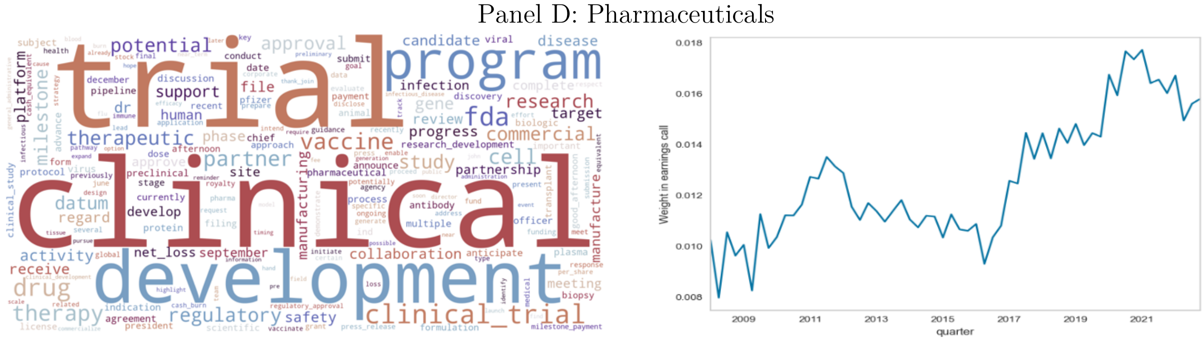


Table 1. Summary statistics

This table presents summary statistics for the main variables used in the paper. Panel A reports statistics for fund-by-firm-level variables. Panel B displays statistics for fund-level variables. Panel C shows statistics for firm-level variables. Detailed variable definitions are available in Appendix A.

Panel A: fund-by-firm-level variables

	Count	Mean	SD	Min	P25	P50	P75	Max
Fund Own (%)	6749482	0.15	0.38	0.0000084	0.0031	0.020	0.11	2.50
ΔFund Own (%)	6097589	0.00073	0.053	-0.26	-0.00063	0	0.00061	0.28
Net Dem	6749961	-0.00067	0.26	-1	0	0	0	1
PST	6750123	0.066	0.11	0.000011	0.000063	0.012	0.085	0.87
ΔPST	6098055	0.0026	0.048	-0.48	-0.0092	-0.00	0.0078	0.62

Panel B: fund-level variables

	Count	Mean	SD	Min	P25	P50	P75	Max
TNA ($mil)	83867	2185.6	7963.2	0	88.1	396.1	1497.7	292070.3
Fund age	83867	24.2	14.1	0.47	15.3	22.7	29.2	98.0
NAV	83437	24.5	18.3	6.77	12.9	18.5	28.9	109.1
Mgmt. fee	75532	0.65	0.52	-3.00	0.55	0.71	0.86	1.52
Expense ratio	75445	0.011	0.0036	0.0014	0.0086	0.010	0.013	0.021
Turnover ratio	75157	0.67	0.66	0.030	0.26	0.48	0.82	3.69
Total manager	83867	2.91	2.74	0	1	2	3	38
Democrat	83867	0.12	0.39	0	0	0	0	5
Republican	83867	0.13	0.41	0	0	0	0	5
Non-partisan	83867	0.066	0.28	0	0	0	0	3
Non-donor	83867	2.60	2.75	0	1	2	3	38

Panel C: firm-level variables

	Count	Mean	SD	Min	P25	P50	P75	Max
ME ($mil)	88110	12968.1	55769.0	7.60	641.4	2093.4	7246.6	2901645
B/M	88106	0.52	0.41	-0.12	0.22	0.42	0.72	1.84
ROA	88127	0.0057	0.031	-0.11	0.00083	0.0086	0.020	0.082
Profitability	82029	0.078	0.060	-0.045	0.037	0.069	0.11	0.27
Pandemic/crisis	88170	0.022	0.054	0.00	0.00	0.00	0.00	0.58
Climate change	88170	0.019	0.082	0.00	0.00	0.00	0.00	0.87
Pharmaceuticals	88170	0.0088	0.035	0.00	0.00	0.00	0.00	0.47
Health care	88170	0.011	0.042	0.00	0.00	0.00	0.00	0.75

Table 2. Main result

This table presents the relationship between partisanship and mutual fund trading on partisan-sensitive topics. The dependent variable, *ΔFundOwn*, represents the change in fund ownership of a stock. *ΔPST* captures the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the extent to which a mutual fund leans Democratic, calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter observation. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and mutual fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Variable definitions are provided in Appendix A. Industries are defined by Fama-French 48 industries. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔPST × Net Dem	**-0.0103*****	**-0.0113*****	**-0.0102*****	**-0.0136*****	**-0.0128*****	**-0.0126*****
	(-3.25)	**(-3.22)**	**(-3.01)**	**(-3.85)**	**(-3.60)**	**(-3.54)**
ΔPST	-0.0016	-0.0026**	-0.0023**	-0.0026***	-0.0126***	-0.0061
	(-1.38)	(-2.09)	(-2.28)	(-2.88)	(-3.16)	(-1.51)
Net Dem	0.0002	0.0004	0.0011			
	(0.38)	(0.65)	(1.04)			
Ln(fund size)		0.0006***	0.0020***			
		(5.39)	(8.94)			
Fund age		-0.0001***	-0.0001			
		(-5.85)	(-0.53)			
Fund turnover		-0.0006***	-0.0003			
		(-3.35)	(-0.91)			
Mgmt. fee		-0.0003	-0.0003			
		(-1.63)	(-1.02)			
Expense ratio		0.0517	-0.4173***			
		(1.04)	(-2.84)			
Ln(1 + ME)		-0.0005***	-0.0013***	-0.0016***		
		(-5.69)	(-6.00)	(-8.21)		
B/M		0.0007**	0.0027***	0.0036***		
		(2.25)	(4.22)	(5.51)		
ROA		-0.0295***	-0.0087***	-0.0091***		
		(-9.46)	(-4.19)	(-4.35)		
Profitability		0.0022**	-0.0097***	-0.0091***		
		(2.28)	(-4.28)	(-4.64)		
Fund FE			Y			
Qtr FE			Y			
Firm FE			Y	Y		
Fund × Qtr FE				Y	Y	Y
Firm × Qtr FE					Y	Y
Fund × Firm FE						Y
R^2	0.000	0.001	0.017	0.097	0.135	0.225
N	6097589	4957361	4957316	4956503	4955132	4895449

Table 3. Subsample analysis

This table presents heterogeneous partisan effects across different subsamples. In column (1)-(2), I calculate mutual fund political leaning based on the degree of political polarization. A fund manager is classified as a strong Democrat (Republican) if at least 75% of their donations go to the Democratic (Republican) party, and as a weak Democrat (Republican) if 50% - 75% of donations go to the Democratic (Republican) party. In column (1), *Net Dem* is calculated as (#Strong Dem - #Strong Rep)/#Total managers. In column (2), *Net Dem* is calculated as (#Weak Dem - #Weak Rep)/#Total managers. In column (3)-(4), I split the sample by security ranking in fund portfolios, where securities are ranked by portfolio weights. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔPST* represents the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the degree a mutual fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	Degree of polarization		Security rank	
	(1)	(2)	(3)	(4)
	Strong	Weak	Rank <= 100	Rank > 100
ΔPST × Net Dem	**-0.0170*****	**-0.0098**	**-0.0158*****	**-0.0059***
	(-2.93)	**(-1.19)**	**(-2.89)**	**(-1.83)**
ΔPST	-0.0063	-0.0063	0.0158***	-0.0172***
	(-1.57)	(-1.57)	(2.62)	(-3.24)
Controls	Y	Y	Y	Y
Fund × Qtr FE	Y	Y	Y	Y
Firm × Qtr FE	Y	Y	Y	Y
Fund × Firm FE	Y	Y	Y	Y
R^2	0.225	0.225	0.309	0.261
N	4895449	4895449	2713894	2134273

Table 4. Sentiment-augmented PST index

This table presents the relationship between partisanship and mutual fund trading on partisan-sensitive topics after accounting for topic-level sentiment. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔSent PST* represents the change in sentiment-augmented Partisan Sensitive Topic (PST) index in earnings calls, where *Sent PST* subtracts weights on positively discussed topics from those discussed negatively. *Net Dem* measures the degree a fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see appendix for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ΔSent PST × Net Dem	**-0.0025*****	**-0.0029*****	**-0.0028*****	**-0.0021****
	(-3.03)	**(-3.20)**	**(-3.05)**	**(-2.24)**
ΔSent PST	-0.0003*	-0.0004**	-0.0005***	-0.0018*
	(-1.88)	(-2.43)	(-2.99)	(-1.89)
Net Dem	0.0001	0.0003	0.0010	
	(0.13)	(0.53)	(1.07)	
Controls		Y	Y	Y
Fund FE			Y	
Qtr FE			Y	
Firm FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.016	0.262
N	4214382	3430131	3430089	3355345

Table 5. Partisanship and value-add of stock trading

This table presents the relationship between mutual fund partisanship and the value-add of stock trading to fund performance. The dependent variable, $\Delta Weight_{f,i,t} \times R_{i,t+1}$, represents the change in a stock's portfolio weight in quarter t times the stock return in quarter t+1. *ΔPST* captures the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the degree a mutual fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and mutual fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Industries are defined as Fama-French 48 industries. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0036**	**-0.0056****	**-0.0054****	**-0.0033**
	(-1.48)	**(-2.08)**	**(-2.08)**	**(-1.14)**
ΔPST	0.0003	0.0013**	-0.0036***	-0.0072**
	(0.66)	(2.27)	(-4.44)	(-2.56)
Net Dem	-0.0002*	-0.0003**	-0.0002	
	(-1.77)	(-2.29)	(-1.00)	
Controls		Y	Y	Y
Fund FE			Y	
Qtr FE			Y	
Firm FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.010	0.274
N	6096251	4956191	4956146	4894280

Table 6. Fund characteristics and trading response to earnings calls

This table presents the main regression in equation (3) after controlling for interaction terms between fund characteristics and partisan-sensitive topics. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔPST* captures the change in partisan-sensitive topic weights in earnings calls. *New Dem* measures the degree a fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for detailed variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
ΔPST × Net Dem	**-0.01255*****	**-0.01263*****	**-0.01263*****	**-0.01274*****	**-0.01275*****
	(-3.49)	**(-3.50)**	**(-3.44)**	**(-3.44)**	**(-3.42)**
ΔPST	-0.01210	-0.01387**	-0.01386**	-0.01859**	-0.03221***
	(-1.64)	(-2.08)	(-1.97)	(-2.48)	(-2.58)
ΔPST × Ln(1+fundsize)	0.00030	0.00045	0.00045	0.00060	0.00120**
	(0.70)	(1.18)	(1.19)	(1.57)	(2.01)
ΔPST × Fund age		-0.00006	-0.00006	-0.00008	-0.00009
		(-0.65)	(-0.65)	(-0.87)	(-0.97)
ΔPST × Turnover			-0.00000	-0.00075	-0.00078
			(-0.00)	(-0.58)	(-0.60)
ΔPST × Exp. ratio				0.35630	0.72283**
				(1.34)	(2.02)
ΔPST × Mgmt. fee					-0.00282**
					(-2.04)
Controls	Y	Y	Y	Y	Y
Fund × Qtr FE	Y	Y	Y	Y	Y
Firm × Qtr FE	Y	Y	Y	Y	Y
Fund × Firm FE	Y	Y	Y	Y	Y
R^2	0.225	0.225	0.225	0.225	0.225
N	4895449	4895449	4895449	4895449	4895449

Table 7. Fund headquarter partisanship and trading response to earnings calls

This table reports the main regression from equation (3) after controlling for the political leaning of the state in which a mutual fund is headquartered. *State Dem Vote* is the Democratic voting share in the state where the fund is headquartered during the most recent presidential election before the earnings call. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔPST* is the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the degree to which a mutual fund leans Democratic, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0106*****	**-0.0117*****	**-0.0105*****	**-0.0130*****
	(-3.23)	**(-3.29)**	**(-3.05)**	**(-3.62)**
ΔPST × State Dem Vote	0.0089	0.0138	0.0123	0.0128
	(0.56)	(0.81)	(0.75)	(1.24)
ΔPST	-0.0068	-0.0105	-0.0093	-0.0133*
	(-0.70)	(-1.02)	(-0.98)	(-1.68)
Net Dem	0.0003	0.0004	0.0011	
	(0.55)	(0.70)	(1.05)	
State Dem Vote	-0.0067***	-0.0035*	-0.0082*	
	(-3.30)	(-1.75)	(-1.82)	
Controls		Y	Y	Y
Fund FE			Y	
Firm FE			Y	
Qtr FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.017	0.225
N	5888080	4937923	4937873	4876367

Table 8. A balanced shareholder sample

This table presents the main regression on a balanced shareholder sample with comparable representation from both political sides. The sample is constructed by calculating the aggregate holdings of Democratic and Republican mutual funds for each stock in each quarter, and then retaining firm-by-quarter observations that either have no partisan holdings or where the ratio of total Democratic holdings to total Republican holdings falls within the range of 0.8 to 1.2, allowing for a 20% error margin. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔPST* is the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the degree to which a mutual fund leans Democratic, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0252*****	**-0.0284*****	**-0.0272*****	**-0.0283****
	(-3.10)	**(-3.24)**	**(-3.19)**	**(-2.29)**
ΔPST	-0.0050***	-0.0058***	-0.0055**	-0.0176*
	(-2.91)	(-3.04)	(-2.11)	(-1.82)
Net Dem	-0.0003	-0.0004	0.0002	
	(-0.52)	(-0.61)	(0.14)	
Controls		Y	Y	Y
Fund FE			Y	
Firm FE			Y	
Qtr FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.033	0.527
N	660293	534573	534508	446099

Table 9. Non-partisan CEOs

This table reports the main regression on a subset of firms with non-partisan CEOs. I manually compile a dataset of CEO political donations by matching CEO information from ExecuComp with individual political contributions from the FEC, classifying CEO political leanings based on donation patterns. I then exclude firms led by partisan CEOs and retain only those with non-partisan CEOs, defined as those who make no political donations or donate equally to both parties. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔPST* is the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the degree to which a mutual fund leans Democratic, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see appendix for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered by fund. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0111*****	**-0.0124*****	**-0.0108*****	**-0.0117****
	(-2.96)	**(-3.06)**	**(-2.76)**	**(-2.10)**
ΔPST	-0.0010	-0.0020	-0.0013	-0.0099**
	(-0.81)	(-1.48)	(-0.98)	(-2.06)
Net Dem	0.0001	0.0003	0.0013	
	(0.20)	(0.39)	(1.09)	
Controls		Y	Y	Y
Fund FE			Y	
Qtr FE			Y	
Firm FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.016	0.250
N	2960222	2440667	2440653	2402651

Table 10. Presentation vs. Q&A session

This table presents the main results for the presentation and Q&A sessions separately. In Panel A (B), *ΔPST* is the change in partisan-sensitive topic weights constructed from the presentation (Q&A) session in earnings calls. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *Net Dem* measures the degree to which a mutual fund leans Democratic. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see appendix for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered by fund. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. presentation session

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0069*****	**-0.0075*****	**-0.0067*****	**-0.0069*****
	(-2.77)	**(-2.88)**	**(-2.65)**	**(-2.68)**
ΔPST	-0.0007	-0.0015	-0.0012	-0.0040
	(-0.77)	(-1.50)	(-1.51)	(-1.13)
Net Dem	0.0002	0.0004	0.0011	
	(0.36)	(0.63)	(1.03)	
Controls		Y	Y	Y
Fund FE			Y	
Firm FE			Y	
Qtr FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.017	0.225
N	6092437	4952572	4952529	4890714

Panel B. Q&A session

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0063*****	**-0.0075*****	**-0.0066****	**-0.0047***
	(-2.65)	**(-2.70)**	**(-2.54)**	**(-1.91)**
ΔPST	-0.0015*	-0.0021**	-0.0012**	-0.0058*
	(-1.93)	(-2.40)	(-2.11)	(-1.84)
Net Dem	0.0002	0.0004	0.0011	
	(0.36)	(0.62)	(1.03)	
Controls		Y	Y	Y
Fund FE			Y	
Firm FE			Y	
Qtr FE			Y	
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.017	0.225
N	6092437	4952572	4952529	4890714

Table 11. Placebo test

This table presents the partisan effect on LDA topics that do not exhibit substantial partisan disagreements. Columns (1)-(4) display the results for profits, supply chain, raw material, and investment topics, respectively. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔTopic* is the change in the weight assigned to a specific topic in earnings calls. *Net Dem* measures the degree to which a mutual fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(1+fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered by fund. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Profits	(2) Supply chain	(3) Raw material	(4) Investment
ΔTopic × Net Dem	**0.0026**	**0.0008**	**0.0038**	**-0.0020**
	(0.30)	**(0.14)**	**(0.57)**	**(-0.25)**
ΔTopic	-0.0173*	-0.0232***	0.0002	-0.0156
	(-1.96)	(-2.82)	(0.02)	(-1.49)
Controls	Y	Y	Y	Y
Fund × Qtr FE	Y	Y	Y	Y
Firm × Qtr FE	Y	Y	Y	Y
Fund × Firm FE	Y	Y	Y	Y
R^2	0.225	0.225	0.225	0.225
N	4895449	4895449	4895449	4895449

Table 12. Robustness

This table presents robustness tests of the main regression. In Column (1), I exclude non-partisan funds and retain only those that lean toward either Democrats or Republican. In Column (2), I exclude ESG funds using the sustainable fund list from the Morningstar Sustainable Fund Landscape Report. In Column (3), I use an alternative measure that does not separate the "pandemic/crisis" topic in the LDA model. *ΔFundOwn* is the change in fund ownership of a stock. *ΔPST* is the change in partisan-sensitive topic weights in earnings calls. *Net Dem* measures the degree to which a mutual fund leans Democratic. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*) and fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Exclude non-partisan funds	(2) Exclude ESG funds	(3) Not separating pandemic/crisis topic
ΔPST × Net Dem	**-0.0097*****	**-0.0136*****	**-0.0118*****
	(-2.77)	**(-3.74)**	**(-3.88)**
ΔPST	-0.0253***	-0.0070*	-0.0020
	(-2.85)	(-1.71)	(-0.56)
Controls	Y	Y	Y
Fund × Qtr FE	Y	Y	Y
Firm × Qtr FE	Y	Y	Y
Fund × Firm FE	Y	Y	Y
R^2	0.345	0.226	0.225
N	818257	4740974	4895449

Appendix A. Variable definition

This table provides the definitions of main variables used in the empirical analysis.

Variable	Definition
Panel A: dependent and independent variables	
$FundOwn_{f,i,t}$	Fund *f*'s percentage ownership of stock *i* in quarter *t*. It is calculated as the number of shares of stock *i* held by fund *f* in quarter *t* divided by the total number of shares outstanding of stock *i* in *t-1* times 100.
$\Delta FundOwn_{f,i,t}$	The change in fund *f*'s percentage ownership of stock *i* in quarter t, calculated as: $$\%\Delta Fund\ Own_{f,i,t} = \frac{\#Shares_{f,i,t} - \#Shares_{f,i,t-1}}{\#Shares\ outstanding_{i,t-1}}$$ If the holdings of fund *f* in quarter *t-1* are unavailable or fund *f* does not report stock *i* in its quarter *t-1* holdings, I employ the most recent non-zero holdings of the stock as the substitute for *t-1*.
$NetDem_{i,t}$	The degree a fund leans toward the Democratic party. It is calculated as: $$NetDem_{i,t} = (\#Democrats_{i,t} - \#Republicans_{i,t})/\#Total\ Managers_{i,t}$$ where $\#Democrats_{i,t}$ is the number of Democratic-leaning managers, $\#Republicans_{i,t}$ is the number of Republican-leaning managers, and $\#Total\ Managers_{i,t}$ is the total number of current managers at fund i in month t.
$PST_{i,t}$	The aggregate attention directed towards partisan-sensitive topics during earnings calls of firm *i* in quarter *t*. It is calculated as the sum of weights assigned to the pandemic, climate change, health care, and pharmaceuticals topics.
$\Delta PST_{i,t}$	The change in weights assigned to partisan-sensitive topics in firm *i*'s earnings calls during quarter *t*, relative to the weights when the firm was last held by the fund.
Sent $PST_{i,t}$	The sentiment-augmented PST index, where I(neg) is the sign of the average sentiment across all contexts associated with distinctive words of a particular topic: $$Sent\ PST = I(neg) \times Pandemic + I(neg) \times Climate\ change + I(neg) \times Pharma + I(neg) \times Healthcare$$
Panel B: mutual fund characteristics	
Ln(fund size)	The natural logarithm of fund total net asset (TNA) across all share classes.
Fund age	The difference between the start date (of the earliest share class) and the end date (of the latest share class) of a mutual fund expressed in years.
Fund turnover	Fund Turnover Ratio, calculated as the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month Total Net Assets of the fund.
Mgmt. fee	Management fee ($)/ Average Net Assets ($) represented as percentage unit (%).
Expense ratio	Expense Ratio as of the most recently completed fiscal year in decimal format.
Panel C: firm characteristics	
Ln(1 + ME)	The natural logarithm of 1 plus the market value of a firm (Compustat item: CSHOQ* PRCCQ*1000000).
B/M	The book value of a firm divided by the market value of the firm (Compustat item: SEQQ/ (CSHOQ*PRCCQ)).
ROA	Income before extraordinary items (IBQ) divided by total assets (Compustat item: ATQ).
Profitability	Revenue minus cost of goods sold scaled by assets (Compustat item: (REVTQ – COGSQ)/ ATQ).

Appendix B. LDA Topic Keywords

This table presents the top 15 keywords of each LDA topic. The keywords are generated by the LDA topic model, and the topic names are assigned by referring to the literature and conducting online searches.

Topic Label	Topic Keywords
Steel	ton, demand, production, steel, volume, coal, per ton, inventory, pricing, capacity, mill, plant, shipment, facility, salt
Agriculture	demand, production, plant, crop, ag, season, corn, capacity, yield, industry, animal, ship, farmer, food, joel
Truck/ transportation	volume, service, freight, car, truck, network, capacity, transportation, pricing, driver, rail, shipment, fuel, mile, improvement
Oil & gas production	production, oil, drill, eagle ford, cash flow, barrel, basin, gas, rig, drilling, program, acreage, completion, barrel oil, foot
Airlines	aircraft, airline, flight, travel, airplane, capacity, fly, fleet, air, fuel, aviation, max, passenger, jet, airport
Marine	equipment, fleet, rental, demand, utilization, lease, activity, pricing, vessel, industry, order, maintenance, service, capex, average
Aerospace/defense	order, program, backlog, production, defense, commercial, system, book, booking, aerospace, aftermarket, book bill, bill, award, space
Digital marketing	platform, marketing, consumer, spend, channel, experience, digital, people, user, partner, datum, launch, brand, app, online
Team	team, strategy, deliver, strategic, progress, key, industry, support, execute, target, initiative, create, capability, important, portfolio
People	people, sort, happen, do, guy, make sure, tell, run, always, deal, certainly, anything, understand, keep, buy
Digital entertainment	content, game, digital, ai, launch, video, consumer, world, platform, disney, studio, experience, stream, music, sport
Pandemic/crisis	pandemic, demand, environment, employee, recovery, people, team, trend, challenge, service, decline, pre, march, uncertainty, normal
Climate change	energy, utility, per share, solar, project, power, case, electric, renewable, gas, service, guidance, wind, weather, transmission
Life science	system, instrument, consumable, life, technology, instal base, life science, science, laser, gross margin, dental, platform, service, instal, order
Technology	technology, system, development, design, production, process, loss, application, net loss, lead, support, progress, partner, facility, develop
Transaction/ agreement	pro forma, pro, forma, transaction, acquisition, agreement, license, shareholder, synergy, deal, partner, stock, announce, combine, team
Venture capital	joint venture, industrial, automotive, china, venture, segment, joint, technology, solution, auto, electronic, acquisition, application, demand, semiconductor
Software	service, solution, software, platform, enterprise, subscription, deal, security, datum, technology, partner, recur revenue, expand, sell, data
Wireless network	network, service, wireless, mobile, service provider, satellite, broadband, fiber, carrier, video, cable, device, subscriber, provider, phone
Restaurant/dining	restaurant, guest, brand, franchise, franchisee, basis point, labor, food, unit, store, system, comp, menu, delivery, dining
Resort	real estate, property, hotel, estate, park, pass, real, las vegas, resort, guest, season, occupancy, vegas, room, experience
Inflation	inflation, pricing, gross margin, private label, basis point, category, commodity, inflationary, gross, private, saving, cost saving, label, pressure, top line

(Table A1 continued)

Topic Label	Topic Keywords
Heavy-duty vehicle	power, fuel, energy, plant, carbon, vehicle, truck, battery, emission, charge, electric, nuclear, renewable, waste, gallon
Losses	tax, loss, partially offset, charge, decrease, reduction, decline, asset, primarily due, offset, reduce, impairment, balance sheet, partially, item
Profits	gross profit, net income, gross, gross margin, per share, per diluted, decrease, profit, operating expense, primarily due, press release, balance sheet, risk uncertainty, thank join, chief financial
Debt	facility, debt, cash flow, credit facility, credit, service, balance sheet, good morning, capital expenditure, acquisition, liquidity, bad debt, pay, reduce, morning
Advertising	free cash, digital, free, advertising, medium, local, station, network, radio, political, tv, ad, national, show, news
Cash flow	second half, free cash, segment, basis point, improvement, cash flow, decline, good morning, guidance, free, operating profit, order, outlook, offset, run rate
Banks	billion, environment, guidance, sort, goldman sachs, bank america, morgan stanley, outlook, view, return, trend, reflect, make sure, bank, decline
Payment	payment, card, transaction, bank, volume, account, credit card, credit, merchant, service, digital, mobile app, mobile, process, pay
Life insurance	insurance, agent, claim, life, premium, loss, policy, group, reserve, ratio, operating income, life insurance, experience, annuity, title
Insurance premium	loss, ratio, premium, auto, claim, commercial, property, book, write, state, loss ratio, underwriting, cat, trend, write premium
Sales force	sale force, force, gold, production, mine, project, copper, cash flow, grade, mining, ounce, silver, resource, development, sale rep
Housing	home, community, ppp, land, gross margin, housing, average, basis point, sell, gross, order, closing, demand, entry level, buyer
Natural gas	gas, natural gas, natural, volume, asset, distribution, pipeline, project, capacity, contract, system, storage, unit, cash flow, producer
Crude oil	barrel, crude, oil, gulf coast, project, crude oil, coast, refinery, barrel per, gulf, per barrel, turnaround, west coast, volume, lng
Raw material	volume, material, raw material, raw, demand, segment, capacity, pricing, specialty, inventory, offset, production, plant, packaging, industry
Number	two, three, good morning, amp, five, four, six month, six, yeah, morning, non, please proceed, hi, inaudible, two three
States/cities	new york, state, california, york, water, city, new jersey, florida, texas, jersey, san, facility, massachusetts, location, pennsylvania
Currency	double digit, currency, digit, constant currency, single digit, basis point, single, mid single, double, constant, foreign exchange, foreign, emerge market, top line, foreign currency
M&A	acquisition, organic growth, organic, basis point, tax, guidance, tax rate, earning per, operating income, adjust, cash flow, eps, per share, segment, effective tax
Credit risk management	loan, credit, portfolio, charge, loss, charge off, reserve, bank, provision, branch, off, asset, core, basis point, consumer
Loans	loan, basis point, deposit, balance sheet, mortgage, commercial, bank, portfolio, asset, average, yield, ratio, commercial real, banking, noninterest
Mortgage	portfolio, asset, loan, credit, billion, equity, mortgage, book, book value, agency, per share, return, spread, balance sheet, debt
Surgery	patient, launch, commercial, hospital, procedure, physician, clinical, medical, fda, treatment, approval, device, center, team, guidance
Clinical trials	patient, study, phase, datum, dose, program, treatment, disease, trial, phase ii, phase iii, clinical, iii, ii, safety

(Table A1 continued)

Topic Label	Topic Keywords
Pharmaceuticals	clinical, trial, development, program, clinical trial, fda, drug, vaccine, therapy, partner, cell, therapeutic, regulatory, potential, study
Cancer	cancer, patient, cell, datum, tumor, combination, dose, clinical, cohort, trial, lung, therapy, oncology, pd, study
Education	student, school, program, education, university, enrollment, campus, course, online, learning, college, academy, training, graduate, institution
Health care	health, care, health care, member, patient, hospital, medical, medicare, provider, service, healthcare, program, guidance, model, system
Share repurchase	share repurchase, repurchase, dividend, capital allocation, shareholder, cash flow, per share, buyback, return, stock, free cash, earning per, program, share buyback, allocation
Investment	client, fee, asset, equity, fund, firm, activity, service, volume, trading, global, compensation, private, private equity, balance sheet
Retail/consumer goods	brand, consumer, category, retail, food, channel, pet, distribution, innovation, volume, retailer, launch, portfolio, marketing, segment
Brand/store	brand, store, inventory, gross margin, consumer, retail, category, holiday, commerce, channel, wholesale, gross, season, apparel, digital
Dealership	dealer, vehicle, retail, unit, car, inventory, industry, wholesale, sell, model, consumer, demand, brand, launch, gross
Merchandise	store, basis point, comp, gross margin, category, merchandise, gross, inventory, distribution center, average, traffic, comparable store, week, comparable, program
Operation/ inventory	gross margin, gross, inventory, demand, second half, operating expense, mix, design, sequentially, ramp, guidance, design win, win, capacity, lead
Power generation	oil, oil gas, gas, activity, energy, service, equipment, pressure, pump, industrial, pricing, middle east, sequentially, rig count, order
Global/ international	north america, america, north, europe, north american, china, asia, global, region, latin america, around world, american, international, world, asia pacific
Supply chain	supply, supply chain, chain, demand, inventory, challenge, supplier, gross, team, deliver, global, labor, constraint, shortage, disruption
Government contract	contract, government, federal, state, service, award, cash flow, agency, pipeline, federal government, sign, division, pat, state local, agreement
Offshore drilling	rig, mexico, contract, offshore, gulf mexico, international, drilling, gulf, activity, rig count, drill, john, count, capex, inspection
Financial measure (GAAP)	non gaap, gaap, non, cloud, guidance, measure, financial measure, press release, cash flow, good afternoon, investor relation, reconciliation, per share, website, afternoon
EBITDA	ebitda, adjust ebitda, adjust, adjusted ebitda, adjusted, gaap, measure, non gaap, segment, acquisition, financial measure, net income, guidance, non, press release
Construction	project, backlog, construction, segment, service, infrastructure, activity, pipeline, job, award, bid, sector, group, building, billion
Presentation	slide, turn slide, presentation, show, slide presentation, page, highlight, target, balance sheet, portfolio, key, chart, debt, return, cash flow
Miscellaneous1	nine month, nick, dennis, september, hong kong, keith, nine, asc, partly offset, hong, kong, per diluted, date, unusual item, accounting standard
Testing/ diagnostics	test, testing, audio gap, audio, diagnostic, lab, gap, volume, assay, gene, laboratory, dna, sample, molecular, order
Building/space	indiscernible, ph, square foot, square, development, foot, space, lease, building, sell, asset, transaction, complete, phase, block
Miscellaneous2	fiscal, fy, calendar, puerto rico, segment, decrease, anticipate, partially offset, diluted, operating income, puerto, offset, rico, partially, reflect

Internet Appendix for

"Does Partisanship Affect Mutual Fund Information Processing? Evidence from Textual Analysis on Earnings Calls"

Wanyi Wang
December 2024

Appendix I.A.1 Additional textual analysis details

1.1 Understanding the LDA output

To explore the relationship between LDA topics, I employ two machine learning methods to construct a taxonomy and visualize the topic outputs, following the methodology of Bybee et al. (2024) and Liu, Sheng, and Wang (2024). First, I use hierarchical agglomerative clustering to automatically construct a taxonomy of topics. The result, presented in Figure 2, shows how semantically similar topics are grouped into broader categories. For example, topics such as "mining", "agriculture", "truck/transportation", "drilling", "airlines", and "marine" are clustered together, suggesting a focus on mining and transportation. Similarly, topics like "losses", "profits", "debt", "advertising", and "cash flow" are grouped, indicating a focus on financial matters. The intuitive and economically meaningful structure of the taxonomy validates the topic model's quality.

To further understand the semantic relationships between topics, I use multidimensional scaling (MDS, Torgerson, 1958), a dimensionality reduction method that preserves the original high-dimensional distances between topics in a two-dimensional representation. The output, shown in Figure 3, represents each circle as a topic, with circle size indicating the topic's size and the distance between circles reflecting the semantic similarity between topics. Panel A displays all 70 topics, while Panel B focuses on a more concentrated area within the dashed box.[25] The graph also reveals that semantically similar topics, such as "mining",

[25] Four topics ("testing/diagnostics", "building/space", "miscellaneous1", and "miscellaneous2") are outliers, as they are distant from other topics. This pattern is also consistent with the taxonomy shown in Figure 2.

"drilling", and "agriculture", tend to cluster together. This observation aligns with the taxonomy in Figure 2, further validating the quality of the LDA model.

Overall, this section provides a comprehensive characterization of the topic model, offering a deeper understanding of the content discussed during earnings calls. The findings demonstrate the ability of LDA to uncover a wide range of topics and reveal intuitive, economically meaningful relationships among them.

1.2 Validating partisan-sensitive topics

In this section, I test validating whether the text-based measures accurately quantify firms' exposure to partisan-sensitive issues.

First, I validate the LDA-based measures using external benchmarks. I compare them with firm fundamentals and measures from the literature, and find that LDA-based measures effectively capture discussions on partisan-sensitive topics in an economically meaningful way.

In Table A5 Panel A, I validate the pandemic topic. I first examine the relationship between the pandemic topic weight and firm performance indicators. Since Covid negatively impacted businesses, it is reasonable to expect that firms devoting more time to discussing the pandemic topic would have lower profitability and return on assets (ROA). The results in columns (1) and (2) support this hypothesis. Additionally, I compare the LDA measure with the measure developed by Hassan et al. (2023), which quantifies firms' exposure to the Covid outbreak based on the frequency of disease mentions in earnings calls. As shown in column (3), the strong positive correlation between the two measures validates the LDA-based measure's ability to capture firms' exposure to the pandemic.

In Table A5 Panel B, I validate the climate change topic. I compare the LDA-based method with the measure developed by Sautner et al. (2023), which uses a machine learning keyword discovery algorithm to capture firms' attention to climate change exposure. If the LDA-based method accurately captures climate change related discussions, we would expect a strong positive correlation between the two measures. Indeed, the correlation between the LDA-based climate change topic weight and the external measure is 0.71. Regression results also confirm that the relationship holds across firm characteristics and fixed effects.

Next, since no existing measures validate the healthcare and pharmaceutical topics, I examine the industry distribution of partisan-sensitive topics, considering varying levels of exposure across industries to pandemic, climate change, and healthcare issues. Table A6 reports the top 10 industries by average weight for each partisan-sensitive topic. Panel A shows that sectors such as agriculture, healthcare, restaurants/hotels/motels, and medical equipment have the highest weights on the pandemic topic, aligning with economic intuition.[26] Panel B presents the industry distribution for the climate change topic, where utilities, construction, electrical equipment, and coal have the highest weights, consistent with their strong ties to energy production and consumption.[27] The finding also matches industry patterns observed in prior studies (Li et al., 2024; Sautner et al., 2023). Panels C and D show similar analyses for the pharmaceutical and healthcare topics, revealing intuitive patterns: the pharmaceutical products industry has the highest attention to the pharmaceutical topic, while the healthcare industry has the most exposure to the healthcare topic. These results reinforce the credibility of the LDA-based measure and its ability to accurately quantify firms' exposure to partisan-sensitive topics.

Taken together, results in this section provide strong evidence supporting the reliability and validity of the LDA-based partisan-sensitive topic (PST) index in quantifying firms' exposure to pandemic, climate change, and healthcare issues.

[26] For example, the agriculture sector faces supply chain disruptions, the healthcare sector experiences increased demand for medical services, and the restaurants/hotels/motels sector is impacted by government lockdown orders.

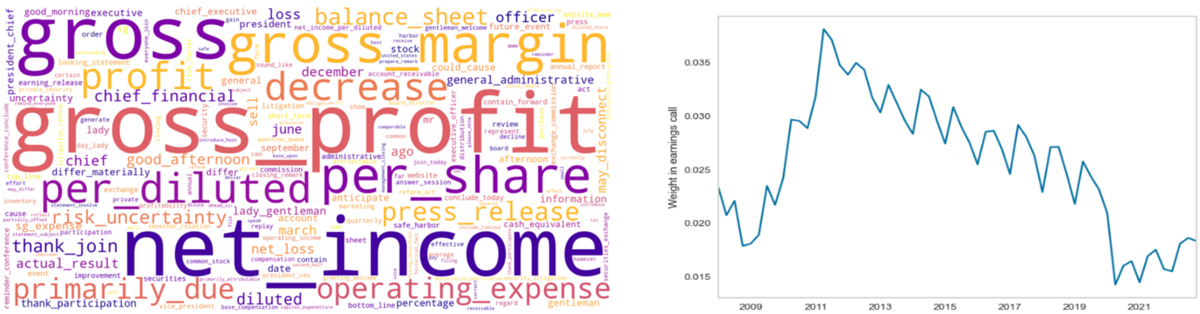
[27] For instance, the utilities and construction sectors play a crucial role in energy generation and distribution, while the electrical equipment and coal industries are directly impacted by the transition to cleaner, renewable energy sources.

Appendix I.A.2 Additional figures and tables

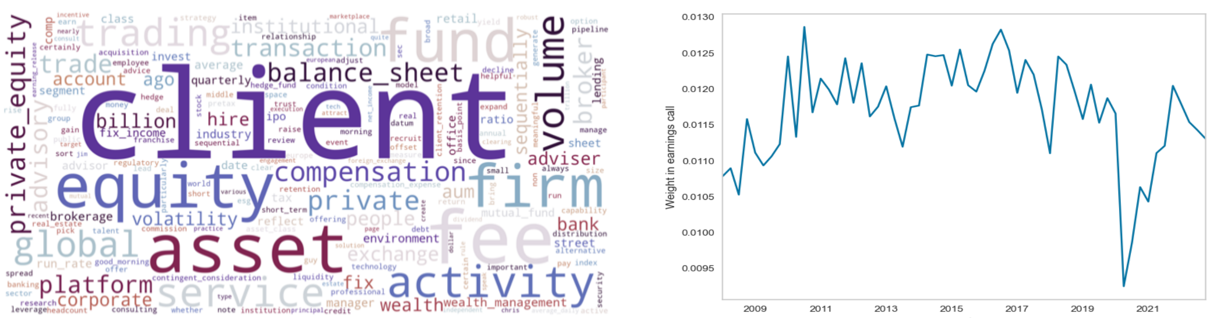
Figure A1. Keywords and time trends of placebo topics

This figure displays the keywords and time trends of the average weight assigned to placebo topics. Panel A presents the profits topic, Panel B represents the investment topic, Panel C shows the supply chain topic, and Panel D illustrates the raw material topic.

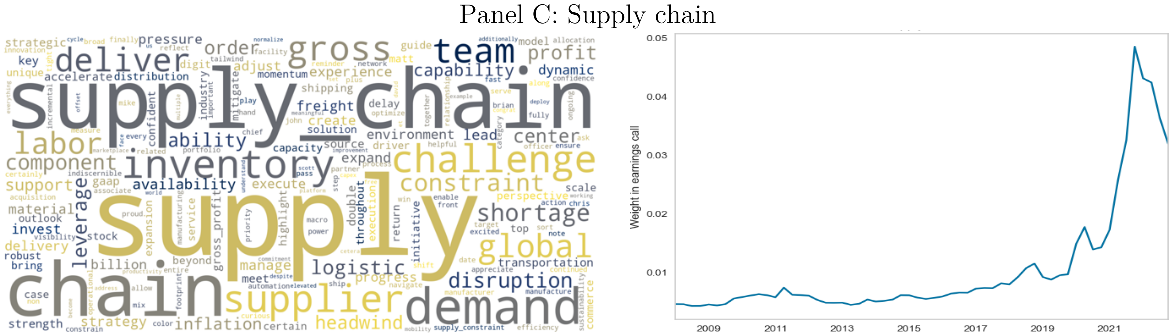
Panel A: Profits



Panel B: Investment



Panel C: Supply chain



Panel D: Raw material

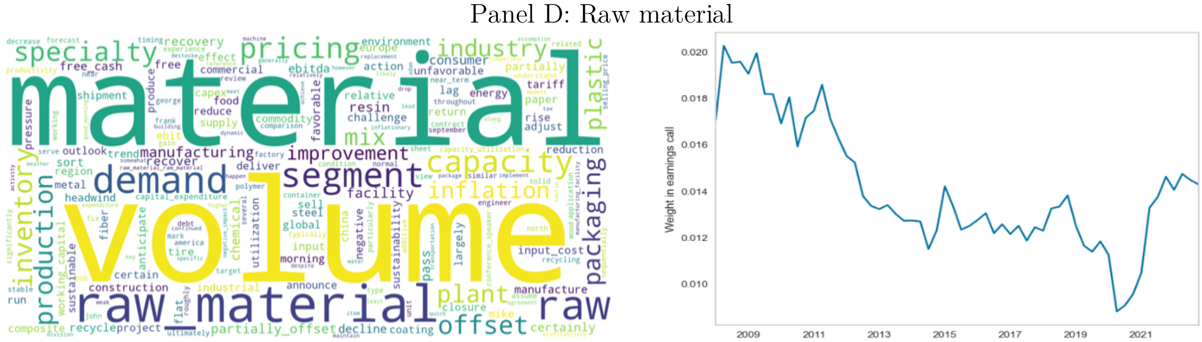


Table A1. Snippets of transcripts with highest partisan-sensitive topic weights

This table presents text snippets from earnings call transcripts with the highest weights on each partisan-sensitive topic, along with the company name, earnings call date, topic weight, and example sentences discussing the topic. Panel A-D show the pandemic, climate change, pharmaceutical, and healthcare topics, respectively.

Company	Earnings Call Date	Topic Weight	Sentence snippets
Panel A: pandemic topic			
Robert Half International Inc.	Jul 23, 2020	57.8%	• Robert Half's second quarter results were clearly affected by the economic crisis resulting from the COVID-19 pandemic, most acutely in our staffing business. • Since the start of the pandemic, we have prioritized the health and safety of our employees and virtually all our global staffing and Protiviti employees have been working remotely. • Only a few short months ago, we discussed our operations in an unprecedented candidate constrained labor market. In 1 quarter's time, we're now operating in a labor market with unprecedented unemployment levels.
UniFirst Corporation	Jul 01, 2020	52.2%	• During the quarter, our revenues were mostly impacted by customer closures related to the Coronavirus pandemic as well as related reductions in workforce for customers who remained open. • We incurred additional costs related to certain employee compensation programs we instituted during the quarter, also discussed by Steve. • As of last week, our weekly revenues were down about 8% from pre-pandemic run rates, primarily related to customer locations that remained closed.
Cross Country Healthcare, Inc.	May 05, 2021	50.2%	• The pandemic has resulted in higher average company costs associated with the significant personal risk each of our frontline workers faces. • Average bill rates for travel nurses peaked in February and have since declined approximately 10%, and are projected to continue to decline as we work with clients to normalize rates as COVID subsides. • Throughout 2021, we expect to see recovery in those areas hardest hit by COVID, such as locum tenants and education.
Panel B: climate change topic			
Alliant Energy Corporation	Aug 07, 2014	87.0%	• In addition to our progress in transforming our Tier 1 units, we are also making progress of preparing our Tier 2 units to be compliant with the utility Mercury and air toxic standards by April 2015 deadline. • We are currently installing low-cost emission controls at our Prairie Creek and Burlington generating stations since they continue to burn coal, and we are converting our M.L. • EPS Clean Power Plan would require states to develop plans to reduce greenhouse gas emissions from existing power plants by 2030. [...] At the same time, we are focused on economically meeting the energy and capacity needs of our customers.
Xcel Energy Inc.	May 02, 2013	86.7%	• As you might recall, last year, we experienced a very warm first quarter which reduced our earnings by about $0.05 per share. • Earnings earnings at NSP at constant increase $0.01 per share due to new electric and gas rates implemented in Colorado or in January and cooler weather. • We've seen I think some I would say wide variety of opportunities of evaluating the wind and the fossil bids.
Ameren Corporation	Nov 04, 2016	84.7%	• This earnings increase reflected higher electric sales to residential and commercial customers, driven by warmer summer temperatures. • When completed, these 3 MISO multi-value projects will deliver significant customer and community benefits such as improved reliability and access to cleaner energy, including wind power from the Western and Northern parts of MISO region, including Northeast Missouri. • We also plan to pursue potential local and regional transmission opportunities to upgrade the grids to maintain system voltages and reliability is generating plants close in response to power market economics of the Clean Power Plan. [...] These opportunities include investments in smart meter, replacement of aging substations and other equipment, modernizing the underground grid and transmission as well as adding renewables.

Company	Earnings Call Date	Topic Weight	Sentence snippets
Panel C: Pharmaceutical topic			
Vical Inc.	Feb-17-2009	55.7%	• In a related significant development this year, last week was the failure of the anti-viral drug Mirabavir [ph] to achieve the primary or the key secondary endpoints in its phase 3 trial. [...] We believe this failure highlights the continuing need for a vaccine to address the shortcoming of the current treatments for this high-risk patient population. • In the fourth quarter we received $1 million milestone payment from Merck related to the start of a new phase 1 cancer vaccine trial. • We also announced a $1.3 million Dengue vaccine program to the US Navy and US Army that will involve contract manufacturing, regulatory and clinical support.
Nabi Biopharmaceuticals	Nov-05-2009	52.7%	• We successfully closed the sale of PentaStaph to GSK and received $21.5 million with an opportunity to receive an additional $26 million contingent on four milestone accomplishments. • We received a $10 million grant from the National Institute on Drug Abuse to partially fund the first NicVAX Phase III trial. • More importantly, we advanced our discussions with potential strategic partners to further develop and commercialize NicVAX. • The SPA, along with the scientific advice, significantly reduces our regulatory risk for the NicVAX program.
Dyadic International, Inc.	Nov 10, 2022	52.6%	• Hopefully, what Joe and I have been able to share with you today is how Dyadic is working to expand and accelerate our monetizable opportunities across our core business segments to focusing our business development efforts on those business segments that are scientific advancements have the greatest ability to drive results.
Panel D: Healthcare topic			
Bright Health Group, Inc.	Nov 11, 2021	75.1%	• We are raising guidance on our end-of-year fiscal year 2021 Bright Health Care membership from 650,000 to 700,000, an increase of nearly 8%, which gives us confidence in the upper end of our prior revenue range. • The strong membership growth to date demonstrates our ability to take share in competitive markets and highlight the appeal of our aligned and integrated model in consumer-driven markets like IFP and Medicare Advantage. • We believe we are well [indiscernible] with our planned pricing in 2022 to gain members and continue to deliver affordable health care while improving margins.
Agilon Health, Inc.	Oct 29, 2021	49.2%	• Starting with our membership growth rate for the third quarter, total members live on the agilon platform increased 83% on a year-over-year basis to 237,000, including both Medicare Advantage and Direct Contracting. • Utilization during the third quarter of this year was in line with our expectations, with higher COVID costs offset by lower utilization of impatient and skilled nursing services. • The year-over-year decline in network contribution reflects the impact COVID had on our prior year medical margin as well as the relative contribution of medical margin across our geographies.
1Life Healthcare, Inc.	May 12, 2021	48.3%	• We saw a record number of net new membership additions in the quarter, as our dedicated team continued to serve our members and communities with service-oriented and value-based high quality care. • Our value proposition continues to resonate in the market as we demonstrate our unique ability to attract and delight members while simultaneously reducing health care costs. • And really, they value helping small employers not only get great health care but manage their total cost of care, and they've seen the impact that our model can make on not only delighting consumers with their high NPS, digital health and in-person care, but also on reducing the total cost of care.

Table A2. Main result on a continuous holding sample

The table presents the main result in two alternative settings. In Column (1), I calculate *ΔFundOwn* and *ΔPST* by subtracting only the values of quarter t-1 from those in quarter t. In Column (2), I examine a continuous holding sample, where a fund maintains ownership of a stock in consecutive quarters. Therefore, changes in fund ownership of a stock and partisan-sensitive topic weights are also calculated by subtracting the quarter t-1 values from those in quarter t. The dependent variable is the change in fund ownership of a stock from quarter *t-1* to quarter *t* (*ΔFundOwn*). *ΔPST* represents the change in weights on partisan-sensitive topics in earnings calls from quarter *t-1* to quarter *t*. *Net Dem* measures the degree to which a mutual fund leans Democratic, calculated as *(#Dem - #Rep)/#Total managers*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*), fund characteristics (*Ln(fund size), Fund age, Expense ratio, Management fee, Fund turnover*). Please see Appendix A for variable definitions. Industries are defined as Fama-French 48 industries. Standard errors are clustered at the fund level. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Only subtract quarter t-1 from quarter t	(6) Continuous holding sample
ΔPST × Net Dem	**-0.0081***** **(-2.98)**	**-0.0234***** **(-3.93)**
Controls	Y	Y
Fund*Qtr FE	Y	Y
Firm*Qtr FE	Y	Y
Fund*Firm FE	Y	Y
R^2	0.243	0.333
N	4518213	1967067

Table A3. Partisan-sensitive topics and earnings call sentiment

This table presents the relationship between weights assigned to partisan-sensitive topics and overall sentiment expressed during earnings calls at the firm-quarter level. The dependent variable is *Overall Sentiment*, calculated as (#positive words - #negative words)/#total words within a transcript, and subsequently standardized. *PST* represents the weight on partisan-sensitive topics in earnings calls. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*). Please see Appendix A for variables definitions. Industries are defined using Fama-French 48 industries. Standard errors are double clustered at firm and quarter levels. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
PST	**-0.7388****	**-0.5976***	**-1.6386*****	**-1.7651*****
	(-2.26)	**(-1.99)**	**(-5.01)**	**(-5.41)**
Constant	-0.1056***	-1.4025***	0.0833	-0.0492
	(-2.74)	(-6.78)	(0.24)	(-0.15)
Controls		Y	Y	Y
Firm FE			Y	Y
Qtr FE			Y	Y
FF48 × Qtr FE				Y
R^2	0.006	0.081	0.487	0.517
N	88120	81937	81836	81794

Table A4. Partisan-sensitive topic weights and stock returns

This table presents the relationship between stock performance and exposures to partisan-sensitive issues at the firm-quarter level. The dependent variable is $R_{i,t+1}$, the return of stock *i* in quarter *t+1*. *ΔPST* is the change in weights on partisan-sensitive topics in earnings calls in quarter *t*. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*). Please see Appendix A for variables definitions. Industries are defined using Fama-French 48 industries. Standard errors are clustered at the quarter level. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
ΔPST	**0.0370**	**0.0608**	**0.0284**	**0.0139**
	(0.25)	**(0.39)**	**(0.84)**	**(0.69)**
Ln(1+ME)		-0.0029**	-0.0757***	-0.0737***
		(-2.19)	(-9.29)	(-10.14)
B/M		0.0416***	0.0293***	0.0358***
		(3.14)	(2.82)	(4.02)
ROA		0.3773*	0.6748***	0.6817***
		(1.97)	(9.43)	(10.77)
Profitability		0.1418***	0.2961***	0.3361***
		(3.51)	(4.17)	(5.94)
Firm FE			Y	Y
Qtr FE			Y	Y
FF48 × Qtr FE				Y
R^2	0.000	0.012	0.367	0.442
N	77466	71938	71832	71761

Table A5. Measure validation

This table validates the text-based measures using external benchmarks at the firm-quarter level. Panel A validates the pandemic topic, while Panel B validates the climate change topic. In Panel A, *Covid Exposure*, a measure from Hassan et al. (2023), is computed by counting the number of Covid-related synonyms in a transcript and dividing it by the total number of sentences in the transcript. In Panel B, the dependent variable is *Climate change exposure*, a measure developed by Sautner et al. (2023), which captures the frequency of climate-change-related bigrams scaled by the total number of bigrams in the transcript. Control variables include firm characteristics (*Ln(1+ME), B/M, ROA, Profitability*). Please see Appendix A for variables definitions. Industries are defined using Fama-French 48 industries. Standard errors are double clustered at firm and quarter levels. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A. Validate Pandemic-related topic

	(1)	(2)	(3)
	ROA	Profitability	Covid Exposure
Pandemic	**-0.011****	**-0.026*****	**3.367*****
	(-2.31)	**(-3.31)**	**(10.70)**
Ln(1+ME)	0.010***	-0.001	-0.023**
	(19.31)	(-0.81)	(-2.19)
B/M	-0.003***	-0.026***	0.000
	(-2.97)	(-12.32)	(0.02)
ROA			-0.001
			(-0.00)
Profitability			0.035
			(0.33)
Firm FE	Y	Y	Y
Industry × Qtr FE	Y	Y	Y
R^2	0.630	0.839	0.724
N	87937	81844	76467

Panel B: Validate climate-change-related topics

	(1)	(2)	(3)
Climate change	**8.675*****	**8.531*****	**8.694*****
	(24.44)	**(24.68)**	**(11.54)**
Ln(1+ME)		-0.026***	-0.008
		(-3.23)	(-0.86)
B/M		-0.049*	-0.051**
		(-1.86)	(-2.19)
ROA		1.520***	-0.319*
		(5.83)	(-1.99)
Profitability		-1.352***	0.186
		(-7.39)	(1.50)
Firm FE			Y
Industry × Qtr FE			Y
R^2	0.499	0.505	0.793
N	79149	73693	73504

Table A6. Industry distribution of partisan-sensitive topics

This table presents the top 10 industries for partisan-sensitive topics, where industries are defined by Fama-French 48 industries. I calculate the average weight for each topic by industry, and report summary statistics at the firm-year level. Variable definitions are provided in Appendix A.

	Mean (%)	**STD (%)**	**N**
Panel A: Pandemic			
Agriculture	3.95	6.00	73
Healthcare	3.70	7.58	1589
Restaurants, Hotels, Motels	3.28	6.86	1771
Medical Equipment	3.23	6.36	2699
Personal Services	3.06	6.95	1078
Business Services	3.12	7.07	10841
Real Estate	3.02	6.23	609
Entertainment	2.92	6.05	1168
Defense	2.84	5.96	170
Printing and Publishing	2.74	6.02	323
Panel B: Climate change			
Utilities	38.33	19.49	3162
Construction	3.39	6.63	1646
Electrical Equipment	2.83	4.94	1185
Almost Nothing	2.55	6.53	858
Coal	2.25	2.91	230
Candy & Soda	1.57	2.94	202
Measuring and Control Equipment	1.15	3.08	1862
Shipbuilding, Railroad Equipment	1.02	1.92	376
Steel Works Etc	0.96	2.27	1179
Machinery	0.86	2.11	3130
Panel C: Pharmaceuticals			
Pharmaceutical Products	11.25	8.64	5059
Medical Equipment	2.01	4.09	2699
Rubber and Plastic Products	1.50	3.32	468
Tobacco Products	1.30	1.54	134
Healthcare	1.21	2.90	1589
Measuring and Control Equipment	1.12	2.40	1862
Trading	0.41	2.21	3022
Business Service	0.36	1.80	10841
Candy & Soda	0.28	0.64	202
Chemicals	0.21	0.67	2045
Panel D: Healthcare			
Healthcare	20.10	11.05	1589
Insurance	4.42	10.03	3426
Wholesale	1.69	4.56	3238
Business Service	1.41	3.70	10841
Medical Equipment	1.28	2.34	2699
Personal Service	1.15	2.55	1078
Business Supplies	1.10	2.10	633
Pharmaceutical Products	1.08	1.95	5059
Rubber and Plastic Products	1.01	1.76	468
Computers	0.64	2.32	2212