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

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Abstract

This paper examines the influence of partisanship on mutual fund information processing at the firm level. Through textual analysis of earnings call transcripts, I identify discussions on partisan-sensitive topics, such as climate change, pandemic, and healthcare. I find that Democratic-leaning funds react more strongly to topics aligned with Democratic beliefs and trade more stocks after firms increase discussions on these topics compared to Republican funds. The effect is stronger for funds with greater polarization and firms with larger weights in fund portfolios. Moreover, the observed pattern does not improve fund performance, indicating that the effect is driven by non-financial considerations rather than rational expectations about future stock returns. Overall, these finding suggest that partisan funds react stronger to information consistent with their pre-existing beliefs.

Keywords: Partisanship, Political polarization, Mutual fund, Climate finance, Pandemic, Healthcare finance, Textual analysis, Machine learning.

JEL classification: G11, G23, G41.

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1 Introduction

Political polarization has been on the rise in recent years, with widening divisions between Democrats and Republicans on a broad range of issues. This polarization has extended into the realm of finance, as increasing evidence suggests that investors' political beliefs affect their investment decisions (Kaustia and Torstila, 2011; Sheng, Sun and Wang, 2023). Among various investor groups, institutional investors, particularly mutual funds, play a crucial role in financial markets. While existing literature has examined the impact of partisanship on mutual funds' portfolio holdings, such as sin stocks, stocks with similar political affiliations, high-beta stocks, and international capital allocation (Hong and Kostovetsky, 2012; Wintoki and Xi, 2019; Cassidy and Vorsatz, 2021; Kempf et al., 2023), it remains unclear whether and how partisanship influences mutual funds' information processing at the firm level.

In this paper, I examine the relation between partisanship and mutual fund firm-level information processing by comparing whether Democratic and Republican funds respond differently to firms' exposures to partisan-sensitive issues, such as climate change, healthcare, and the COVID pandemic. This question is important for several reasons. First, it speaks to factors that influence investment decisions beyond traditional financial metrics. By understanding how political beliefs influence investment decisions, we can gain a deeper understanding of the broader societal and political context within which financial decisions are made. Second, given the influential role of institutional investors in financial markets, it could create potential risks for investors and the overall economy if partisanship influences their investment decisions. Finally, by identifying any potential biases that may arise from partisan influences, policymakers and investors can work to mitigate these biases.

To measure mutual fund partisanship, I infer fund managers' political leaning based on individual-level political donations (Hong and Kostovetsky, 2012; Vorsatz, 2022; Sheng, Sun, and Wang, 2023). Using a comprehensive dataset provided by Federal Election Committee (FEC), I filter out donations made by fund managers and classify a manager as a Democrat or a Republican based on whether the manager's contribution favors one party over the other. Then, the net political leaning of a mutual fund is determined by the composition of Democratic and Republican managers within the fund's team.

To examine the impact of partisanship on mutual fund information processing, it is crucial to identify the specific *information* that may trigger divergent responses among funds with varying political leanings. This involves a two-step approach: 1) identifying issues typically associated with partisan disagreements; and 2) quantifying the extent to which individual firms are exposed to these issues. However, it is often challenging to execute the two steps. For one thing, political disagreements encompass a wide range of topics, such as climate change, gun control, and immigration policy, making it difficult to identify the most concerning issues to firms and investors. For another, comprehensive firm-level data on their specific exposure to these issues is often lacking.

To address these challenges, I conduct textual analysis on quarterly earnings conference call transcripts to construct time-varying measures that capture the nature and extent of partisan-sensitive issues faced by individual companies. Earnings conference calls serve as a valuable platform for firms to communicate performance, strategy, and future prospects to analysts and investors. By analyzing transcripts, we can gauge the level of attention given to particular issues in these calls. If a firm is increasingly exposed to a particular issue, it is reasonable to expect that call participants will discuss it more extensively. Thus, I quantify a firm's exposure to partisan-sensitive topics by assessing the weight given to these issues in earnings calls at a point in time. This approach follows recent studies that utilize earnings calls as a source to identify firms' exposures to hard-to-measure issues (Hassan et al., 2019; Sautner et al, 2023).

In the absence of strong priors on which partisan-sensitive topics are frequently discussed during earnings calls, I adopt a data-driven approach and employ an unsupervised machine learning algorithm known as Latent Dirichlet Allocation (LDA).[2] Using over 80,000 earnings calls transcripts between January 2008 and June 2022, I train an LDA model with 70 topics.[3] It summarizes earnings calls into a distribution of topics, where topic weights represents the relative importance of topics during earnings calls. I then identify each of the 70 topics using keywords of the LDA model. To explore the relation between topics, I construct a taxonomy and a visualization of the topic model using two additional machine learning techniques. Taken together, I provide a comprehensive characterization of topics of interest to investors and analysts, and quantify the attention firms allocated to these topics.

To identify specific partisan-sensitive topics in earnings calls, I combine LDA topics with survey data. Using the American Trends Panel survey by Pew Research Center (2020), I sort subjects Americans perceive as critical issues in the U.S. by the degree of partisan disagreement, and then overlay these issues with topics generated by the LDA model. Using this two-step approach, I identify the following partisan-sensitive topics frequently discussed in earnings calls: "pandemic" (related to the severity of Covid), "climate change" (associated with the issue of climate change), and "healthcare" and "pharmaceuticals" (connected to healthcare affordability concerns). I then define the Partisan-Sensitive Topics (PST) index as the sum of weights on these topics to measure the overall attention paid to partisan-sensitive topics during earnings calls. I validate the PST index through a series of tests. First, I show that the measure demonstrates meaningful variation across industries, aligned

[2] LDA is a topic modeling approach that helps identify latent themes or topics within a collection of documents. It achieves this by estimating the probability distribution of words across these topics and the probability distribution of topics across documents. LDA has gained significant popularity in the finance and economic literature and has proven successful in a range of financial contexts (Hansen, McMahon and Prat, 2018; Liu, Sheng and Wang, 2021).

[3] A 70-topic model is the model that yields the most coherent topic modelling output. In section 3.2, I provide detailed explanations on how the optimal number of topics is determined.

with existing literature. I also compare the measure with firm fundamentals and external measures, and find consistent correlations that support the accuracy of the PST index in quantifying firms' exposure to relevant issues.

After verifying the measure, I explore the connection between mutual fund partisanship and information processing at the firm level. Specifically, I analyze whether Democratic and Republican funds have different trading behaviors, as reflected by their changes in fund holdings, in response to variations in firms' exposure to partisan-sensitive issues. The results reveal that when a firm increases its discussions on partisan-sensitive issues that Democrats hold more negative views about, such as the pandemic, climate change, and healthcare, Democratic funds are more inclined to sell their stock shares compared to Republican funds.[4] The economic magnitude of this effect is substantial. For a mutual fund consisting of Democratic managers only, a 1% rise in the weight assigned to partisan-sensitive topics is associated with a 14% decrease in the fund's ownership of the stock compared to the average fund ownership change. The relation continues to hold after including an exhaustive set of firm-level and fund-level controls, and remains robust when accounting for high-dimensional fixed effects (FE), including fund, firm, quarter FEs, and even fund-by-quarter, firm-by-quarter, and fund-by-firm FEs in some specifications. These FEs absorb all time-invariant and time-varying characteristics of both funds and firms, whether observed or unobserved, as well as any potential effects arising from fund-firm pairings. These findings suggest that partisanship is related to how mutual funds process firm-level information.

[4] One might be concerned about the tone companies use when discussing partisan-sensitive issues, considering the potential positive or negative context. For instance, companies like Pfizer gained from the pandemic due to vaccine development, so expecting Democratic funds to divest from Pfizer due to increased pandemic discussions might not be reasonable. To address this, I explore how sentiment aligns with weights assigned to partisan-sensitive topics, and find that companies with higher weights on partisan-sensitive topics tend to adopt a more negative tone overall, indicating a generally pessimistic stance. Further, I introduce a more nuanced approach by constructing a topic-level sentiment measure, and show that incorporating contextual sentiment yields consistent results.

Next, I examine how the partisan effect vary across different groups of mutual funds and portfolio companies. First, I analyze whether the differential trading responses between Democratic and Republican funds are more pronounced among fund managers 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 exhibit a stronger reaction to partisan-sensitive topics, providing support for the hypothesis that the effect is indeed driven by partisanship. Also, I explore if the partisan effect varies with the importance of individual stocks in fund portfolios. As funds hold numerous stocks, their attention paid to a certain company's earnings calls may be limited. Therefore, I expect a more pronounced effect for companies with higher weights in the fund's portfolio, as a result of greater attention from fund managers. Empirical tests also confirm this prediction.

Taken together, the analyses above support the argument that partisan disagreement on controversial issues contributes to differential trading responses between Democratic and Republican funds. This difference can either be attributed to differences in funds' belief updating regarding firms' risk exposure to these issues or differences in their expectations for future cash flows. For example, when a firm increases its discussions on partisan-sensitive issues that Democrats consider more significant (such as the Covid pandemic), Democratic funds may develop more pessimistic beliefs about the firm's future cashflows or perceive a higher level of risk exposure to the pandemic compared to Republican funds. Consequently, these factors result in a lower stock valuation and a more pronounced selling behavior.

After documenting the partisan effect in mutual fund trading responses to partisan-sensitive issues, an interesting follow-up question is whether the effect is due to *rational expectation* about future returns or *non-financial considerations*. The *rational expectation* explanation states that Democratic funds sell stocks more because they accurately foresee that firms with heightened exposure to partisan-sensitive issues will underperform in the future. In this case, these trades should add value to the fund. On the contrary, the *non-financial consideration* explanation posits that Democratic funds' response is not based on beliefs about future stock returns. In this scenario, these trades should not generate profits for Democratic funds. To distinguish between the two explanations, I construct a measure to assess whether a trade adds value to a fund. This measure involves multiplying a mutual fund's trading of a stock in quarter t by the return of the stock in quarter $t+1$. I then replace the dependent variable in the main regression with this new measure. Regression results show that Democratic funds do not profit from trading in response to firm exposure to partisan-sensitive issues. This finding confirms the non-financial consideration story, but contradicts the rational expectation explanation.

Next, to establish the robustness of the finding, I test several alternative explanations. The first concern is that particular fund characteristics associated with partisanship might confound how funds react to earnings call contents. To address this concern, I control for fund characteristics using interaction terms, and show that these characteristics do not explain the main finding. The second alternative scenario is that the result could be due to mutual funds catering to their investors' preferences. Democratic funds may react stronger to partisan-sensitive topics to curb potential outflows from Democratic investors. To rule out this story, I control for the partisanship of fund investors using the political leaning of the state in which the fund is headquartered (Hong and Kostovetsky, 2012), and show that funds catering to investor preferences does not drive the main result. The third alternative explanation relates to the strategic disclosure of firms in earnings calls, where CEOs may adjust discussions based on their shareholders' political leanings or their own political affiliations. This strategic adjustment could introduce measurement errors in assessing the weights on partisan-sensitive topics. To address this concern, I filter out a subset of companies with an equal mix of investors representing both political sides, as well as a subset of companies with non-partisan CEOs. I confirm that the main result continues to hold on both samples. The last possibility is that the text-based measure from earnings calls might reflect not only firms' actual exposure to partisan-sensitive issues, but also investors' pre-existing concerns about these issues, as call participants may raise more questions about these issues during the Q&A session. To address this, I repeat the main analysis on the presentation session of earnings calls, and show that the results continue to hold. Taken together, these results reinforce the overall reliability of the main findings.

Finally, I perform a number of robustness checks. First, I conduct a placebo test on LDA topics without partisan disagreement. The intuition is that, if the differential response of partisan funds is indeed due to partisanship, there would be no effect on topics without partisan disagreement. This hypothesis is supported by empirical tests. Second, I consider an alternative measure that does not separate the "pandemic/crisis" topic of the LDA model, and demonstrate that the main results remain robust. Finally, I implement a perturbation test by excluding one topic at a time from the partisan-sensitive topic (PST) index, and show that the main result is not driven by any individual topic.

This paper contributes to several strands of literature. First, it contributes to the literature on how partisanship affects financial market participants (Kaustia and Torstila, 2011; Hutton, Jiang and Kumar, 2014; Giuli and Kostovetsky, 2014; Jiang, Kumar and Law, 2016; Cookson, Engelberg and Mullins, 2020; Dagostina, Gao and Ma, 2020; Kempf and Tsoutsoura, 2021; Meeuwis et al., 2022; Zhang, 2022; Kempf et al, 2023; Sheng, Sun and Wang, 2023; Wu and Zechner, 2024). Focusing on mutual funds, Hong and Kostovetsky (2012) show that fund managers who make campaign donations to Democrats hold less of their portfolios in companies that are deemed socially irresponsible. 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 (2021) find that Republican mutual fund teams actively purchase more equity, especially in high beta industries, before and after the 2016 Presidential election. Different from aforementioned 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*, and documents that funds respond more strongly to information more consistent with their political beliefs.

This paper also 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 (Hassen et al., 2019), corporate culture (Li et al., 2021a; Li et al., 2021b), epidemic exposure (Hassen et al., 2021), supply chain risk (Wu, 2022), and climate exposure (Sautner et al., 2020; Li et al., 2020; Chava, Du and Malakar, 2021; Dzieliński et al., 2022; Jaunin and Terracciano, 2022). This paper contributes to the literature by providing a *complete characterization* of topics of interest to investors, analysts, and other market participants. As noted in Hassen et al. (2019), "any issue raised during an earnings call will tend to be of some concern either for 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 potentially be explored for other research questions.

2 Data and Measurement

This section provides an overview of the data and measures used in the empirical analysis. Section 2.1 describes the data sources. Section 2.2 explains the methodology employed to infer fund partisanship based on the political contributions of fund managers. Section 2.3 presents summary statistics for the key variables utilized in the study.

2.1 Data

To construct the main dataset, I combine data from various sources. I start 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 keep 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 average within each fund. I further restrict the sample to domestic equity funds, given that the paper focuses on earnings calls conducted by U.S. public companies. Additionally, index funds are excluded from the sample, as this paper examines the impact of fund managers' political beliefs on portfolio holdings.

Next, to infer mutual fund partisanship, I hand-collect a dataset of political donations made by mutual fund managers. I first download a list of U.S. open-end mutual funds from Morningstar, which 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 contribution records from Federal Election Committee (FEC). Section 2.2 details the matching process. I am able to identify 1,630 fund managers with at least one donation record between 1980 and 2021. The sample is as least comparable to, if not larger than, the size of 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 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 filter out political donations made by mutual fund managers, I combine a list of fund manager names from Morningstar with individual political donations from Federal Election Committee (FEC).[5] The data contains information on the contributing individual's name, employer, occupation, the contribution's date, amount, and the committee receiving the contribution. I first match by fund managers' first and last names, and then use middle names, employer names, and occupation to rule out incorrect matches.[6]

[5] This data is publicly available on FEC website. The method used to include contributions in this dataset has changed 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 is over $200 from 2015 to present.

[6] Specifically, I first drop observations with inconsistent middle names if the information is available in both datasets. Then, I perform textual analyses to match employer names, given that the employer information in the FEC dataset is self-reported. To facilitate the process, I first pre-process employer names by removing punctuations, extra blank spaces, and common company suffixes. I then compare the similarity of firm names in both datasets and keep observations with a similarity score above 60%. Finally, I manually check all remaining match based on occupation, zip code, and other information that can be used to infer the political contributor's identity to ensure accurate matches between both datasets.

To infer fund manager partisanship, I label the political leaning of each political donation record. Since each donation is made to a political action committee (PAC) rather than an individual, I classify the political leaning of the donation based on the receiving PAC's party affiliation. Specifically, if the money goes to a committee already registered with a party, I use the party affiliation to label the donation. Otherwise, I infer the committee's political leaning based on how the PAC spends its money. Following Vorsatz (2022), a committee is labeled as leaning towards Republican (Democrat) if it spends more than 2/3 on Republican (Democratic) candidates.

Next, I use fund managers' political donations in the past 10 years to infer their political leanings at any point in time.[7] By focusing only on donations in the 10 years preceding the measurement, I avoid forward-looking bias and allow the political leaning of a fund manager to vary over time. Consequently, a fund manager is classified as a Democrat if she donated more to the Democratic party, a Republican is she donated more to the Republican party, and a non-partisan if she donated the same amount to both parties or if she donated to committees with no clear party affiliations.

Lastly, I aggregate fund manager partisanship to the fund level. I first calculate the proportion of Democratic- and Republican-leaning managers in a mutual fund team, and 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

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

$\#Total\ Managers_{i,t}$ 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 following analysis.

2.3 Summary statistics

Table 1 presents the summary statistics for main variables used in the empirical analysis. At the fund level, an average fund exhibits 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 of these funds stand at 0.65% and 1.1%, 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 the Republican party, 0.13 managers favoring the Democratic party, 0.07 managers identifying as non-partisans, and the remaining 2.60 managers being non-donors. At the firm level, an average portfolio company exhibits 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 hold 0.15% ownership of a stock on average, and a typical fund includes 311 assets in its portfolio.

3 Partisan-sensitive discussions 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 earnings calls, I perform textual analysis on earnings call transcripts. Specifically, I utilize an unsupervised machine learning method known as Latent Dirichlet Allocation (LDA), proposed by Blei, Ng, and Jordan (2003). LDA has gained popularity in the finance and economic literature and has been successfully applied in various contexts. For instance, researchers employ LDA on FOMC transcripts (Hansen, McMahon and Prat, 2018), business news (Bybee et al., 2023), employee reviews (Sheng, 2022), and crypto whitepapers (Liu, Sheng and Wang, 2021). 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 is particularly suitable for this study for at least two reasons: first, its unsupervised nature means that one does not need to have extensive prior knowledge about the specific topics of interest. Since there is no predefined set of topics for partisan-sensitive discussions, LDA can automatically identify topics based on word patterns and distributions in the documents. Second, instead of focusing on a single concept, LDA has the ability to discover multiple underlying topics. Considering the diverse range of topics discussed during earnings calls, LDA provides a comprehensive understanding of topics 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 corpus of documents and the desired number of topics.

To construct the corpus, I transform each transcript into a bag-of-words representation. I apply standard preprocessing procedures prior to transformation, including tokenization, removing stop words, converting words to original forms (i.e. lemmatization), and forming bigrams (i.e. common two-word phrases). The resulting bag-of-words representation is created by counting the frequency of each word within each transcript.

To determine the optimal number of topics, a range of LDA models is trained using different numbers of topics, specifically 10, 20, ..., 90, and 100. Due to the large size of the transcript dataset, LDA models are trained on a 20% random sample of the full dataset. I then evaluate model performance using the coherence value, which measures the semantic coherence of words within a topic and indicates interpretability and meaningfulness of topics (Röder et al., 2015). A higher coherence value means that the words within a topic are more related and provide a clearer thematic interpretation. The results, illustrated in Figure 1, indicate that a 70-topic model achieves the best performance, yielding the most coherent output. Consequently, the 70-topic LDA model is chosen as the optimal model and applied to the entire transcript dataset.

3.2 Understanding LDA output

In this section, I explore in detail the output generated by the trained LDA topic model. The output comprises two components: the distribution of terms for each topic and the distribution of topics for each transcript. It is important to note that LDA does not automatically label the topics it learns, and researchers often manually assign labels to LDA topics to enhance interpretability. In line with this convention, I use top keywords to label each topic by referring to relevant literature (Bybee et al., 2023), conducting online searches, and drawing from my own expertise. Appendix B presents the label and top 15 keywords of each topic. The output suggests that LDA identifies coherent topics with good interpretability. 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".

To further explore the relationship between topics, I employ two additional machine learning techniques to construct a taxonomy and a visualization of topic outputs, following the methodology in Bybee et al. (2023) and Liu, Sheng, and Wang (2023). First, I use hierarchical agglomerative clustering to automatically construct a taxonomy of topics. The resulting output is presented in Figure 2, which displays 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, and topics like "losses", "profits", "debt", “advertising”, and “cash flow” are grouped together, indicating a focus on matters related to finances. The intuitive and economically meaningful nature of the taxonomy further validates the quality of the topic model.

To gain further insights into the semantic relationship between topics, I employ 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 is presented in Figure 3. Each circle represents a topic, with the size of the circle indicating the topic’s size, and the distance between circles reflecting the distance between topics. Panel A displays all 70 topics, while Panel B zooms in on a more concentrated area within the dashed box.[8] The graph also shows that semantically similar topics tend to be close to each other, as observed with the proximity of topics like “mining”, “drilling”, and “agriculture”. This finding reinforces the patterns observed in the taxonomy in Figure 2, further affirming the quality of the LDA model.

Taken together, results in this section provide a comprehensive characterization of the topic model, offering a deeper understanding of the contents discussed during earnings calls. The findings highlight the ability of LDA to uncover a diverse range of topics and reveal intuitive and economically meaningful relationships between them.

3.3 Identifying partisan-sensitive topics

To examine the impact of partisanship on mutual fund information processing, it is crucial to identify discussions in earnings calls that are associated with political disagreements. However, not all topics identified by LDA exhibit sensitivity to partisan viewpoints. To filter out partisan-sensitive topics, I refer to the American Trends Panel survey conducted by Pew Research Center in 2020. The survey posed the following question: “How much of

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

a problem do you think each of the following are in the country today?" Ten issues considered in the survey are as follows: 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 get an idea of the extent of partisan disagreement on these issues, I aggregate survey responses based on the political leanings of participants and rank the issues accordingly. The results are depicted in Figure 4. Among these issues, climate change exhibits the largest partisan disagreement, with over 90% of Democrats considering it a very big or moderately big problem, while only 32% of Republicans share the same perspective. Other issues that exhibit notable partisan disagreements include minority treatment by the justice system, illegal immigration, Covid severity, and healthcare affordability. By overlaying these issues with the topics identified through the LDA model, I am able to identify partisan-sensitive topics that are frequently discussed during earnings calls.

The first identified topic, referred to as the "pandemic/crisis" topic, closely relates to Covid severity. As shown in Figure 5 Panel A, this topic encompasses keywords such as "pandemic, demand, environment, employee, recovery", and witnessed a significant surge in discussions in 2020.[9] Another identified topic, the "climate change" topic, aligns with the issue of climate change. As illustrated in Figure 5 Panel B, it consists of keywords such as "energy, utility, solar, power, renewable, gas, wind". These keywords overlap significantly with the top-10 bigrams captured by climate change exposure in Sautner et al. (2023).[10]

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

[10] 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.

Additionally, the topics of "healthcare" and "pharmaceuticals" are connected to the issue of 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 suggest that these topics received heightened attention during periods when the Democratic party took office and during the health crisis period.

To comprehensively capture the overall attention given to partisan-sensitive topics in earnings calls, I aggregate the previously mentioned topics and introduce an index called the Partisan-Sensitive Topics (PST) index. It is defined as the sum of the weights assigned to the individual topics, namely:

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

The combined weights assigned to these topics collectively indicate the aggregate 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 on the pandemic topic, 2% on the climate change topic, 1% on the healthcare topic, and 0.9% on the pharmaceutical topic during earnings calls. Collectively, these partisan-sensitive topics account for approximately 6% of the aggregate attention received in earnings calls. Besides, Table A1 in the online appendix presents short snippets of transcripts with the highest weights on each partisan-sensitive topic, demonstrating how firms' exposure to these topics are discussed in earnings calls.[11]

[11] For example, during its July 2020 conference call, UniFirst Corporation acknowledged that "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," providing tangible evidence of the pandemic's adverse effects on the company. Similarly, Alliant Energy Corporation noted 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," underscoring the challenge of balancing regulatory mandates with the company's financial imperatives.

3.4 Validating partisan-sensitive topics

In this section, I conduct a series of validation tests to establish the effectiveness of the text-based measure in accurately quantifying firms' exposure to partisan-sensitive issues.

First, I examine the industry distribution of these topics, considering the varying degrees of exposure of industries to pandemic, climate change, and healthcare issues. Table 2 reports top 10 industries of the average weight on each partisan-sensitive topic. Panel A shows that sectors such as agriculture, healthcare, restaurants/hotels/motels, and medical equipment have the highest weight on the pandemic topic, aligning with the economic intuition.[12] Panel B presents the industry distribution of the climate change topic. The industries with the highest weights on this topic are utilities, construction, electrical equipment, and coal. This is also consistent with intuition, as these industries are closely linked to energy production and consumption.[13] The finding also match the industry patterns observed in prior studies (Li et al., 2022; Sautner et al., 2023). Similar analyses are conducted for the pharmaceutical and the healthcare topic in Panel C and D, which also reveal intuitive patterns. The pharmaceutical products industry has the highest attention allocated to the pharmaceutical topic, while the healthcare industry demonstrates the highest exposure to the healthcare topic. These results strengthen the credibility of the text-based measure and its ability to accurately quantify firms' exposure to partisan-sensitive topics.

Next, I use external benchmarks to further validate LDA-based measures. I compare with both firm fundamentals and measures from the literature, and show that LDA-based measures indeed capture discussions related to partisan-sensitive topics in an economically meaningful way.

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[12] For instance, the agriculture sector is affected by supply chain disruptions, the healthcare sector by increased demand for medical services, and the restaurants/hotels/motels sector by government lockdown orders.

[13] The utilities and construction sector, for example, plays a crucial role in the generation and distribution of energy, while the electrical equipment industry and coal industry are directly impacted by the transition to cleaner and renewable energy sources.

In Table 3 Panel A, I validate the pandemic topic. I first investigate the relation between the pandemic topic weight and firm performance indicators. Given the adverse impact of Covid on businesses, it is reasonable to expect that firms devoting more time to discussing the pandemic topic would exhibit lower profitability and return on assets (ROA). The empirical results in columns (1) and (2) support this hypothesis. Furthermore, I compare my measure with the epidemic exposure measure developed by Hassen et al. (2022), which quantifies firms' exposure to the Covid outbreak based on the frequency of disease mentions in earnings calls. A strong positive correlation between the two measures would indicate the accuracy of my pandemic topic measure. The finding in column (3) confirms this correlation.

In Table 3 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 the attention paid to firm climate change exposures. If the LDA-based method accurately captures climate change related discussions, we should expect a strong positive correlation between the two measures. Indeed, there is a robust positive correlation of 0.71 between the climate change topic weight and the climate change exposure measure. Regression-based analyses also confirm that the relation is robust to firm characteristics and various fixed effects.

Taken together, the results in this section provide robust 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. I then link PST with mutual fund partisanship and fund holdings to understand whether partisanship affect mutual funds' processing of firm-level exposure to partisan-sensitive issues.

4 Results

4.1 Baseline result

In this section, I analyze the relation between partisanship and mutual fund firm-level information processing. Specifically, I investigate whether Democratic and Republican funds exhibit distinct trading patterns, as indicated by changes in their fund holdings, in response to changes in firm exposures to partisan-sensitive issues, such as climate change, healthcare affordability, and the Covid pandemic. These exposures are measured by topic weights on partisan-sensitive issues during earnings calls. To conduct this analysis, 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.[14] In cases where fund holdings in quarter *t-1* are unavailable or if fund *f* does not report stock i in quarter *t-1* holdings, I use the most recent non-zero fund holdings of the stock.[15] I use fund ownership rather than portfolio weights, because ownership solely depends on the fund's active trades of a particular stock (Chen, Jegadeesh, and Wermers, 2000), while portfolio weights can be influenced by stock price movements as well as the buying and selling of other stocks in the portfolio. $\mathit{\Delta PST}_{i,t}$ captures the change in weights assigned to

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

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

[15] To establish robustness, Table A1 in the online appendix considers a continuous holding sample, wherein a fund maintains ownership of a stock in consecutive quarters. As a result, the calculation of changes in fund ownership of a stock and changes in partisan-sensitive topic weights always involves subtracting the values from quarter t-1. The main results continue to hold in the continuous holding sample.

partisan-sensitive topics (PST) in firm *i*'s earnings calls during quarter t, relative to PST weights when the firm was last held by the fund. I use the change rather than a level variable to capture the effect of new information on mutual fund stock trading. $Net\ Dem_{f,t}$ 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-market ratio, ROA, and profitability) and fund characteristics (fund size, fund age, expense ratio, management fee, and fund turnover). Standard errors clustered at the fund level.

The key coefficient of interest in equation (3) is β_1, which captures whether there are differing responses between Democratic and Republican funds when faced with changes in exposures to partisan-sensitive topics. Given that issues like the Covid pandemic, climate change, and healthcare affordability are frequently advocated as serious problems by the Democratic party, their potential impact on companies are generally viewed more negatively by Democratic supporters. Therefore, it is reasonable to expect a more negative response from Democratic funds, as reflected by more selling, when companies are increasingly exposed to these issues (indicated by $\beta_1 < 0$). However, one might be concerned about whether companies discuss these issues in a positive or negative context. To illustrate, Pfizer profited significantly from the pandemic due to vaccine development, so it does not make sense to expect Democratic funds to divest from Pfizer in response to heightened discussions on the pandemic topic.

To address this concern, I delve into the relationship between weights assigned to partisan-sensitive topics and the sentiment expressed during earnings calls. I compute the net sentiment of an earnings call as the percentage of positive words minus the percentage of negative words within a transcript, using the Loughran and McDonald (2011) dictionary. The findings, presented in Table A2, reveal that companies with larger aggregate weights assigned to partisan-sensitive topics exhibit a more negative overall tone during their earnings calls, suggesting that firms generally adopt a pessimistic stance when discussing such topics. However, one might still worry whether the overall sentiment of an earnings call truly reflect the sentiment related to a specific topic. To tackle this consideration more carefully, I introduce a nuanced approach. In section 4.5, I develop a sentiment measure at the topic level. I supplement the Partisan Sensitivity Index (PST) with the sentiment of each individual topic, and show that the finding remains robust with this refined analysis.

The regression results of equation (3) are presented in Table 4. The coefficient on the interaction term ($\Delta PST_{i,t} \times Net\ Dem_{f,t}$) is negative and statistically significant at 1% level. This finding implies that when a firm experiences an increase in its exposure to partisan-sensitive issues that Democrats hold more negative views about, Democratic funds are more inclined to sell off their stock shares compared to Republican funds. Furthermore, the economic impact of this effect is substantial. In column 1, the coefficient derived from the univariate regression is -0.0103 (with a t-statistic of 3.25). This indicates that for a mutual fund team comprised entirely of Democrats (i.e., Net Dem = 1), a 1% rise in the weight assigned to partisan-sensitive topics is associated with a 0.0001% reduction in the fund's ownership of the stock. While this percentage may initially appear small, it represents a considerable 14% decrease compared to the average fund ownership change of 0.00073%.[16]

In Table 4 column 2, I include firm-level and fund-level control variables to explore whether these characteristics may account for the observed univariate result. I observe that certain characteristics affect fund trading behavior. For instance, larger funds and younger funds are associated with more substantial changes in mutual fund holdings. However, the coefficient on the interaction term remains negative and statistically significant, indicating that the partisan effect persists and is not explained by these control variables.

[16] 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 4 column 3, I further control for fund, firm and quarter fixed effects. By including fund fixed effects, I account for any time-invariant factors that are common to a specific fund, such as the fund's headquarter location or its investment category (e.g., whether it is categorized as an ESG fund). Firm fixed effects, on the other hand, capture time-invariant firm characteristics, such as the industry in which the firm operates. This is particularly relevant as the industry could influence the topics discussed by firms during earnings calls. Lastly, quarter fixed effects absorb general economic trends that might drive 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 significantly negative, suggesting that the result cannot be attributed to fund-, firm-, or time-level invariant factors.

In Table 4 column 4, I employ an even more stringent specification by including fund-by-quarter fixed effects in the regression. This approach effectively absorbs all time-varying fund characteristics, both observed and unobserved. By doing so, it addresses any concern that other fund characteristics associated with partisanship may directly influence mutual fund trading behavior. Since the regression operates at the fund-firm-quarter level, we can still identify the coefficient on the interaction term. Importantly, the main result continues to hold, indicating that the partisan effect on mutual fund trading is not explained by other fund characteristics related to partisanship.

In Table 4 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 negative and significant. This helps alleviate the concern that unobservable firm characteristics, which may be correlated with the topic distribution in earnings calls, might confound the main result.

Finally, in Table 4 column 6, I consider the strongest specification by incorporating fund-by-firm fixed effects in the regression. These fixed effects effectively absorb any potential fund-firm pairing effects, including social connections between mutual funds and portfolio companies, time-invariant fund-firm political preference alignment, 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 demonstrate that Democratic funds react more negatively to partisan-sensitive issues that Democrats advocate as significant concerns, and tend to sell more stocks following firms' increased discussion on these topics in earnings calls. This relationship remains robust, even after controlling for various control variables and employing a comprehensive set of fixed effects. These findings suggest that partisanship plays a 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 various subgroups of 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 more pronounced among funds managers with more polarized political beliefs. To assess the level of polarization, I classify a fund manager as a strong or a weak partisan based on the proportion of contributions to a single party, consistent with prior literature (Vorsatz, 2022). Specifically, a fund manager is labeled as a "strong Republican (Democrat)" if at least 75% of donations are directed towards the Republican (Democratic) party. Conversely, a fund manager is classified as a "weak Republican (Democrat)" if the contributions towards Republicans (Democrats) fall within the range of 50% to 75%. For the subgroup of strong partisan fund managers, the net political leaning of a mutual fund is *(#Strong Dem - #Strong Rep)/#Total managers*. Similarly, for weak partisan managers, the net political leaning of a fund is *(#Weak Dem - #Weak Rep)/#Total managers*.

The regression results, presented in Table 5 columns (1) - (2), reveal 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 approximately half the magnitude and statistically insignificant. These findings suggest that mutual fund managers with more polarized political beliefs indeed exhibit a stronger reaction to partisan-sensitive topics compared to less polarized fund managers, consistent the argument that partisanship affects mutual fund reactions to earnings call discussions.

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 a large number of stocks in their portfolios, it is plausible that they may not have sufficient attention to devote to the earnings calls of each portfolio company. Thus, it is reasonable to expect that the effect will be more pronounced for firms with higher weights in fund portfolios, as these stocks are likely to 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 ranked by portfolio weights in descending order. The results, presented in Table 5 columns (3) - (4), show that the partisan effect is stronger for stocks ranked higher in the portfolio. Conversely, the coefficient on the lower-ranking subgroup is approximately one-third of its magnitude and only marginally significant at 10% level, consistent with the hypothesis that the partisan effect is more pronounced for firms with higher weights in the portfolio.

Taken together, the analyses above provide support for the argument that partisan disagreement regarding controversial issues contributes to the divergent trading responses between Democratic and Republican funds. This divergence can be attributed to differences in fund belief updating regarding firms' risk exposure to these issues or their future cashflow expectations. For example, when a firm intensifies its discussions on issues that Democrats consider significant (e.g. the Covid pandemic), Democratic funds may develop more negative expectations regarding the firm's future cash flows. They may also perceive a higher level of risk exposure for the firm to the pandemic, in contrast to Republican funds. These factors, in turn, lead to a lower stock valuation and a more pronounced selling behavior. Due to the lack of data on fund-stock-quarter-level risk assessment and cashflow expectations, the paper does not delve into distinguishing between the risk-based and the cashflow-based explanation. However, the subsequent section examines whether the differential trading responses to partisan-sensitive topics can be attributed to rational decision-making or if they are influenced by non-financial considerations.

4.3 Is overselling by Democratic funds rational or not?

The current findings reveal that Democratic funds exhibit a stronger negative reaction to partisan-sensitive issues that align with Democrats' significant concerns, and tend to sell more heavily in response to firms' discussions on these issues. Two potential explanations could account for this behavior. The first explanation is based on *rational expectations*, suggesting that Democratic funds sell more heavily because they accurately foresee that firms with heightened exposure to partisan-sensitive issues will underperform in the near future. If this is the case, these trades should be beneficial for Democratic funds and add value to their overall portfolio. The second explanation revolves around *non-financial considerations*. It proposes that Democratic funds' response may not be based on beliefs about future stock returns, or they might be reacting based on a potentially mistaken belief that these firms will underperform in the future due to their exposure to partisan-sensitive issues. If this is true, Democratic funds would not profit from these trades. To distinguish between the two explanations, it is crucial to understand whether Democratic funds actually benefit from their trading decisions in response to firms' exposure to partisan-sensitive issues.

To quantify mutual funds' profits 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 times the return of the stock in quarter t+1 ($\Delta Weight_{f,i,t} \times R_{i,t+1}$).[17] If a fund sells a stock and the stock price decreases later (i.e. both $\Delta Weight_{f,i,t}$ and $R_{i,t+1}$ are less than 0), or if a fund buys a stock and the stock price increases subsequently (i.e. both $\Delta Weight_{f,i,t}$ and $R_{i,t+1}$ are greater than 0), this measure will be positive. I then use this new measure as the dependent variable and run the following regression:

$$\Delta Weight_{f,i,t} \times R_{i,t+1} = \alpha + \boldsymbol{\beta_1} \Delta PST_{i,t} \times Net\ Dem_{f,t} + \beta_2 \Delta PST_{i,t} + \beta_3 Net\ Dem_{f,t} \\ + Controls_{f,i,t} + FEs + \varepsilon_{f,i,t} \quad (4)$$

where $\Delta Weight_{f,i,t}$ is the change in the weight of stock i in the portfolio of fund f 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' increased exposure to partisan-sensitive issues. The regression results are displayed in Table 6. The β_1 coefficient on the interaction term is negative across all specifications, but not always statistically significant. The results show that Democratic funds do not gain benefits and may even lose money from trading based on firms' exposure to partisan-sensitive issues. This finding contradicts the rational expectation explanation and supports the notion that mutual fund information processing is influenced by the non-financial considerations of fund managers.

Another approach to distinguish between the two explanations is to examine the performance of portfolio companies. By determining whether firms actually underperform after facing increased exposure to partisan-sensitive issues, we can also gain valuable insights

[17] For example, if a fund with \$1 million asset under management (AUM) reduces the holding of 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 $\frac{(\$5000 - \$10000) \times (-10\%)}{\$1,000,000} = 0.05\%$.

into whether the selling behavior of Democratic funds is driven by rational expectations or non-financial motives. 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 are reported in Table A2 in the Internet Appendix. The coefficient on ΔPST is statistically insignificant across all columns, also suggesting that firms with increased exposure to partisan-sensitive topics do not experience lower returns in the following quarter. Consequently, Democratic funds would not profit from selling these stocks more heavily than Republican funds. Again, this finding is consistent with the non-financial consideration explanation, but inconsistent with the rational expectation story.

4.4 Alternative explanations

While a comprehensive set of control variables and fixed effects have already been included in the main regression, there could still be other factors that might confound the main result. In this section, I explore four non-mutually-exclusive alternative explanations to provide robustness for the main analysis.

4.4.1 Are the results explained by a particular fund characteristic?

The first alternative explanation is that the observed partisan effect may be attributed to other fund characteristics associated with mutual fund partisanship. While the *direct* impact of fund characteristics on mutual fund trading has been addressed through the inclusion of fund-by-quarter fixed effects, it 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 a more significant influence on portfolio companies. If they disapprove of a firm's earnings calls, they might choose to express their opinions through proxy voting (monitoring with hands) rather than selling off the company (monitoring with feet). Thus, if Republican funds tend to be larger funds in general, their weaker trading responses to partisan-sensitive topics may be attributed to size rather than political beliefs.

To address this concern, I incorporate interaction terms between fund characteristics and partisan-sensitive topics (PST) 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 are presented in Table 7. The finding suggests that fund size is related to how funds react to partisan-sensitive topics, as indicated by the significant coefficient of ΔPST $\times$ Ln(1+fundsize) in column (5). However, the inclusion of these interaction terms does not affect the coefficients on the primary variable of interest, ΔPST $\times$ Net Dem, suggesting that the main result is not merely capturing the effects of other mutual fund characteristics, but rather reflects the actual impact of partisanship.

4.4.2 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 be due to their inherent preference but rather because they cater to the preferences of fund investors. For instance, Democratic-leaning investors might be averse to increased exposure to issues that the Democratic party advocates as significant problems, such as climate change, healthcare affordability, and the pandemic. Consequently, these investors might withdraw their money if they perceive that the funds they support do not adequately respond to such critical issues. Meanwhile, it is possible that Democratic funds are more likely to attract Democratic investors, especially since investors often exhibit a preference for local funds due to local bias (Bailey et al., 2011). To prevent outflows, these Democratic funds might adjust their portfolio holdings, reducing investments in firms with increased discussions on partisan-sensitive topics. In this scenario, changes in fund holdings are not driven by the political attitudes of the fund managers, but by the preferences of the fund's investors.

To investigate this alternative explanation, I follow Hong and Kostovetsky (2012) and utilize the political leaning of the state in which the mutual fund is headquartered to control for the partisanship of fund investors. The underlying assumption is that if a fund's clients are mainly local, the political leaning of the state in which the fund is headquartered can serve as a proxy for the political values of the clientele. To measure the state-level political leaning, I construct *state Dem vote*, the Democratic voting share in the state where the fund is headquartered during the most recent presidential election before the earnings call. I then introduce an interaction term between *state Dem vote* and *PST* in the main regression to account for the influence of local investors' preferences on mutual funds' response to earnings calls. The regression results, presented in Table 8, show that this new variable does not explain differences in mutual fund trading responses, as the coefficient on *ΔPST × State Dem Vote* is statistically insignificant. Moreover, the coefficient on *ΔPST × Net Dem* remains significant across all specifications, suggesting that this new variable has little impact on the main result. Therefore, the differential trading response between Democratic and Republican funds is not driven by funds' tendency to cater to investor preferences.

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

The third concern arises from the perspective of portfolio companies. So far, the paper assumes that the text-based measures from earnings calls accurately reflect a firm's exposure to partisan-sensitive issues. However, there is a possibility of bias when CEOs strategically adjust the emphasis on these topics based on their shareholder base's political leanings or their own political affiliations. For example, if a company's investors predominantly lean towards the Democratic party during the pandemic, the CEO may carefully navigate discussions related to the pandemic. To prevent panic selling, they might downplay its significance. Conversely, if shareholders express high concern, the CEO might discuss it more. The political leanings of CEOs themselves can also influence the topics discussed in earnings calls. A Democratic CEO might be more inclined to talk about 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 during earnings calls may introduce measurement errors in assessing firms' exposure to partisan-sensitive topics. Consequently, this may lead to biased estimation of the actual partisan effect on mutual fund trading responses to earnings calls.[18]

To address the concern about strategic disclosure influenced by partisan shareholders, I identify a subset of companies that possess a balanced mix of mutual fund shareholders with comparable representation from both political sides.[19] This selection process allows for an examination of the main findings within a controlled setting, reducing external pressures on these companies to selectively disclose information. The regression results are presented in Table 9. To create this subset, I calculate the aggregate holdings of Democratic and Republican mutual funds for each stock in each quarter. I then retain firm-by-quarter observations without partisan holdings or if the ratio of total Democratic holding to total Republican holding falls within the range of 0.8 and 1.2 (i.e. allowing for a margin of error of 20%). While this results in a much smaller sample compared to the entire dataset, the coefficient on the interaction term remains negative and significant at a level of at least 5%. These results address the concern regarding selective information disclosure by portfolio companies to cater to partisan shareholders.

[18] It is possible that the text-based measure does not introduce systematic bias to the main findings, but rather acts as a noisy proxy for firms' exposure to partisan-sensitive issues. In the above example involving the Covid pandemic, since firm CEOs could either downplay or emphasize partisan-sensitive topics, the resulting coefficient could be underestimated but unbiased. In this case, the interpretation of the main finding continues to hold. Nonetheless, I take a conservative approach and run additional tests to examine the strategic disclosure issue more carefully.

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

Next, to mitigate the impact of CEO partisanship on firms' strategic disclosure, I construct another subset of companies whose CEOs have demonstrated non-partisanship by either refraining from making political donations or donating equally to both parties. I use the CEO political contribution data provided by Babenko et al. (2020) to determine the partisanship of firm CEOs, similar to how fund managers' political leanings are inferred in section 2.2.[20] I then exclude firms whose CEOs have ever been classified as partisan in any election cycle, and repeat the main analysis on the remaining sample. The empirical results are presented in Table 10. Notably, the coefficient on ΔPST × Net Dem remains negative and statistically significant across all specifications. Thus, the main finding persists on the non-partisan firm sample, providing reassurance against concerns of potential biased information disclosure due to the personal beliefs of company CEOs.

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

The last concern is that the text-based measure derived from earnings calls might be influenced not only by firms' actual exposure to specific partisan-sensitive issues, but also by investors' pre-existing concerns regarding these issues. For instance, if Democratic investors exhibit stronger concern about climate change, it might manifest during earnings calls through an increased number of questions on this topic. Consequently, the resulting text-based measure, while capturing firms' actual issue exposure, might also mirror investors' specific concerns related to climate change. In such a scenario, the higher weights on the climate change topic in earnings calls and the stronger trading reactions from Democratic funds could both be rooted in investors' pre-established concerns about the company preceding the earnings calls.

[20] A limitation of the Babenko et al. (2020) data is that it only covers the political contributions of CEOs from S&P 1500 firms between 1999 and 2014. Thus, information regarding the political leanings of non-S&P1500 firms and firms listed after 2014 is not available.

To address this concern, I concentrate on the presentation section within earnings calls. This choice is motivated by the fact that call participants have limited influence over the information presented during this segment. Thus, the presentation section offers a more controlled environment where the information is relatively exogenous. I divide transcripts into the presentation section and the subsequent Q&A section after filtering out operator messages, and then calculate the weights of LDA topics independently for both sections. I run the main regression independently on both sections, and report the results in Table 11. As shown in Panel A, the coefficient on *ΔPST × Net Dem* remains negative and statistically significant, suggesting that the main result continues to hold on the presentation section. Consequently, this rules out the concern that the results are due to investors' pre-existing concerns driving the conversation.

In summary, the results presented in this section provide strong evidence that the relation between mutual fund partisanship and their trading responses to firms' exposure to partisan-sensitive issues cannot be attributed to several alternative explanations, including particular fund characteristics, the tendency of funds to cater to investors, firms' strategic disclosure in earnings calls, and investors' pre-existing concerns. These findings further reinforce the overall reliability of the main finding that partisanship plays a role in explaining mutual fund firm-level information processing.

4.5 Sentiment-augmented PST index

While I have already established a negative relation 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 within the calls. In this section, I address this concern by introducing a method to gauge sentiment at the topic level. This approach refines the Partisan Sensitivity Index (PST) by incorporating the sentiment associated with each specific topic.

Developing a topic-level sentiment measure requires a two-step process. The initial step involves identifying keywords associated with each topic, followed by understanding the sentiment encompassing these keyword contexts. However, a measurement challenge arises due to the non-mutually-exclusive nature of LDA topic keywords—frequent terms tend to appear across multiple topics. This makes it difficult to assign keywords to individual topics. To identify distinctive terms for each topic, I adopt the methodology in Sievert and Shirley (2014) and Bybee et al. (2023) and scales topic-term weights by total term frequency:

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

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 words in the corpus, and overweighs terms that are uniquely associated with a particular topic. I then rank words based on the scaled weight ($\tilde{\phi}_{k,w}$), and use the top 100 words as the set of distinctive terms for each respective topic.

The second step involves comprehending the sentiment of the context containing these distinctive terms. Following Hassen et al. (2019), I define "context" as the ten words surrounding the distinctive term on each side. Subsequently, I quantify the net sentiment of this context by calculating the proportion of positive and negative words within, using the Loughran and McDonald (2011) dictionary.[21] This process can be expressed as follows:

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

[21] 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 the 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%.

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. The sentiment of each topic is then derived as the average sentiment across all the contexts associated with distinctive words within that topic. I further normalize the sentiment measure by subtracting the overall sentiment of a transcript from the topic-level sentiment, motivated by the observation that firms often maintain a positive tone during earnings calls, even in the presence of unfavorable news.

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

$$\begin{aligned} Sent\ PST = {} & I(neg) \times Pandemic + I(neg) \times Climate\ change \\ & + I(neg) \times Pharmaceuticals + \ I(neg) \times Healthcare \end{aligned} \tag{7}$$

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 no distinctive term of a topic present within the transcript. In other words, I subtract weights on topics that are discussed positively from topics that are discussed negatively, so that it aligns with the expectation that Democrat funds should respond more negatively to firms' exposure to these issues.

I repeat the main analysis with the sentiment-augmented PST index, and present the result in Table 12. The coefficient on *ΔSent PST × Net Dem* is negative and statistically significant across all specifications, suggesting that the main result continues to hold after taking the topic-level sentiment into account.

4.6 Robustness

In this section, I perform several robustness tests to provide additional evidence supporting the main finding. First, I conduct a placebo test on LDA topics that do not involve partisan disagreement. The rationale is that, if the divergent trading response between Democratic and Republican funds is driven by factors other than partisanship, we should observe similar partisan effect on all topics, not just partisan-sensitive topics. Conversely, if the effect is indeed due to partisanship, there would be no effect on topics without partisan disagreement.

I examine several commonly discussed topics. The first topic is “profits”, since earnings calls primarily provides 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 a company’s operations discussed in earnings calls to help investors and analysts assess the associated potential risks and returns. Additionally, I examine the topics of “supply chain” and “raw material”, as they relate to a firm’s daily operations. Figure A1 shows visualizations of keywords and time trends associated with these topics. Importantly, these topics are not highly polarizing issues. Therefore, they are not typically associated with significant partisan disagreement. The regression results, displayed in Table 13, reveal that the coefficients on $\Delta Topic \times Net\ Dem$ are both economically small and statistically insignificant for the non-partisan-sensitive topics. This finding alleviates the concern that the differential trading response between Democratic and Republican funds is due to factors other than mutual fund political leanings, providing further support for the main finding.

Next, I examine an alternative measure of the pandemic topic. In the main specification, 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 subjective nature of this manual adjustment. To address this concern, I repeat the main analysis without separating the two topics. The regression outputs are presented in Table 14 Panel A. The results indicate that the findings remain robust even in the absence of implementing this separation, indicating that the separation itself does not significantly impact the main result.

Lastly, one might be concerned that the main result could be driven by a single topic in the partisan-sensitive topic (PST) index. To further establish robustness, I conduct a perturbation test that excludes one topic at a time from the PST index. I then re-run the main regression using the new PST index. The results of this test are presented in Table 14 Panel B. Notably, all columns in the table remain statistically significant, indicating that the overall result is not driven by any individual topic.

5 Conclusion

This paper sheds light on the relationship between partisanship and mutual fund firm-level information processing. Applying textual analysis on earnings call transcripts, I document distinct trading patterns between Democratic and Republican funds in response to firms' exposures to partisan-sensitive issues, such as climate change, healthcare, and the Covid pandemic. Specifically, Democratic funds demonstrate a higher inclination to sell off stock shares when firms discuss issues that Democrats hold a more negative view about, whereas Republican funds exhibit lower sensitivity to such issues. The partisan effect is more pronounced in funds with higher political polarization and among firms with greater weights in fund portfolios. Importantly, the overselling behavior observed in Democratic funds does not contribute positively to fund performance, underscoring that the observed pattern is driven by non-financial considerations rather than rational expectations about future returns. I also rule out several alternative explanations, including the influence of particular fund characteristics, fund catering to investors, strategic disclosure by firms during earnings calls, and investors' pre-existing concerns driving the result. Additional robustness tests further validate the findings.

In conclusion, this study presents compelling evidence that partisanship plays a significant role in mutual funds' processing of firm-level partisan-sensitive information. The research emphasizes the importance of considering political beliefs in investment decisions. These findings have practical implications for investors, policymakers, and our broader understanding of the societal context in which financial decisions are made. By recognizing and addressing potential biases arising from partisan influences, steps can be taken to mitigate risks and foster more informed and unbiased investment decision-making.

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

This figure plots the performance of multiple LDA models trained with varying numbers of topics, ranging from 10 to 100. The x-axis represents the number of topics employed in each LDA model, 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, resulting in a more distinct and meaningful thematic interpretation. The findings highlight that the LDA model with 70 topics exhibits the most favorable performance based on the coherence value.

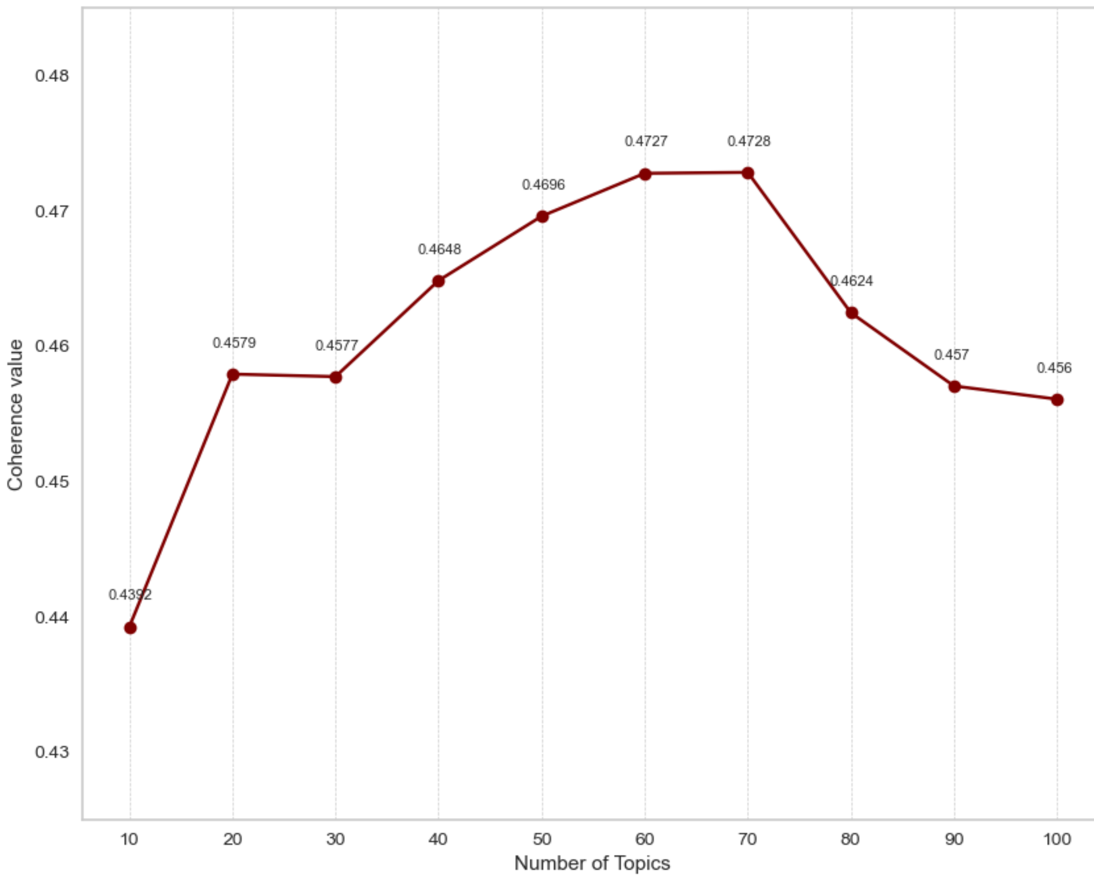


Figure 2. A taxonomy of earnings call topics

This figure presents a taxonomy of LDA topics derived from earnings call transcripts. The taxonomy is generated using hierarchical agglomerative clustering, a machine learning technique that clusters topics based on their semantic similarities to form broader categories. Please refer to Appendix B for a detailed list of keywords associated with each topic.

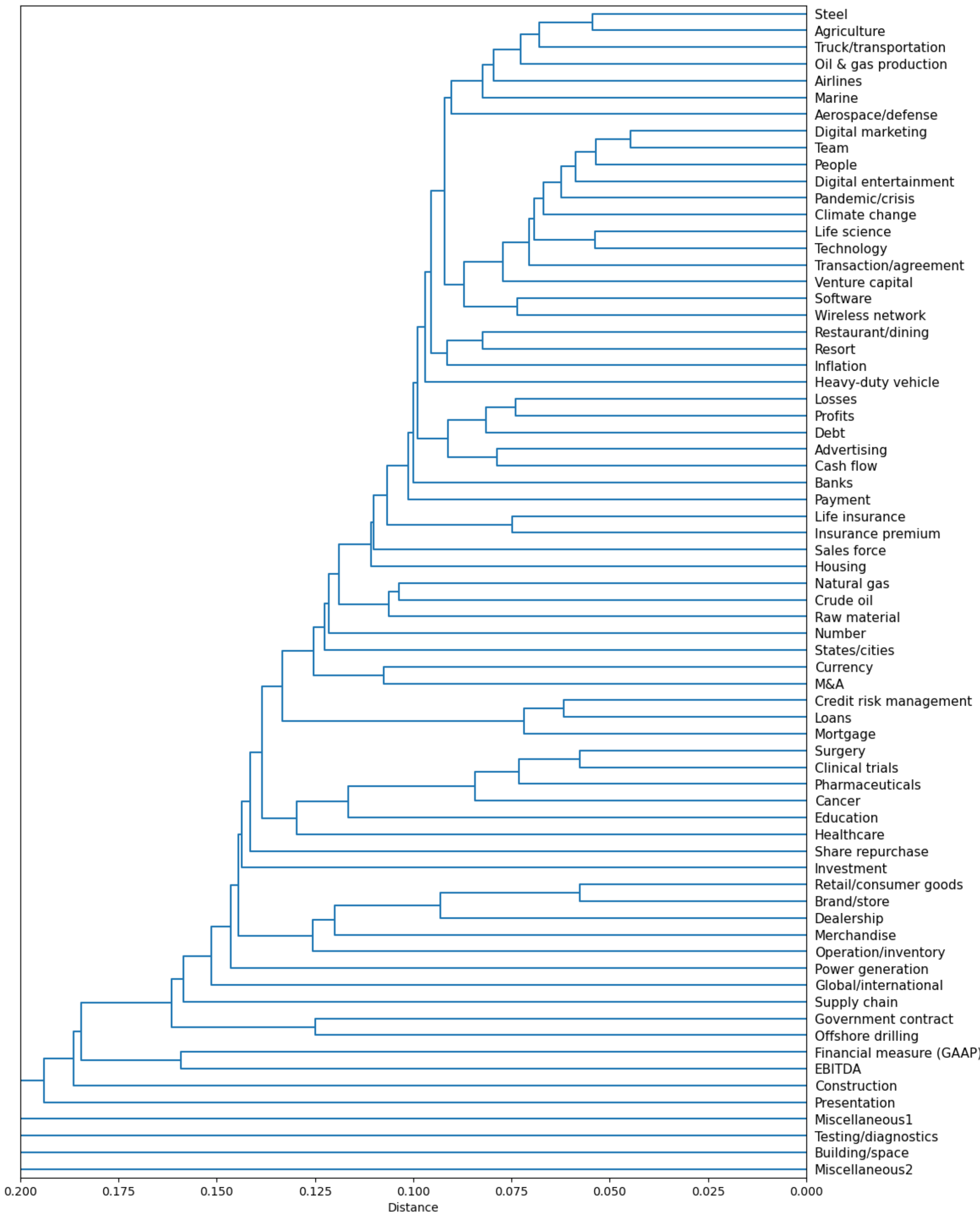
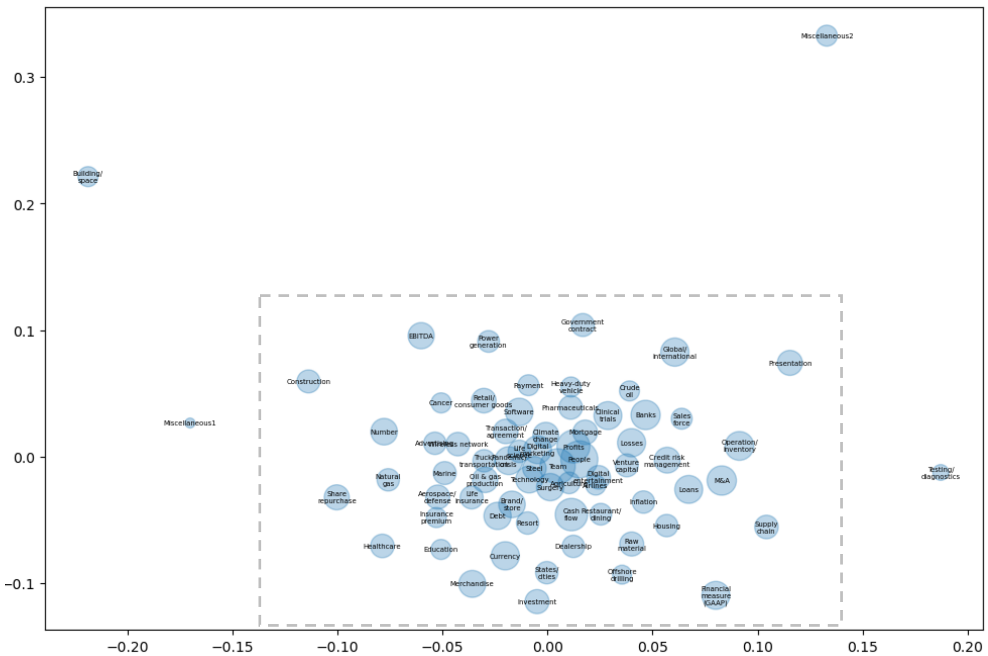


Figure 3. Topic Distance via Multi-Dimensional Scaling

This figure plots the semantic relation between topics using multi-dimensional scaling, a dimensionality reduction technique that preserves the original high-dimensional distances between topics in a 2D layout. Each circle represents a topic, with circle size indicating topic size and distance reflecting semantic distance. Panel A shows all 70 topics. Panel B zooms in on the more concentrated area within the dashed box.

Panel A: 70 topics



Panel B: exclude outliers

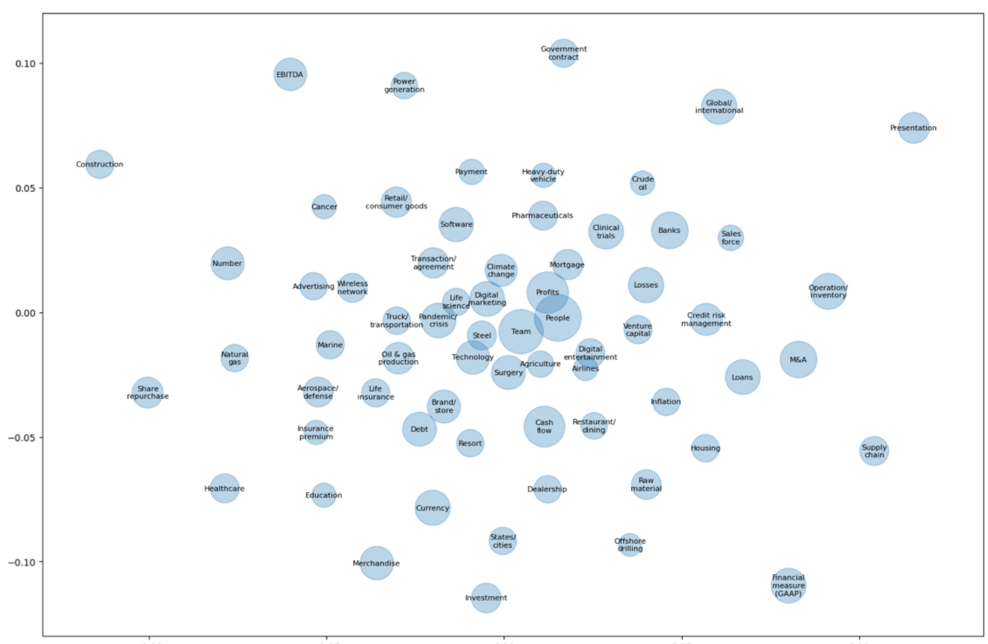


Figure 4. Partisan disagreement over certain issues

This figure illustrates the level of partisan disagreement across ten issues surveyed in the American Trends Panel survey by Pew Research Center in 2020. The survey asked the following question: “How much of a problem do you think each of the following are in the country today?” The ten issues examined 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. The survey responses are aggregated and categorized based on participants’ political leanings, and the figure ranks the issues according to the degree of partisan disagreement observed.

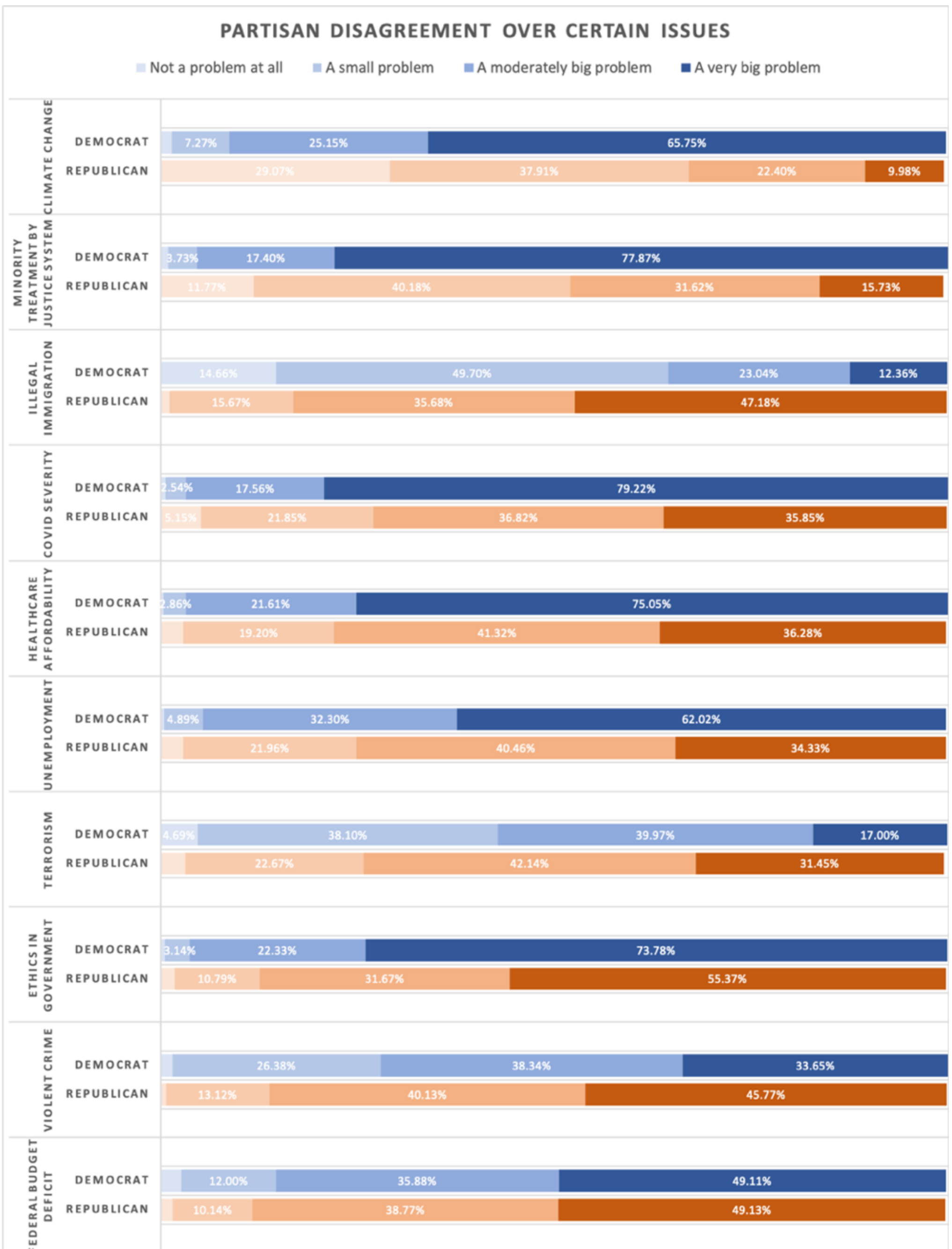
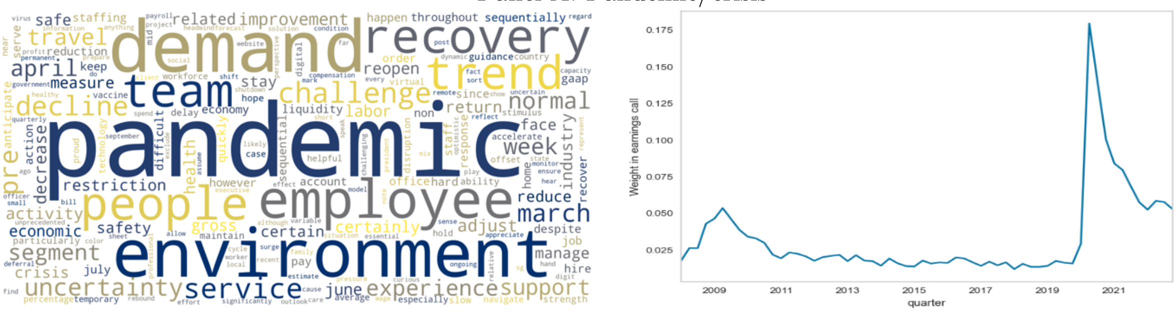


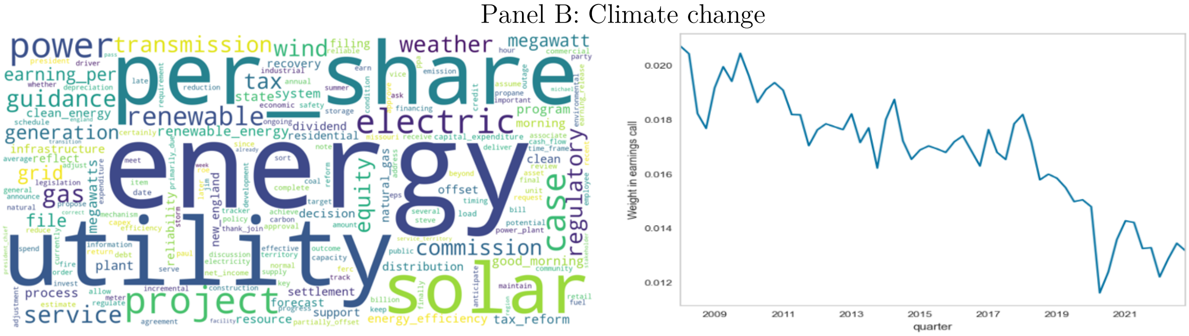
Figure 5. Keywords and time trends of partisan-sensitive topics

This figure displays the keywords and the time trend of the average weight assigned to specific topics in earnings calls. Panel A represents the pandemic/crisis topic, Panel B shows the climate change topic, and Panels C and D depict the healthcare and pharmaceuticals topics, respectively.

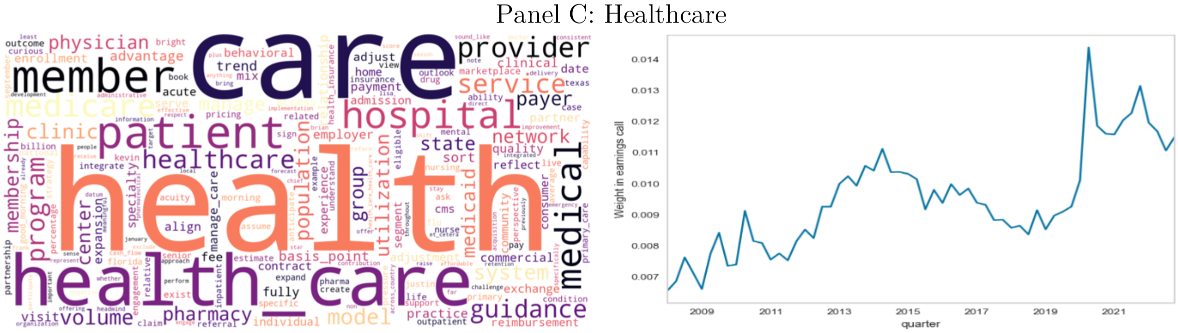
Panel A: Pandemic/crisis



Panel B: Climate change



Panel C: Healthcare



Panel D: Pharmaceuticals

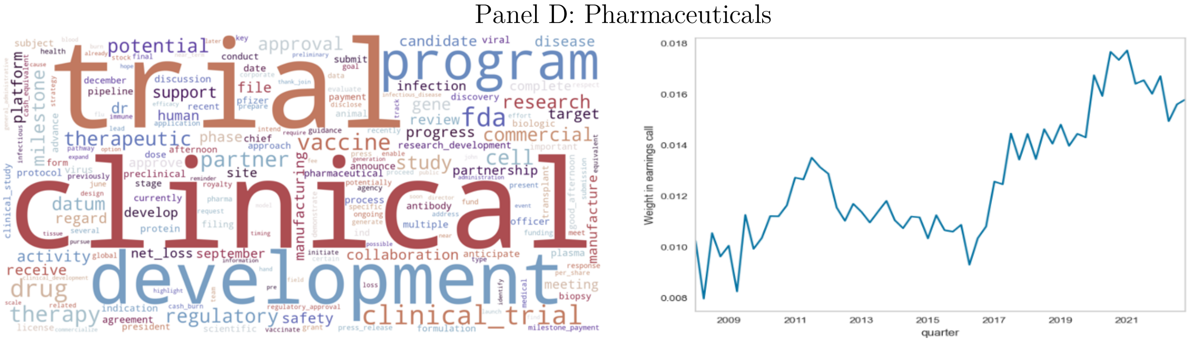


Table 1. Summary statistics

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

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. Industry distribution of partisan-sensitive topics

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

	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

Table 3. Measure validation

This table validates the text-based measures with external benchmarks at the firm-quarter level. Panel A focuses on validating the pandemic topic, while Panel B validates the climate change topic. *Covid Exposure*, a variable from Hassen et al. (2022), 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 as Fama-French 48 industries. Standard errors are double clustered at firm and quarter level. 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)
Constant	-0.214***	0.108***	0.636***
	(-18.14)	(5.05)	(2.79)
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)
Constant	-0.151***	0.546***	0.053
	(-9.86)	(2.97)	(0.25)
Firm FE			Y
Industry × Qtr FE			Y
R^2	0.499	0.505	0.793
N	79149	73693	73504

Table 4. Main result

This table presents the relation between partisanship and mutual fund trading on partisan-sensitive topics. The dependent variable, *ΔFundOwn*, is the change in fund ownership of a stock. *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* for each fund-quarter. 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)	(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)		
Constant	0.0007***	0.0022	-0.0042	0.0364***	0.0008***	0.0008***
	(4.93)	(1.03)	(-0.62)	(8.19)	(58.93)	(55.22)
Fund FE			Y	Y	Y	Y
Quarter FE			Y	Y	Y	Y
Firm FE			Y	Y	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 5. Subsample analysis

This table presents heterogeneous partisan effects across different subsample. In column (1)-(2), I calculate mutual fund political leaning based on the degree of political polarization. Specifically, a fund manager is classified as a strong Democrat (Republican) if at least 75% of her donations goes to the Democratic (Republican) party. A fund manager is classified as a weak Democrat (Republican) if 50% - 75% donations goes 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* for each fund-quarter observation. 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 FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Quarter FE	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 6. Partisanship and value-add of trading

This table presents the relation between partisanship and the value-add of trading to fund performance. The dependent variable, $\Delta Weight_{f,i,t} \times R_{i,t+1}$, is the change in the portfolio weight of a stock 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* for each fund-quarter. 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)	
Constant	0.0003***	0.0011*	-0.0114***	0.0003***
	(9.52)	(1.93)	(-4.39)	(29.97)
Controls	N	Y	Y	Y
Fund FE			Y	Y
Firm FE			Y	Y
Qtr FE			Y	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 7. Fund characteristics and trading response to earnings calls

This table reports 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* for each fund-quarter observation. 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)
Constant	0.00075***	0.00075***	0.00075***	0.00075***	0.00075***
	(55.83)	(55.77)	(55.46)	(55.40)	(55.17)
Controls	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Quarter FE	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 8. Fund headquarter partisanship and trading response to earnings calls

This table reports the main regression in equation (3) after controlling for the political leaning of a 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 a mutual fund leans toward the Democratic party. It is calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter observation. 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)	
Constant	0.0046***	0.0037	0.0002	0.0008***
	(3.80)	(1.47)	(0.02)	(53.76)
Controls		Y	Y	Y
Fund FE			Y	Y
Firm FE			Y	Y
Qtr FE			Y	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 9. A balanced shareholder sample

This table reports 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 funds for each stock in each quarter, and then retaining firm-by-quarter observations without any partisan holdings or if the ratio of total Democratic holding to total Republican holding falls within the range of 0.8 and 1.2, allowing for an error margin of 20%. 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 a mutual fund leans toward the Democratic party. It is calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter observation. 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)	
Constant	0.0006***	-0.0012	-0.0112	0.0007***
	(3.99)	(-0.47)	(-0.86)	(22.50)
Controls		Y	Y	Y
Fund FE			Y	Y
Firm FE			Y	Y
Qtr FE			Y	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 10. Non-partisan CEOs

This table reports the main regression on a subset of firms with non-partisan CEOs (i.e. either not making political donations or donating equally to both parties). I use the CEO political contribution data provided by Babenko et al. (2020) to determine the partisanship of firm CEOs, and then exclude firms whose CEOs have ever been classified as partisan in any election cycle from the sample. 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 a mutual fund leans toward the Democratic party. It is calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter observation. 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	**-0.0121*****	**-0.0135*****	**-0.0123*****	**-0.0221*****
	(-3.07)	**(-2.94)**	**(-2.74)**	**(-4.26)**
ΔPST	-0.0023	-0.0034**	-0.0025*	-0.0022
	(-1.57)	(-2.08)	(-1.73)	(-0.42)
Net Dem	-0.0000	0.0001	0.0010	
	(-0.06)	(0.14)	(0.76)	
Constant	0.0012***	-0.0004	-0.0066	0.0012***
	(6.33)	(-0.17)	(-0.75)	(64.97)
Controls		Y	Y	Y
Fund FE			Y	Y
Firm FE			Y	Y
Qtr FE			Y	Y
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.002	0.019	0.253
N	3218704	2612348	2612304	2572100

Table 11. Presentation vs. Q&A session

This table presents the main result for the presentation session and the Q&A session 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 a mutual fund leans toward the Democratic party. 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)	
Constant	0.0007***	0.0022	-0.0042	0.0007***
	(4.93)	(1.01)	(-0.62)	(63.79)
Controls		Y	Y	Y
Fund FE, Firm FE, Qtr FE			Y	Y
Fund × Qtr FE, Firm × Qtr FE, 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)	
Constant	0.0007***	0.0022	-0.0042	0.0008***
	(4.94)	(1.01)	(-0.62)	(84.80)
Controls		Y	Y	Y
Fund FE, Firm FE, Qtr FE			Y	Y
Fund × Qtr FE, Firm × Qtr FE, Fund × Firm FE				Y
R^2	0.000	0.001	0.017	0.225
N	6092437	4952572	4952529	4890714

Table 12. Sentiment-augmented PST index

This table presents the relation between partisanship and mutual fund trading on partisan-sensitive topics, accounting for sentiment at the topic level. The dependent variable is the change in fund ownership of a stock (*ΔFundOwn*). *ΔSent PST* is the change in sentiment-augmented Partisan Sensitive Topic (PST) index in earnings calls, where *Sent PST* subtracts weights on topics that are discussed positively from topics discussed negatively. *Net Dem* measures the degree a fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter observation. 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)	
Constant	0.0006***	0.0020	0.0010	0.0006***
	(5.01)	(1.05)	(0.15)	(620.11)
Controls		Y	Y	Y
Fund FE			Y	Y
Quarter FE			Y	Y
Firm FE			Y	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 13. Placebo test

This table presents the regression results examining the partisan effect on LDA topics that do not exhibit substantial partisan disagreements. Columns (1)-(4) display the results for the 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 a mutual fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter observation. 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 FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Quarter FE	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 14. Robustness

This table presents robustness tests of the main regression. In Panel A, I do not separate the "pandemic/ crisis" topic of the LDA model. In Panel B, I exclude one topic at a time from PST. *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 a mutual fund leans toward the Democratic party. 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.

Panel A: Not separating the pandemic/crisis topic

	(1)	(2)	(3)	(4)
ΔPST × Net Dem	**-0.0101*****	**-0.0110*****	**-0.0099*****	**-0.0118*****
	(-3.83)	**(-3.73)**	**(-3.58)**	**(-3.88)**
ΔPST	0.0004	-0.0003	0.0006	-0.0020
	(0.43)	(-0.32)	(0.77)	(-0.56)
Net Dem	0.0002	0.0004	0.0011	
	(0.36)	(0.62)	(1.02)	
Constant	0.0007***	0.0022	-0.0043	0.0007***
	(4.90)	(1.02)	(-0.63)	(85.67)
Controls		Y	Y	Y
Fund, Firm, Qtr FE			Y	Y
Fund × Qtr FE				Y
Firm × Qtr FE				Y
Fund × Firm FE				Y
R^2	0.000	0.001	0.017	0.225
N	6097589	4957361	4957316	4895449

Panel B: Excluding one topic at a time

	(1)	(2)	(3)	(4)
	Exclude	Exclude	Exclude	Exclude
	Climate change	Pharmaceuticals	Healthcare	Pandemic
ΔPST × Net Dem	**-0.0097*****	**-0.0096*****	**-0.0115*****	**-0.0085***
	(-2.63)	**(-2.83)**	**(-3.27)**	**(-1.89)**
ΔPST	-0.0027**	-0.0020*	-0.0026**	-0.0016*
	(-2.07)	(-1.87)	(-2.33)	(-1.78)
Net Dem	0.0011	0.0011	0.0011	0.0011
	(1.03)	(1.03)	(1.04)	(1.02)
Constant	-0.0042	-0.0042	-0.0042	-0.0042
	(-0.62)	(-0.62)	(-0.62)	(-0.62)
Controls	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
R^2	0.017	0.017	0.017	0.017
N	4957316	4957316	4957316	4957316

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 name and top 15 keywords of each LDA topic. The keywords are generated by the trained LDA topic model, and the topic names are labelled by referring to the literature, conducting online searches, and drawing from my own expertise.

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"

August 2024

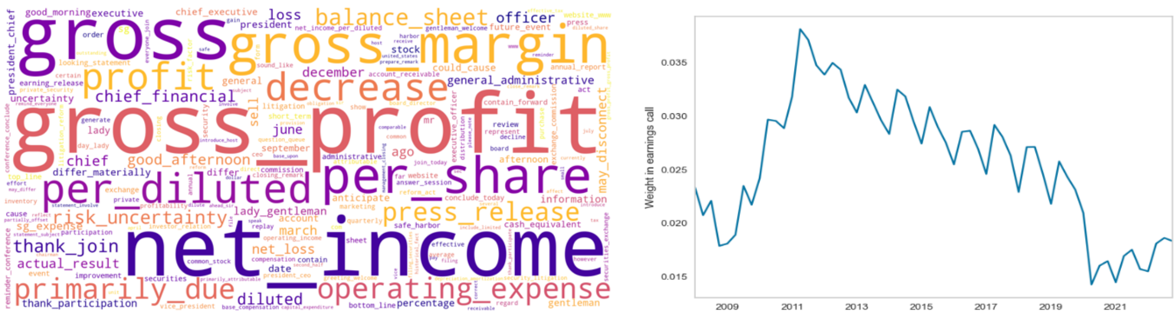
This Internet Appendix provides additional figures and tables used in the paper.

List of Figures and Tables

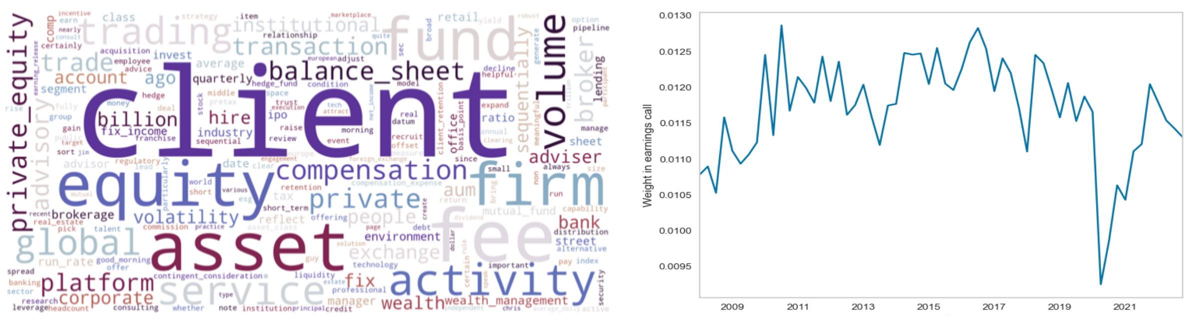
Figure A1. Keywords and time trends of placebo topics

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

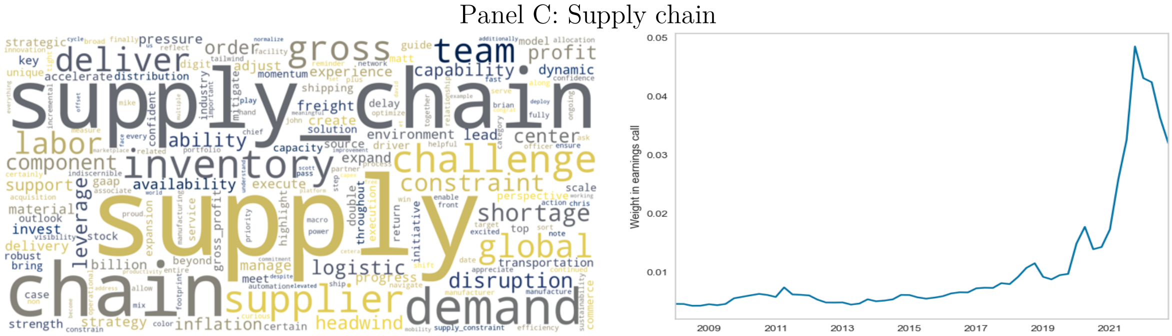
Panel A: Profits



Panel B: Investment



Panel C: Supply chain



Panel D: Raw material

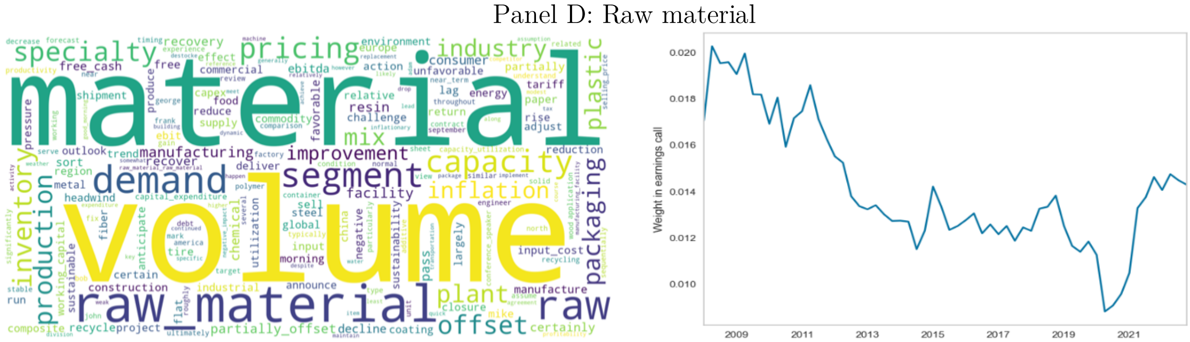


Table A1. Snippets of transcripts with highest partisan-sensitive topic weights

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

This table presents the relationship between weights assigned to partisan-sensitive topics and the overall sentiment expressed during earnings calls at the firm-quarter level. The dependent variable is *Overall Sentiment*, which is calculated as (#positive words - #negative words)/#total words within a transcript, and is standardized subsequently. *PST* is 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 as Fama-French 48 industries. Standard errors are double clustered at firm and quarter level. 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)
R^2	0.006	0.081	0.487	0.517
N	88120	81937	81836	81794
Controls		Y	Y	Y
Firm FE			Y	Y
Qtr FE			Y	Y
FF48 × Qtr FE				Y

Table A3. Main result on a continuous holding sample

The table repeats the main table based on a continuous holding sample, wherein a fund maintains ownership of a stock in consecutive quarters. As a result, the calculation of changes in fund ownership of a stock and changes in partisan-sensitive topic weights always involves subtracting the values from quarter t-1. The dependent variable is the change in fund ownership of a stock from quarter *t-1* to quarter *t* (*ΔFundOwn*). *ΔPST* is the change in weights on partisan-sensitive topics in earnings calls from quarter *t-1* to quarter *t*. *Net Dem* measures the degree a mutual fund leans toward the Democratic party, calculated as *(#Dem - #Rep)/#Total managers* for each fund-quarter. 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)	(2)	(3)	(4)	(5)	(6)
ΔPST × Net Dem	**-0.0090****	**-0.0110****	**-0.0120*****	**-0.0213*****	**-0.0204*****	**-0.0234*****
	(-2.19)	**(-2.33)**	**(-2.61)**	**(-3.42)**	**(-3.35)**	**(-3.93)**
ΔPST	0.0024**	0.0008	-0.0003			
	(2.02)	(0.67)	(-0.31)			
Net Dem	0.0008	0.0011*	0.0013			
	(1.30)	(1.67)	(1.13)			
Ln(fund size)		-0.0004*	-0.0001			
		(-1.69)	(-0.46)			
Fund age		0.0910	-0.2191			
		(1.40)	(-1.29)			
Fund turnover		-0.0005**	-0.0008*			
		(-2.08)	(-1.94)			
Mgmt. fee		-0.0001***	0.0001			
		(-4.10)	(0.96)			
Expense ratio		0.0006***	0.0019***			
		(4.80)	(6.48)			
Ln(1 + ME)		-0.0006***	-0.0013***	-0.0015***		
		(-6.04)	(-4.51)	(-5.54)		
B/M		-0.0003	0.0021**	0.0032***		
		(-0.58)	(2.10)	(3.28)		
ROA		-0.0330***	-0.0042	-0.0052		
		(-7.48)	(-1.14)	(-1.48)		
Profitability		-0.0003	-0.0145***	-0.0145***		
		(-0.22)	(-4.55)	(-4.84)		
Constant	0.0011***	0.0037	-0.0066	0.0356***	0.0011***	0.0011***
	(6.10)	(1.35)	(-0.71)	(5.61)	(3586.33)	(3914.95)
Fund FE			Y	Y	Y	Y
Quarter FE			Y	Y	Y	Y
Firm FE			Y	Y	Y	Y
Fund*Qtr FE				Y	Y	Y
Firm*Qtr FE					Y	Y
Fund*Firm FE						Y
R^2	0.000	0.001	0.022	0.129	0.197	0.333
N	2553541	2020151	2020090	2017601	2014807	1967067

Table A4. Partisan-sensitive topic weights and stock returns

This table presents the relation 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 as 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)
Constant	0.0306*	0.0600	1.6239***	1.5748***
	(1.87)	(1.56)	(9.10)	(9.89)
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