Professional Investors and Media Topics

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Abstract

I investigate the impact of media topics on the portfolio strategies of active equity mutual funds. Using 1.5 million *Wall Street Journal* articles from 1984 to 2023, I use ChatGPT to distill media news information into 59 distinct topics, and quantify each topic's time-varying share of news attention and sentiment. I then define a fund as having exposure to a topic if it overweights stocks expected to perform well when the topic grows in importance, and hence attention. I find that the topics that fund managers choose to have high exposure to are high-sentiment topics, but not those with high attention. This strategy leads to mutual fund underperformance but attracts investor flows. Topic-oriented strategies account for a large fraction, specifically 37%, of mutual fund tilts, and are a key driver of the underperformance associated with active tilts.

Keywords: Media news, large language model, professional investors, asset management
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1 Introduction

The traditional way to understand an investor's portfolio focuses on industry tilt or tilt toward certain stock characteristics, such as value or growth. However, investors are exposed to multifaceted information on a daily basis and make decisions based on this complex information set. Since this information often aligns with specific topics, it is important to learn how investors adjust their portfolio strategies in response to these topics. Addressing this question is challenging due to the complex and dynamic nature of media news information. In this paper, I show for the first time how investors adjust their portfolio strategies in response to media news topics.

To summarize the complex information set in the form of topics, media news serves as a valuable resource. As a critical intermediary of information, the media not only report facts but also interpret their importance, convey a positive or negative sentiment about them, and make forecasts about their future impact. While the news is produced by media outlets, its content represents an equilibrium between the perspectives of news producers and the demands of news consumers (Mullainathan and Shleifer, 2005). In the context of financial media, where investors are the primary audience, the financial news offers insights into both the topics shaping the economy and the attention and sentiment of investors.

In recent years, the development of state-of-the-art natural language processing (NLP) techniques, such as large language models (LLMs), has revolutionized the analysis of textual data. These advancements enable us to summarize complex information into topics, allowing us to track how the importance and sentiment of various events evolves over time. This offers a unique opportunity to deepen our understanding of how investors adjust their portfolio strategies in response to media topics.

In this paper, I investigate the impact of media topics on the portfolio strategies of an important group of investors: active equity mutual funds. The paper has three main sets of results. First, it develops a novel prompt-based methodology that uses the advanced LLM, ChatGPT, to quantify the media topics from 1.5 million *Wall Street Journal (WSJ)* news articles from 1984 to 2023. I first use this approach to extract media topics from these articles in the form of 59 topics, and then quantify each topic's time-varying share of news attention and sentiment. Second, I analyze how active equity mutual funds adjust their portfolio strategies in response to media topics. I define a fund as having exposure to a topic if it overweights stocks that are expected to perform well when the topic grows in importance, and hence attention, in the future. I find that the topics that funds have high exposure to are high-sentiment topics, not high-attention topics. This strategy leads to mutual fund underperformance, but nonetheless attracts investor flows, which explains why funds use it. Third, I examine how much media topics can explain mutual fund tilts away from the market portfolio. I find that the topic-oriented behavior explains a large fraction, specifically 37%, of the variation in the aggregate active mutual fund tilt toward stocks. In addition, the negative Carhart alpha associated with the aggregate active mutual fund tilt is entirely attributable to the topic-driven component. Once this component is isolated and removed, the residuals show no significant alpha, suggesting that the underperformance of the active tilts is entirely due to topic-driven behavior.

Stepping back from these three specific results, the broader contribution of this paper is to offer a new way of thinking about investors' portfolios – not in terms of industry tilts or tilts towards value or growth or other stock characteristics, but in terms of exposure to different media topics. And AI tools play an important role here – they allow me to summarize the complex information set that investors take into account when making portfolio decisions.

In my first result, I provide a novel prompt-based methodology that uses ChatGPT in combination with media news to measure the topics that the media focus on in each month. I use this approach to distill news articles into a comprehensive list of 59 topics, and then quantify the time-varying attention and sentiment associated with each topic. For media news data, I focus on the business news of 1.5 million *WSJ* articles from 1984 to 2023. For ChatGPT, the analysis is conducted using OpenAI's GPT-4o mini model released on July 18, 2024. This model can handle approximately 96,000 words (128K-token context window) per prompt at just 3% of the cost of the previous GPT-4o model. The combination of a long context window and lower cost provides a unique opportunity to quantitatively measure topics from a vast number of news articles.

I use an iterative prompt design to extract the topic list. This design overcomes the limit on the number of tokens in each ChatGPT prompt, which makes it infeasible to input all articles in a single prompt. Specifically, I first input all news articles for each day into a prompt, and ask ChatGPT to summarize the topics for that day; ChatGPT may return, say, 10 topics for a total of 200 news articles on a given day. Then, I input all daily topics in each month into a prompt and ask ChatGPT to summarize the topics for the month; for example, ChatGPT may summarize the 300 daily topics within one month into 30 monthly topics. In this way, I aggregate the topics from the daily level to the monthly level. Then I aggregate the monthly topics into annual topics, and then into five-year topics, and eventually, I combine them into a comprehensive list of 59 topics from 1984 to 2023.

Since the topics are summarized from daily events, each topic represents a series of related events that span a certain period. For example, the topic *Pandemic and Vaccine Development* includes COVID-19 in 2020 and severe acute respiratory syndrome (SARS) in 2003. Similarly, the topic *Geopolitical Tensions and Economic Impact* includes six key peaks of attention, corresponding to the Gulf War in 1990, the Kosovo War in 1999, the September 11 attacks in 2001, the Iraq War beginning in 2003, Russia's annexation of Crimea in 2014, and the 2022 Russian invasion of Ukraine. I also further categorize the 59 topics into 14 overarching metatopics, such as economic outlook, economic stimulus, and financial stability.

To measure the time-varying attention and sentiment for each topic, I first input each article along with the entire topic list into ChatGPT in a single prompt. The prompt asks ChatGPT to determine the topic the article belongs to, assign a confidence score for the topic choice (ranging from 0 to 1, with 1 indicating the highest confidence), and provide a sentiment score (ranging from -1 for the most negative to 1 for the most positive). To calculate topic attention and sentiment, I only consider articles with confidence scores above 0.9, which constitute approximately 90% of all articles. Monthly sentiment for each topic is calculated by averaging the sentiment scores of all articles linked to that topic in that month. Monthly attention to a specific topic is computed as the number of articles related to that topic in a month divided by the total number of processed articles for the month. This approach provides a dynamic view of attention and sentiment for each topic over time.

The second set of results in this paper show how investors adjust their portfolio strategies in response to media topics. The investors I focus on are U.S. active equity mutual funds. I define a fund as having exposure to a topic if it overweights stocks that will perform well (or underweights stocks that will perform poorly) when attention to a topic increases. Then, I then examine what kinds of topics mutual funds choose to have high exposure to. Do they increase their portfolio exposure to topics that have high sentiment, high attention, or a high sentiment-attention interaction? The answer is not clear, ex-ante. I find that the topics that funds have high exposure to are high-sentiment topics – not topics with high attention or a high combination of sentiment and attention.

To measure a mutual fund's portfolio exposure to a topic, I first compute each stock's exposure to all 59 topics. A stock's exposure to a topic is defined as the coefficient when regressing the stock's excess returns on changes in topic attention.[1] As such, if a stock has a high exposure to a topic, it tends to perform well when attention to this topic increases. For example, during the COVID-19 pandemic in 2020, Pfizer had a positive topic exposure of 0.25 to the *Pandemic and Vaccine Development* topic, indicating that its returns tended to be high as attention to the pandemic increased. In contrast, Boeing exhibited a negative topic exposure of -1.17, reflecting low returns as attention to the pandemic intensified. I then define an active fund's portfolio exposure to a given topic as the difference between the average stock exposure of the fund's portfolio to that topic and the average stock exposure of the market portfolio to that topic. Intuitively, a fund has a high exposure to a topic if it overweights stocks that will perform well when the topic grows in importance.

To empirically test what kinds of topics mutual funds have high exposure to, I regress fund exposure on topic sentiment, topic attention, and their interaction, while controlling for seven additional fund characteristics, namely net return, flow, expense ratio, age, total net

[1] The methodology follows the approach used in Bybee et al. (2023).

assets (TNA), turnover ratio, and load. The estimated coefficient on sentiment is significantly positive at 0.1 with a t-statistic of 2.48, indicating that a fund's exposure to a topic increases by 118% relative to the average fund's exposure of 0.08 when the topic sentiment increases by one standard deviation during the same quarter. In contrast, the coefficients on attention and on the interaction between sentiment and attention are not statistically significant. Further analysis by metatopics reveals that the positive sentiment coefficient is primarily driven by topics related to economic growth, including *ESG*, *Financial Markets*, *Economic Outlook*, *Labor/Income*, *Economic Stimulus*, and *Financial Stability*.

These findings imply that active equity mutual funds have high portfolio exposure to high-sentiment topics, rather than to topics receiving high attention or a combination of sentiment and attention. To interpret this, suppose that fund managers start by choosing topics that they think are likely to grow in attention in the future, and then position their portfolios accordingly by buying stocks that will perform well if these topics indeed grow in attention. My results suggest that, in deciding which topics will increase in attention, managers choose those that currently have high sentiment. The rationale is that topics generating enthusiasm today are likely to grow in importance—and therefore attract greater attention—in the future. Conversely, managers may avoid focusing on topics already receiving high attention at the current moment, perceiving them as having peaked and unlikely to see further growth.

Do funds profit from this strategy of having high portfolio exposure to high-sentiment topics? The answer is no. I find that the more a fund is exposed to high-sentiment topics, the lower its Carhart alpha. Specifically, I sort funds into 10 deciles according to their sentiment-weighted exposure (SWE) across all topics. Funds in the highest decile (Decile 10) have a strongly positive SWE, indicating high exposure to high-sentiment topics. In contrast, the lowest decile (Decile 1) has the most negative SWE, indicating negative exposure to high-sentiment topics. I find that funds with high SWE consistently underperform those with low SWE. In terms of Carhart alpha based on fund net returns in a one-month out-of-sample period, high-SWE funds (Decile 10) underperform low-SWE funds (Decile 1) by 39 basis points (bps) per month (4.68% annually) in TNA-weighted portfolios and by 32 bps per month (3.84% annually) in equal-weighted portfolios. This performance gap is robust to other fund return measures, including fund raw returns and returns constructed from fund holdings.

The underperformance immediately raises the question: Why would funds use this strategy if it leads to underperformance? My results show that they use this strategy because it attracts higher flows, which in turn increases their fee-based revenue. Specifically, I document a strong positive relationship between fund SWE and fund flows. High-SWE funds (Decile 10) attract significantly more inflows than low-SWE funds (Decile 1), by 31 bps per month (3.72% annually) for both TNA-weighted and equal-weighted portfolios in a one-month out-of-sample period. This relationship is confirmed by regressing future fund flows on SWE, while controlling for fund-specific characteristics. The coefficient on SWE is 0.05 with a t-statistic of 2.25, indicating that the monthly flow increases by 5 bps in the following month when SWE increases by one standard deviation in the current month. Thus, funds appear to use this strategy to attract higher flows, which in turn increases their fee-based revenue.

After examining how mutual funds form strategies in response to media topics, the following question arises: How much can media topics explain mutual fund tilts away from the market portfolio? Answering this question is the goal of the third set of results in this paper.

To answer this question, I define the aggregate active tilt to each stock as the stock weight in the aggregate active equity mutual fund portfolio divided by the stock weight in the value-weighted portfolio of the same stock universe.[2] To assess how much of the stock-level active tilts are driven by media topics, the ideal regression model would be to regress the aggregate active tilt on topic signals for each stock. However, the regression is infeasible due to the data limitation of having only quarterly holdings and to the large number of topic signals. I address the data limitation issue by using an instrumented regression approach,

[2] I conduct the analysis at the stock level by aggregating fund tilts rather than using individual fund tilts to allow for an examination of the alpha of stock portfolios sorted by aggregating fund tilts.

which introduces stock characteristics as instruments for parameter estimation.[3] The results of the instrumented regression show that topic signals explain a large fraction, specifically 37%, of the active tilts in an expanding window framework. This finding suggests a strong link between media topics and fund managers' active stock selection behavior.

Furthermore, the analysis reveals that the Carhart alpha associated with the aggregate active mutual fund tilt is entirely attributable to the topic-driven component. To conduct this test, I decompose the aggregate active tilt for each stock into the topic-driven tilt and the residual tilt that cannot be explained by topic information. I then sort stocks into ten deciles at the end of each quarter by each of active tilts, topic-driven tilts, and residual tilts. Decile 1 has the lowest tilts, and decile 10 has the highest tilts. To measure the stock performance associated with each type of tilt, I calculate the difference in Carhart alphas between decile 10 and decile 1. If the alpha of the active tilts is primarily driven by the topic information, we would expect the topic-driven tilts to exhibit an alpha similar to that of the active tilts, while the residual tilts would have no significant alpha.

The empirical results show that the equal-weighted active tilt portfolio has a significantly negative alpha of -1.86% per month with a t-statistic of -2.24 in the month after sorting.[4] This suggests that, on average, the stocks in the top active tilt decile underperform those in the bottom decile. The topic-driven tilt portfolio also has a significantly negative alpha of -2.23% with a t-statistic of -2.40, whose magnitude is comparable to that of the active tilt portfolio. The residual tilts, which represent the portion of active tilts unexplained by the topic-driven component, show no significant alpha. This absence of alpha in the residual tilts suggests that, after accounting for the topic-driven tilts, there is no remaining evidence of persistent underperformance or outperformance in the active tilt portfolio. The results

[3] I follow the literature that models factor loadings as functions of observables. See, for example, Rosenberg (1974), Ferson and Harvey (1991), Daniel and Titman (1997), Chordia et al. (2017), and Kelly et al. (2019).

[4] Negative alpha is observed under two specific conditions: (1) in equal-weighted portfolios, and (2) with a one-month holding period after sorting at the end of each quarter. In contrast, the value-weighted and holdings-weighted portfolios show no significant alpha, consistent with findings in previous literature, such as Cremers and Petajisto (2009) and Chen et al. (2000), where holdings-weighted portfolios generally show no alpha. A detailed discussion can be found in Section 4.2. This non-positive alpha does not conflict with the positive alpha observed in the mutual fund active share literature; see Section 4.3 for further details.

imply that the topic-driven tilts fully explain the negative alpha in the equal-weighted active tilt portfolio.

In summary, the third result of the paper is to show that the topic-driven component explains a large fraction – specifically 37% – of the aggregate mutual fund tilt away from the market portfolio, and drives the negative Carhart alpha associated with the active tilts. After isolating and removing the topic-driven tilts, the residuals exhibit no significant alpha.

Related Literature

This paper first contributes to a rapidly growing literature in economics that uses text as data.[5] Topic models have only recently begun to be explored in empirical economics research.[6] In this literature, the paper most closely related to mine is Bybee et al. (2024), who estimate a topic model using Latent Dirichlet Allocation (LDA) that summarizes the business news from *WSJ* into 180 interpretable topics and quantifies the proportion of news attention allocated to each topic over time. LLMs and ChatGPT are becoming popular in the literature after the latter was introduced on November 30, 2022 by OpenAI.[7] In this paper, I apply the LLM model, ChatGPT, as a topic model to extract a list of 59 topics and a measure of the attention and sentiment associated with each topic. While ChatGPT-generated topics share some similar topics with LDA, ChatGPT offers several advantages over traditional topic models. These include i) that we can obtain time-varying sentiment in addition to attention for each topic, ii) that the topics are more interpretable and relevant as a summary of complex events, and iii) that text preprocessing is not required. [8]

This paper also contributes to the literature on asset manager performance and fund flows.[9] One strand of this literature examines how asset managers respond to sentiment. For example, Brunnermeier and Nagel (2004) show that, during the technology bubble, hedge

[5] See Gentzkow et al. (2019) for a recent review.

[6] See, for example, Hansen et al. (2018), Larsen and Thorsrud (2019a), Larsen and Thorsrud (2019b), Ke et al. (2019), Thorsrud (2020), and Cong et al. (2024).

[7] Some recent examples are Lopez-Lira and Tang (2023), Bybee (2023), Xie et al. (2023), Kim et al. (2024), and Khan and Umer (2024).

[8] See the comparison in Section 2.4 for more details.

[9] See Cremers et al. (2019) and Christoffersen et al. (2014), Chapter 5, for a survey.

funds invested heavily in tech stocks, riding the bubble until its collapse. This finding aligns with my results, where asset managers increase exposure to stocks tied to high-sentiment topics and then adjust in a timely way as sentiment changes.

Another related paper is Massa and Yadav (2015), who find that active mutual funds employ portfolio strategies based on market sentiment as measured using the index in Baker and Wurgler (2006). They observe that a sentiment contrarian strategy leads to high flows due to superior performance, while sentiment catering strategies fail to attract significant flows. My paper differs from Massa and Yadav (2015) in two ways. First, I focus on the sentiment of individual topics rather than overall market sentiment. In other words, my analysis emphasizes the cross-sectional sentiment across topics, while their approach centers on the time series of market sentiment. Second, I obtain different results by using the cross-sectional topic sentiments. My findings show that active mutual funds attract significant flows by catering to high-sentiment topics, despite the underperformance that this leads to. In contrast, results of Massa and Yadav (2015) suggest that funds catering to overall market sentiment fail to attract more investor flows due to their underperformance. Instead, a sentiment contrarian strategy achieves higher inflows by delivering outperformance.

The third literature this paper contributes to is on the asset allocation of institutional investors.[10] This paper adds to this literature by showing that the asset allocation of active mutual funds is largely driven by media topics. I show that the topic-driven component explains a large fraction, namely 37%, of the aggregate mutual fund active tilt away from the market portfolio, and that the negative Carhart alpha associated with the aggregate active mutual fund tilt is entirely attributable to the topic-driven component.

The paper is organized as follows. In Section 2, I describe how I apply ChatGPT to *WSJ* news articles to obtain a topic list as well as a measure of attention and sentiment for

[10]See, for example, Grinblatt and Titman (1989), Daniel et al. (1997), Wermers (2000), Gompers and Metrick (2001), Bennett et al. (2003), Brunnermeier and Nagel (2004), Kacperczyk et al. (2005); Basak et al. (2007); Cremers and Petajisto (2009); Hugonnier and Kaniel (2010); Cuoco and Kaniel (2011); Lewellen (2011); Agarwal et al. (2013), Kacperczyk et al. (2014), Sialm et al. (2015), Blume et al. (2014), Lettau et al. (2018); Koijen and Yogo (2019); Pástor et al. (2020), Pástor et al. (2020), Dou et al. (2022), Ben-David et al. (2022), Kaniel et al. (2023), DeMiguel et al. (2023), and An et al. (2024).

each topic. Section 3 examines how active equity mutual funds construct portfolio strategies exploiting media news information. Section 4 characterizes the explanatory power of media news information for the aggregate active tilt of mutual funds. Section 5 concludes.

2 Media Topics

This section describes a novel prompt-based methodology that uses ChatGPT to quantify the media topics from news articles. I use this approach to extract media news information in the form of 59 topics, and then quantify each topic's time-varying share of news attention and sentiment.

2.1 *The Wall Street Journal* Data Set

The text data set I use consists of *Wall Street Journal (WSJ)* articles between 1984 and 2023. Data from January 1984 to December 2021 is purchased from the Dow Jones Historical News Archive. Data between January 2022 and December 2023 is from the *WSJ Archive* database.

The *WSJ* covers a broad array of topics, emphasizing economics, finance, and business. As the second-largest newspaper by readership in the U.S., it is widely considered a leading source for business and financial news. This makes it a fitting choice for information that GPT can use to summarize events influencing mutual fund managers' portfolio choices.

I implement several measures to standardize the data sample and to minimize the potential confounding effects of organizational changes at the *WSJ* over time. First, although the Dow Jones Historical News Archive contains data starting from 1979, only article abstracts are available prior to 1984. To ensure consistency in article definitions throughout the sample, I exclude all data before 1984, resulting in a total of 1,587,858 articles from 1984 to 2023. Second, *WSJ* introduced various non-core sections, such as "Personal Journal" (launched in 2002), "Weekend Journal" (launched in 2005), and "Off Duty" (launched in 2012). To maintain uniformity in topical content, I omit articles from these non-core sections. Third, since my focus is on economic news, I also exclude articles tagged with subjects like reviews (tag "N/RVW") and arts (tag "N/ART"). Lastly, I remove articles titled "Corrections & Amplifications," as they address adjustments to multiple previous articles. After these refinements, the final dataset consists of 1,478,555 articles.

Figure A.15 in the Appendix shows the post-processing monthly article count over time. Despite the efforts to standardize the data, it is important to acknowledge that the *WSJ* is a dynamic publication that has undergone structural changes over the course of the sample period.

2.2 Topic List Generation

In this section, I begin by outlining an iterative prompt design to extract a comprehensive set of topics, including the steps for topic extraction, summarization, and subsequent refinement of the topic list. I then present the final structure of the comprehensive topic list.

2.2.1 Iterative Prompt Design

I now outline an iterative prompt design for generating a topic list from the *WSJ* using ChatGPT. This design overcomes the limit on the number of tokens in each ChatGPT prompt, which makes it infeasible to input all articles in a single prompt.

Specifically, I first extract topics on a daily basis, which are then aggregated by month. In subsequent steps, I consolidate the monthly topics into annual topics, and the annual topics into 5-year periods. Finally, I compile these 5-year topics into a comprehensive topic list. Queries are made to OpenAI's GPT-4o mini model, which was released on July 18, 2024. This model can handle approximately 96,000 words (128K-token context window) per prompt at just 3% of the cost of the GPT-4o model, enabling efficient summarization of topics from news text.

Step 1 involves extracting daily topics from all news articles for each day. I begin by obtaining topics from the day's news articles, due to the 128K-token limitation for each prompt. If the length of a day's news exceeds this limit, I split the news into smaller parts, ensuring that each part is within the 128K-token constraint. Each part is then processed with individual prompts. The following prompt format is used to query GPT:

```
Below is a day's worth of news. Identify at least 10 topics from
   this day, listed in descending order of the attention they
   draw. Provide a description of each topic and an explanation
   of why each topic was chosen.
Output format:
[{"topic":"<topic>","description":"<description>","reason":"<
   reason>"},
{"topic":"<topic>","description":"<description>","reason":"<
   reason>"}, ...]
Return only the list, with no additional output.
News of the day: "%s"
```

Step 2 involves summarizing the topics for the entire month. I take the output of topics and descriptions from the first step and input them using the following prompt:

```
Below is a list of topics and their descriptions. Combine the
   topics by merging duplicated and similar ones, listed in
   descending order of duplication frequency in the original list
   . Provide a description for each combined topic.
Output format:
[{"topic":"<topic>","description":"<description>"},
{"topic":"<topic>","description":"<description>"},...]
Return only the list, with no additional output.
Topics with descriptions: "%s"
```

The prompts for Step 3 to Step 5 are identical to those used in Step 2. In Step 3, I summarize the topics for each year using the monthly topics and descriptions as input, following the same process as in Step 2. This step produces a total of 1,627 topics. Figure 1

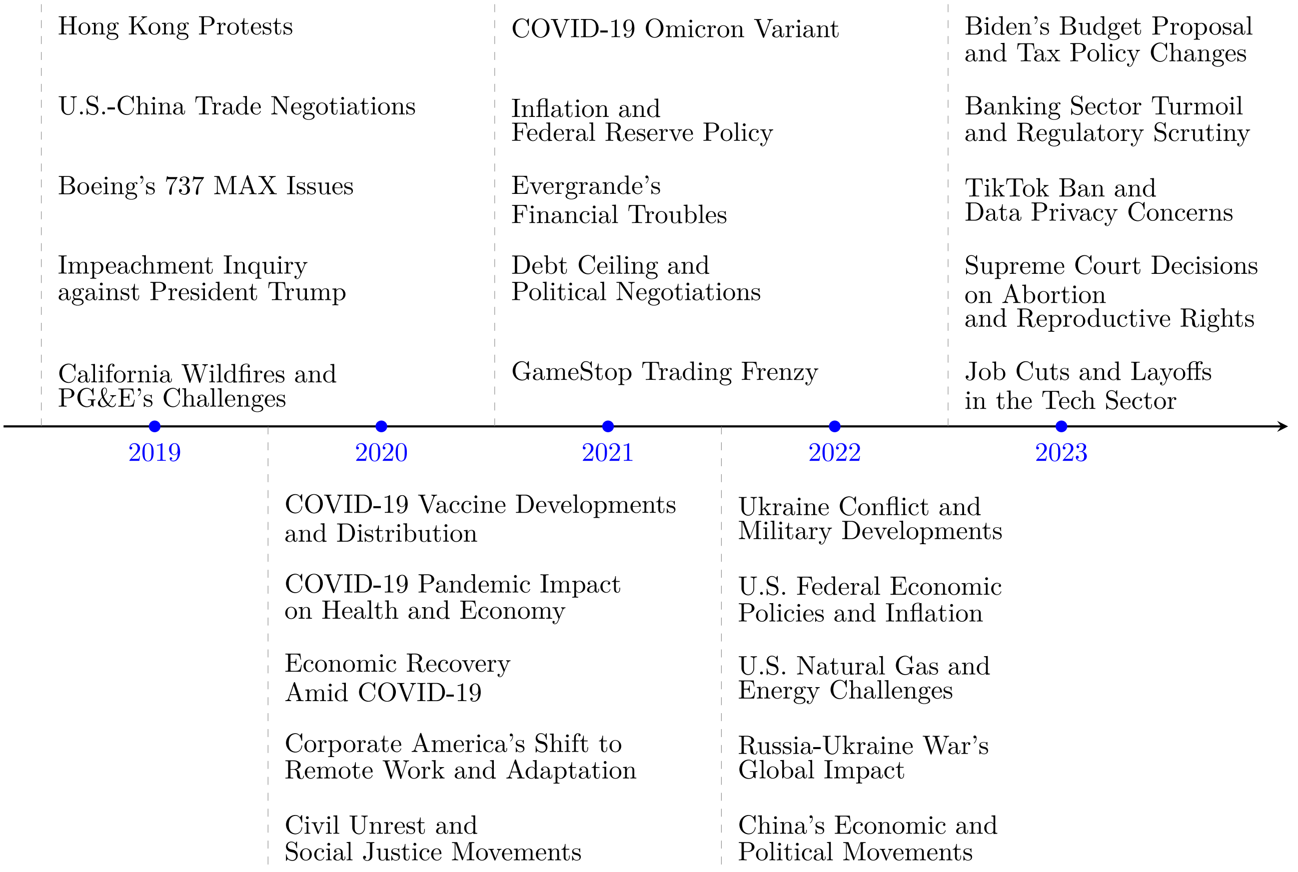

Figure 1: Annual Topic Examples: 2019–2023

Note: Examples of annual topics from 2019 to 2023, summarizing monthly topics for each year.

presents examples of annual topics from 2019 to 2023. Since the list of topics and descriptions from Step 3 exceeds the token limit for a single prompt, in Step 4, I further summarize the topics for each five-year period (e.g., 1984–1988, ..., 2019–2023) using the yearly topics from Step 3 as input. This step results in 356 output topics. In Step 5, I compile the 5-year list into an initial comprehensive topic list from 1984 to 2023.

Step 5 may omit some topics in each summary. To ensure broader coverage, Step 6 repeats Step 5 an additional 99 times, incorporating new topics into the original Step 5 list. Specifically, after each repetition, I use the following prompt to extract marginal information from the new list and merge it with the original:

```
Here are the original and new topic lists, each with descriptions
```

```
   . Please output the topics from the new list that are not
   included in the original list, excluding similar topics. If
   there are no new topics, output [].
Output format:
[{"topic":"<topic>","description":"<description>"}},
{"topic":"<topic>","description":"<description>"},...]
Original topic list with descriptions: "%s"
New topic list with descriptions: "%s"
```

The combined topic list from Step 6 has a broader coverage of topics but may still contain duplicated topics. Therefore, I apply Step 7 to merge duplicated or similar topics by the following prompt:

```
Here is a topic list with descriptions for each topic. Please
   combine the topics by merging duplicated and similar ones, and
    send a new topic list with descriptions.
Output format:
[{"topic":"<topic>","description":"<description>"},
{"topic":"<topic>","description":"<description>"},...]
Topic list with descriptions: "%s"
```

In Step 8, I check if there are any duplicated topics in the topic list by the prompt:

```
Can you check if there are any duplicated/similar topics in the
   topic list?
Topic list with descriptions: "%s"
```

The reply from ChatGPT-4o mini is:

```
There are no exact duplicated topics or highly similar topics (
   with a cosine similarity threshold of 0.8) in the CSV file.
   The topics list appears to be unique and well-differentiated.
```

Step 9 is the final step to ensure that the final topic list includes all relevant topics from the Step 5 prompts. In this step, I use the following prompt to cross-reference each topic generated from the 100 Step 5 iterations with the topic list from Step 8:

```
Given a topic and a list of summarized topics with descriptions,
   match the topic to the most relevant topic in the summarized
   list. If no suitable match is found, return None.
Output format:
[{"corresponding topic index in the topic list": "<corresponding
   topic index in the topic list>",
  "corresponding topic name in the topic list": "<corresponding
     topic name in the topic list>"}]
Return only the list, with no additional output.
Topic with its description: "%s"
Topic list with descriptions: "%s"
```

If no corresponding topic is found in the Step 8 list, the unmatched Step 5 topic is added to the summarized topic list. Repeat Step 9 until all topics from the 100 Step 5 iterations have a corresponding match in the summarized topic list. The final summarized topic list will be used as the definitive topic list. The final topic list contains 59 topics.

In summary, Steps 1–5 focus on extracting and summarizing topics from news articles, while Steps 6–9 refine the topic list to ensure it is comprehensive and free of duplications. These steps are outlined in the flowchart in Figure 2.

2.2.2 The Structure of Topics

The finalized topic list consists of 59 topics. As emphasized by Bybee et al. (2024), an intuitive metatopic hierarchy enables the examination of attention to news topics at varying levels of granularity. To categorize the 59 topics into metatopics, I used the following prompt to generate metatopic labels:

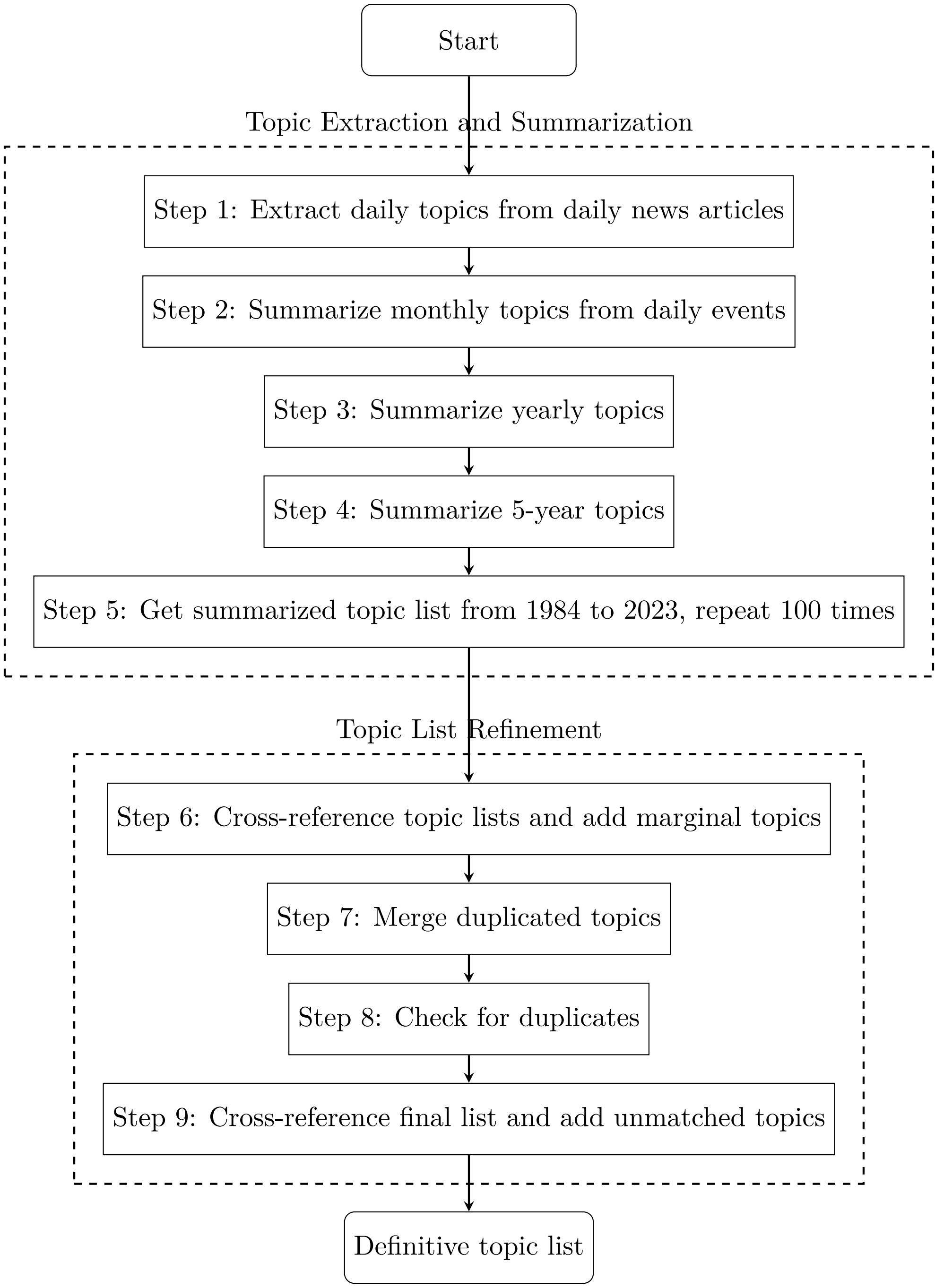

Figure 2: Flowchart for Topic List Generation

Note: Flowchart illustrating the process of generating the definitive topic list. The steps include topic extraction and summarization, as well as topic list refinement to ensure a comprehensive, non-duplicated result.

```
Below is a list of topics and their descriptions. Classify the
   topics into metatopics.
Output format:
[{"topic":"<topic>","metatopic":"<metatopic>"},
{"topic":"<topic>","metatopic":"<metatopic>"},...]
Return only the list, with no additional output.
Topic list with descriptions: "%s"
```

The 59 topics are grouped into 14 distinct metatopics. Figure 3 illustrates the relationship between topics and their corresponding metatopics. Notably, the metatopic labels have been refined and adjusted from the initial ChatGPT output. Table A.1 in the Appendix lists all topics with descriptions, and their metatopics.

2.3 Attention and Sentiment Estimation

After establishing the topic list, I shift to estimating topic attention and topic sentiment. These metrics quantitatively transform the news content, providing numerical data for empirical analysis of economic hypotheses. My estimates reveal how media attention and sentiment are allocated across topics and how this allocation changes over time.

To estimate topic attention and sentiment, I begin by evaluating the topic and sentiment for each article. For this, I use the following prompt, incorporating the article and the topic list with their descriptions as input:

```
Below is a news article followed by a list of topics/events with
   descriptions. For each article, indicate which topic/event
   index it belongs to and describe the reason for your choice.
   Provide a confidence score between 0 and 1  for your topic
   choice, with 0 being the least confident and 1 being the most
   confident.
Then, indicate the sentiment of this article. Provide a score
```

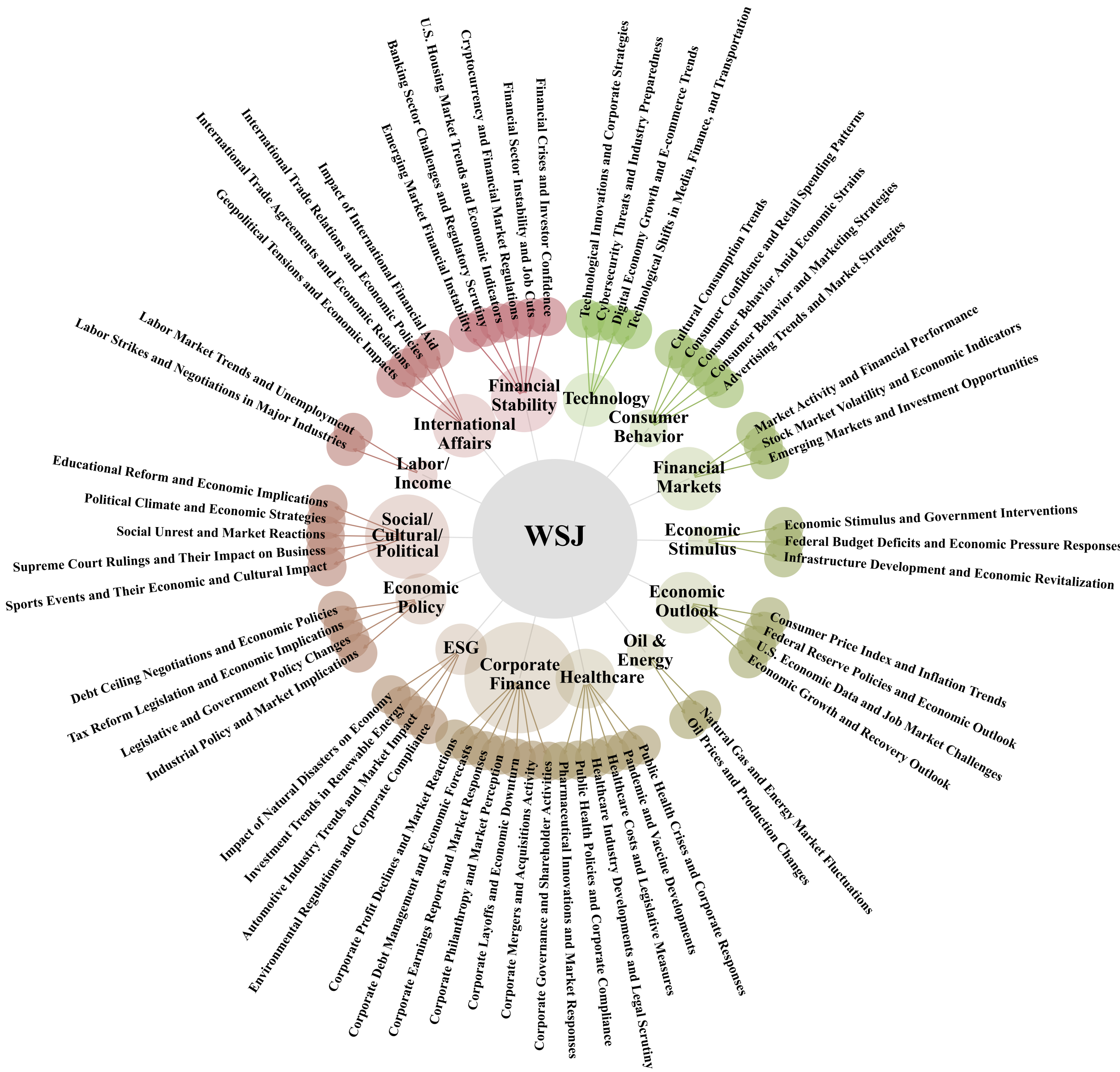

Figure 3: Topics and Metatopics

Note: This figure shows 59 topics grouped into 14 corresponding metatopics from the definitive topic list. The size of each metatopic node represents its average attention over time. The color gradient of the metatopic nodes, ranging from green to red in a clockwise direction, reflects the sentiment distribution. Green indicates the most positive sentiment, and red represents the most negative. The intensity of the color corresponds to the strength of the sentiment within each metatopic.

```
between -1 and 1, with -1 being the most negative and 1 being
the most positive. Describe the reason for your choice.
```

```
Output format:
[{"topic index": "<topic index>",
"topic name": "<topic name>",
"topic reason": "<topic reason>",
"topic confidence score": "<topic confidence score>",
"sentiment": "<sentiment>",
"sentiment reason": "<sentiment reason>"}]
Return only the list, with no additional output.

Article: "%s"
Topic list with descriptions: "%s"
```

It is crucial to ask ChatGPT to include the reasoning process. ChatGPT provides more reliable answers when employing a chain of thought, leading to more accurate responses when the reasoning behind them is explicitly required.

To ensure that ChatGPT consistently returns a deterministic solution for each individual prompt, I adjust two key parameters from the default settings.

First, I set the sampling temperature to 0. The temperature parameter, which ranges from 0 to 2, determines the degree of randomness in ChatGPT's responses. Higher values result in more creative and variable outputs, while lower values make the responses more focused and deterministic. Since the topic and sentiment of each article should have fixed answers, I select a temperature of 0 to ensure greater accuracy and consistency. However, when generating a topic list, I use a default temperature of 1, as some level of creativity is necessary to effectively summarize information. Setting the temperature to 0 in this case would lead ChatGPT to repeat previous topic lists instead of generating new summaries.

Second, I specify a seed value of 123 to ensure that the answers to each prompt are

Table 1: Confidence Score Distribution

Note. This table provides a comparison of the confidence score distribution between temperature 0 (deterministic) and temperature 1 (more creative) settings. The focus is on how articles match the confidence score condition in both settings and the extent of overlap in their topic assignments. The column *Matched Number* refers to the total number of articles that meet the required confidence score condition for each temperature setting. The column *Matched Rate* is calculated as *Matched Number* divided by the number of post-processing articles 1,478,555, which measures the proportion of articles that meet the confidence score condition. The column *Overlapping Number* represents the number of articles that not only meet the confidence score condition for both temperature settings but also have the same topic assigned by both temperatures. The column *Overlapping Rate* is computed by dividing the *Overlapping Number* by the average *Matched Number* of both temperature settings. It reflects the consistency between the two temperature settings in assigning the same topic to articles that satisfy the confidence score condition.

Topic	Temperature 0		Temperature 1		Overlapping	
Confidence Score	Matched Number	Matched Rate	Matched Number	Matched Rate	Overlapping Number	Overlapping Rate
≥ 0	1,478,465	99.99%	1,475,316	99.78%	1,192,698	80.76%
≥ 0.1	1,478,464	99.99%	1,475,313	99.78%	1,192,698	80.76%
≥ 0.2	1,478,429	99.99%	1,475,229	99.78%	1,192,652	80.76%
≥ 0.3	1,478,232	99.98%	1,475,117	99.77%	1,192,554	80.76%
≥ 0.4	1,477,708	99.94%	1,474,930	99.75%	1,192,299	80.76%
≥ 0.5	1,476,631	99.87%	1,474,654	99.74%	1,191,702	80.76%
≥ 0.6	1,476,423	99.86%	1,474,409	99.72%	1,191,627	80.77%
≥ 0.7	1,473,121	99.63%	1,473,180	99.64%	1,189,705	80.76%
≥ 0.8	1,457,460	98.57%	1,465,279	99.10%	1,180,545	80.78%
≥ 0.9	1,321,071	89.35%	1,370,321	92.68%	1,076,954	80.03%

replicable. When the seed is set, ChatGPT attempts to sample deterministically, meaning that repeated requests with the same seed and parameters should yield identical results.

Additionally, for robustness and consistency checks on the attention and sentiment results, I run an alternative setting with the default temperature of 1 and no seed to validate the reliability of the output.

Table 1 presents the distribution of topic confidence scores for the two settings, highlighting their alignment and overlap. The column labeled *Matched Number* shows the total number of articles that meet the confidence score threshold for each temperature setting. The *Matched Rate* is calculated by dividing the *Matched Number* by the total number of post-processed articles (1,478,555), indicating the proportion of articles that meet the confidence score threshold. Even with the stringent condition of *Topic Confidence Score* $\geq$ 0.9, the *Matched Number* remains around 90% for both settings, demonstrating that ChatGPT assigns topics with high confidence to the vast majority of articles.

The column labeled *Overlapping Number* refers to articles that meet the confidence score criteria in both settings and receive the same topic assignment. The *Overlapping Rate* is calculated by dividing the *Overlapping Number* by the average of the two corresponding *Matched Numbers* for the temperature settings, reflecting the consistency between the two settings in assigning identical topics to articles that meet the confidence score condition. Across all confidence score thresholds, the *Overlapping Rate* hovers around 80%, indicating high consistency and robustness between the two settings.

Now that each article is assigned to a topic, I describe how to obtain the time-varying attention and sentiment for each topic. To calculate topic attention and sentiment, I only consider the articles with *Topic Confidence Score* ≥ 0.9. The articles that do not satisfy this condition are on a topic that is not covered in the topic list, or do not have a clear topic.

Topic attention is estimated monthly as the ratio of articles related to the topic divided by the total number of post-processed articles. Specifically, the attention for topic k in month t is calculated as:

$$\text{Attention}_t^k = \frac{\text{article count with } \textit{Topic Index} = \text{k and } \textit{Topic Confidence Score} \geq 0.9 \text{ in month } t}{\text{post-processing article count in month } t}. \tag{1}$$

The sentiment of topic k in month t is calculated as the average sentiment of articles with

Topic Index = k and *Topic Confidence Score* ≥ 0.9 in that month. Table A.1 in the Appendix presents the average attention and sentiment for each topic over time.

Attention and sentiment for each metatopic are aggregated in a similar way. Metatopic attention is computed as the sum of the attention scores of all topics within each metatopic, while metatopic sentiment is represented as the average sentiment across all articles associated with those topics.

Figure 3 displays the ranking of metatopics based on both attention and sentiment. The size of each metatopic node is proportional to its average attention over time. The six metatopics receiving the greatest attention are *Corporate Finance* (0.21), *Political/Social/-Cultural* (0.12), *Financial Stability* (0.08), *International Affairs* (0.07), *Financial Markets* (0.07), and *Economic Outlook* (0.07).

The sentiment distribution, ranging from most positive to most negative, is indicated by the color gradient of the metatopic nodes, moving from green to red in a clockwise direction. Green corresponds to positive sentiment, while red indicates negative sentiment, with the intensity of the color reflecting the strength of the sentiment. The metatopic with the most positive sentiment is *Technology*, driven primarily by the topics *Digital Economy Growth and E-commerce Trends*, *Technological Innovations and Corporate Strategies*, and *Technological Shifts in Media, Finance, and Transportation*. Conversely, *Financial Stability* registers the most negative sentiment, influenced by topics such as *Financial Crisis and Investor Confidence*, *Financial Sector Instability and Job Cuts*, and *Emerging Market Financial Instability*.

Figure 4 presents the time series variation in attention and sentiment for a subset of eight illustrative topics.[11] The black line, corresponding to the left vertical axis, represents the attention given to each topic as a percentage of total monthly WSJ news production. The red line, aligned with the right vertical axis, reflects the average sentiment of the articles associated with each topic.

[11] Appendix Section F presents the attention and sentiment time series for all 59 topics across 14 metatopics.

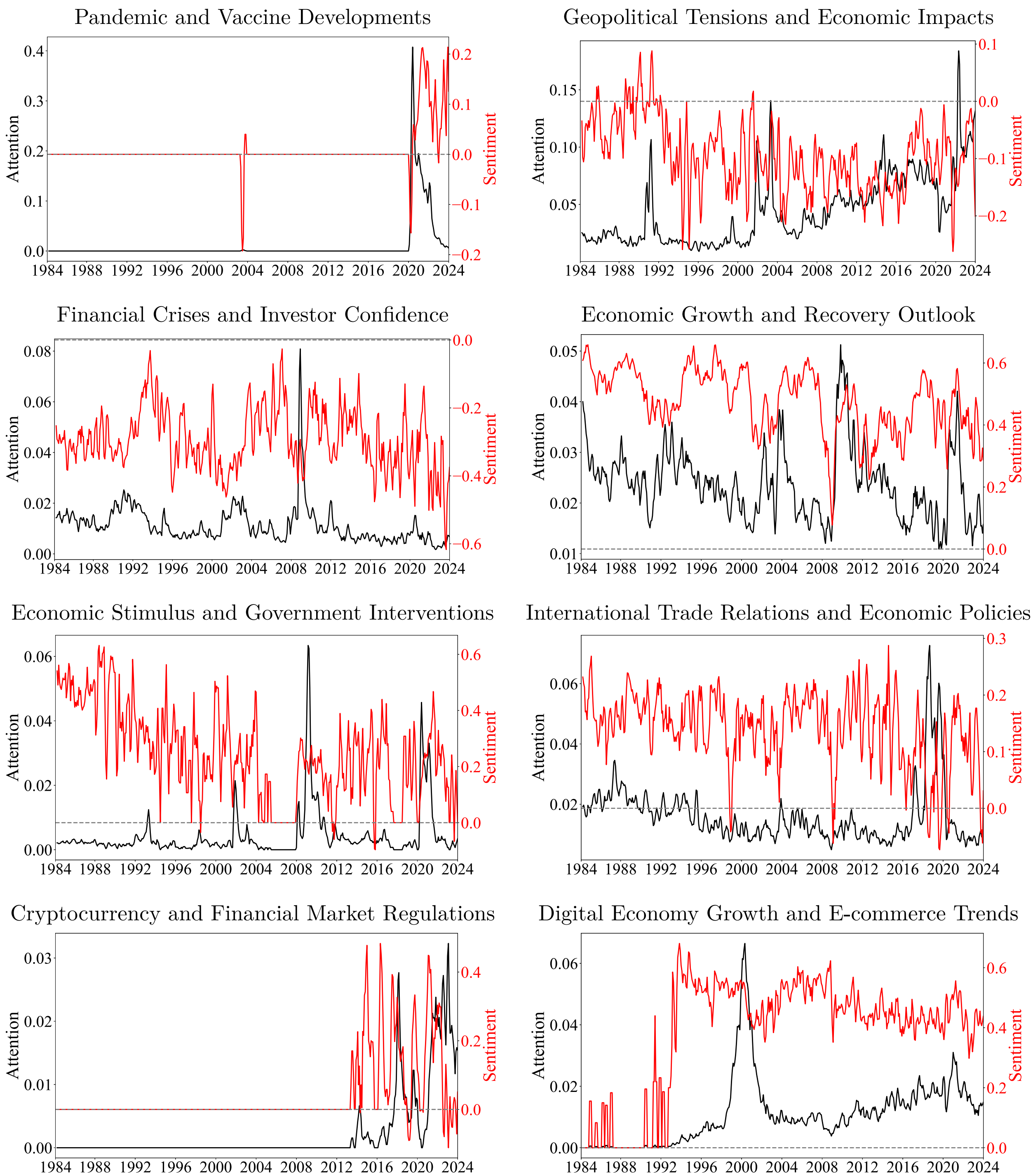

Figure 4: Topic Attention and Sentiment Time Series

Note: The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

Two smoothing conditions are applied in these plots. First, the figure shows the 3-month moving average for both the attention and sentiment time series. Second, attention and sentiment values are set to zero when a topic has three or fewer articles in a given month. These adjustments apply only to the plots of attention and sentiment time series in Figure 4 and Appendix Section F.

The eight illustrative topics in Figure 4 serve as an intuitive way to validate the topic attention and sentiment assignments.

The first topic *Pandemic and Vaccine Development* has the description "The COVID-19 pandemic has significantly affected health and economic conditions globally. Multiple pharmaceutical companies, including Pfizer, Moderna, and AstraZeneca, have developed COVID-19 vaccines with high efficacy rates. Distribution plans face logistical challenges and vaccine hesitancy. COVID-19 variants have necessitated booster shots and further public health measures." Attention to this topic surged in 2020 due to the outbreak of the COVID-19 pandemic, with sentiment starting negatively early in the year and improving as vaccines were developed. Attention also rose moderately in 2003 due to the severe acute respiratory syndrome (SARS) outbreak. Sentiment was initially negative, as airline operations were halted during the outbreak, but it shifted to positive as the airline industry recovered. Detailed article examples and corresponding ChatGPT outputs are provided in the Appendix Section A.

The second topic *Geopolitical Tensions and Economic Impact* displays six distinct peaks, corresponding to key global events: the Gulf War in 1990, the Kosovo War in 1999, the September 11 attacks in 2001, the Iraq War beginning in 2003, the Russo-Ukrainian War following Russia's annexation of Crimea in 2014, and the 2022 Russian invasion of Ukraine. Each of these events significantly influenced both global politics and economic stability.

The following two topic plots illustrate the financial crises and subsequent economic recovery. The attention on the bottom left topic, *Financial Crises and Investor Confidence,* highlights the period of the 2008 Great Financial Crisis. Meanwhile, the two recent peaks in the bottom right topic, *Economic Growth and Recovery Outlook,* correspond to recoveries following the Great Financial Crisis and the Covid-19 pandemic. A comparison of sentiment between the two topics reveals that financial crises are associated with negative sentiment, while economic recovery is linked to positive sentiment.

The overview of additional topics is provided in Appendix Section B. All eight plots demonstrate that both topic attention and sentiment are closely aligned with specific world events. This correlation suggests that the time series of topic attention and sentiment can serve as reliable indicators for shifts in public focus and sentiment around key events, as spikes in both are often driven by significant societal or economic occurrences.

2.4 Comparison with LDA Topic Modeling

In this section, I validate the ChatGPT-generated attention time series by comparing it with the topic attention derived from the Latent Dirichlet Allocation (LDA) topic modeling approach introduced by Blei et al. (2003). Bybee et al. (2024) decompose *WSJ* news articles from 1984 to 2017 into 180 topics using LDA. The monthly topic attention data, including time series for all 180 topics, is downloaded from the project website, `www.structureofnews.com`.

Latent Dirichlet Allocation (LDA) is a popular probabilistic topic modeling technique for uncovering hidden themes within a collection of documents. LDA assumes each document is composed of a mixture of topics, where each topic is a probability distribution over words. These keywords per topic are estimated directly from the data without any guidance from article labels or from the researcher. After running the model, Bybee et al. (2024) manually assigns a label to each topic based on the reading of the keyword lists.

Figure 5 compares related topics between ChatGPT and LDA. The black line represents the topic attention generated by ChatGPT, while the red line corresponds to the LDA-generated topic attention from Bybee et al. (2024). The correlation between the two time series, labeled "LDA vs. GPT Correlation," is shown in the legend, along with the respective topic names generated by LDA and ChatGPT.

All correlations between LDA and ChatGPT exceed 0.6, and the trends of both time series

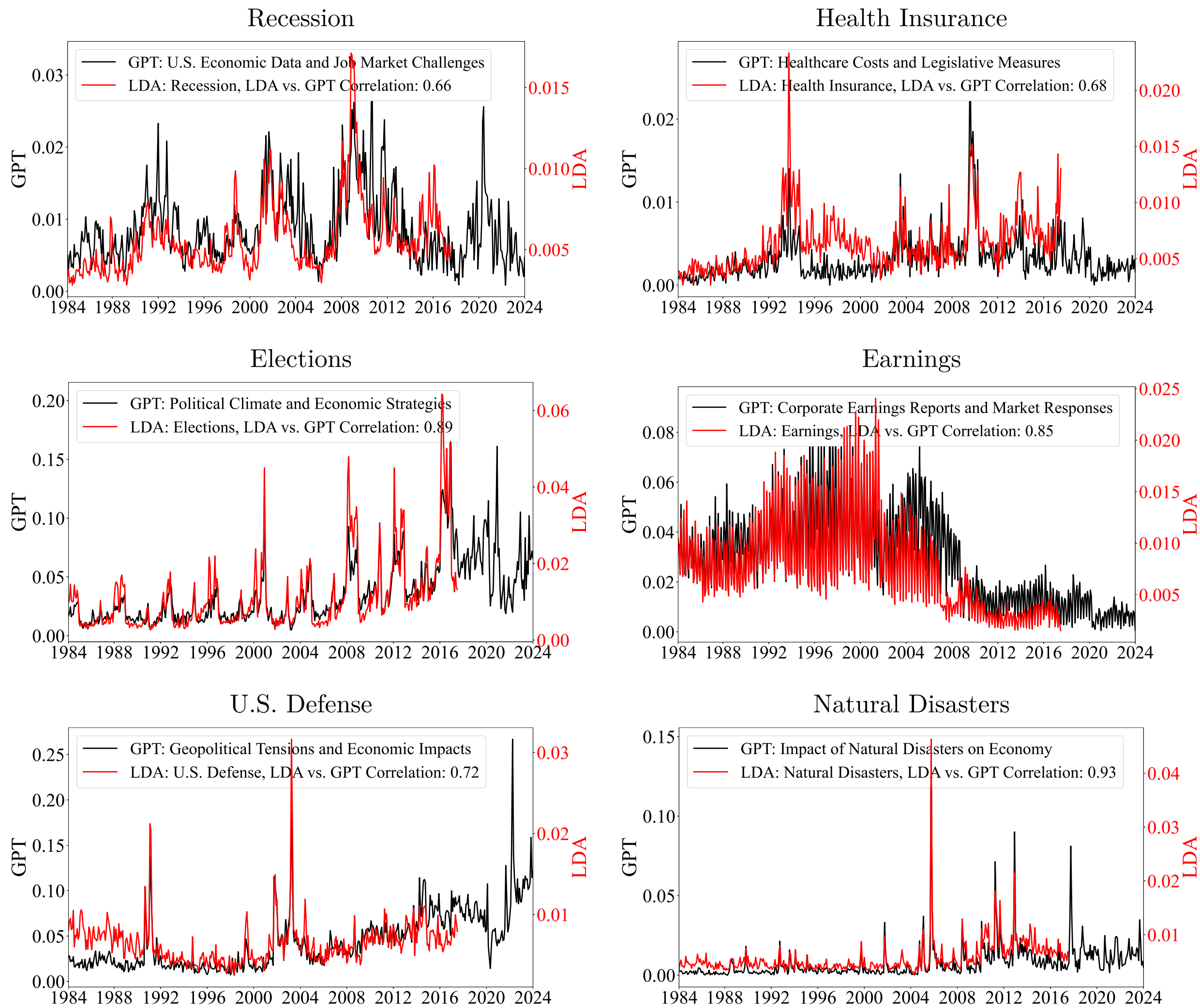

Figure 5: Topic Attention Comparison with LDA

Note: The black line represents the topic attention generated by ChatGPT. The red line corresponds to the topic attention generated by LDA, as described in Bybee et al. (2024). The correlation between the two time series, labeled "LDA vs. GPT Correlation," is shown in the legend, along with the corresponding topic names generated by LDA and ChatGPT.

are aligned. The topic attention plots reveal several key insights about the composition of *WSJ* news as identified by both methods.

First, news attention tends to be persistent over time, as demonstrated in the first two plots. In the initial plot, the LDA topic *Recession* and the related ChatGPT topic *U.S. Economic Data and Job Market Challenges* show sustained and recurrent activity throughout the sample period. Likewise, the LDA topic *Health Insurance* and ChatGPT topic *Healthcare Costs and Legislative Measures* experience significant attention during the discussions surrounding the Clinton Health Plan in 1993 and the Obamacare proposal from 2008 to 2010.

The middle two plots in Figure 5 depict seasonal topics. The LDA topic *Elections* and the corresponding ChatGPT topic *Political Climate and Economic Strategies* follow a predictable pattern, peaking every four years with secondary spikes every two years.[12] Similarly, the LDA topic *Earnings* and the ChatGPT topic *Corporate Earnings Reports and Market Responses* see increases just before each quarterly earnings report season.

The last two plots illustrate emergent topics that typically remain inactive but draw intense focus during specific events. The LDA topic *U.S. Defense* and ChatGPT topic *Geopolitical Tensions and Economic Impacts* capture shifts in coverage, with notable attention during the Gulf War in 1990, the Kosovo War in 1999, the September 11 attacks in 2001, and the Iraq War in 2003. Similarly, the LDA topic *Natural Disasters* and its ChatGPT counterpart *Impact of Natural Disasters on Economy* topics receive limited attention for most of the period but spike dramatically in August 2005 because of Hurricane Katrina.

All six plots in Figure 5 indicate that LDA serves as a reliable validation for the topics generated by ChatGPT.

While LDA and ChatGPT-generated topics share some similarities, ChatGPT offers several distinct advantages over traditional topic models like LDA, Non-negative Matrix Factorization (NMF), Dynamic Topic Models (DTM), and Top2Vec. These advantages stem from the inherent strengths of large language models (LLMs), which go beyond the limitations of older topic modeling methods.

First, ChatGPT offers the additional capability of extracting other types of textual information beyond topic attention, such as sentiment analysis. This is especially valuable in contexts like finance, where understanding the sentiment of news articles can provide deeper

[12] The description for the ChatGPT topic *Political Climate and Economic Strategies* is: "Political developments and election outcomes significantly impact economic policies and strategies, influencing investor strategies and market dynamics." This topic specifically relates to the LDA topic *Elections*.

insights into market reactions or economic trends. Traditional models like LDA are typically limited to identifying word clusters and do not easily incorporate sentiment or other nuanced interpretations of the text.

Second, ChatGPT's ability to generate topics based on a deeper understanding of context makes its results more interpretable and relevant, especially when summarizing complex events. Traditional models, such as LDA, rely heavily on word frequency (the 'bag-of-words' approach), which often results in clustering based on similar words rather than cohesive event-based topics. For example, Bybee et al. (2024) identifies a *Connecticut* topic key terms: *stamford conn, stamford, greenwich conn, conn, haven conn*, which clusters geographic names, offering little insight into any specific events or trends. Similarly, the *Wide Range* topic key terms: *wide range, vary wide, vast majority, broad range, wide variety* groups together synonyms. These generic clusters are less effective when it is crucial to understand specific events and trends. In contrast, ChatGPT leverages its comprehension of the full text to capture the underlying meaning of articles and accurately summarize events, making it better suited for applications where contextual understanding is essential.

Third, unlike LDA and other traditional models, ChatGPT does not require extensive text preprocessing steps like removing stop words, stemming, or lemmatization. These steps, often necessary for LDA to function effectively, can result in the loss of important contextual information. ChatGPT processes the full text, including punctuation and numerical data, making it both more efficient and capable of preserving the richness of the original content. This flexibility reduces the risk of missing key elements in the data and simplifies the overall workflow, making it easier to implement in practice.

In summary, while traditional models like LDA have been foundational for topic modeling, ChatGPT's ability to understand, summarize, and analyze text with greater accuracy and less preprocessing provides a more powerful tool for interpreting complex datasets.

3 Active Mutual Fund Portfolio Exposure to Media Topics

In this section, I analyze how active equity mutual funds adjust their portfolio strategies in response to media topics. I first define a fund as having exposure to a topic if it overweights stocks that are expected to perform well when the topic grows in importance, and hence attention, in the future. I find that the topics that funds have high exposure to are high-sentiment topics, not high-attention topics or topics with a high combination of sentiment and attention.

I then assess the impact of this strategy on fund performance and find that it is, in fact, counterproductive—funds that tilt towards high-sentiment topics tend to underperform. This negative correlation raises the question of why funds pursue this approach. My findings suggest that, despite the adverse effect on performance, funds are incentivized to target high-sentiment topics because doing so attracts greater inflows, which in turn boosts their fee-based revenue, as management fees are typically calculated as a percentage of total net assets (TNA). Thus, the pursuit of inflows, rather than performance, appears to be the driving force behind this behavior.

3.1 Data

I construct my sample by integrating several key datasets. The portfolio holdings of mutual funds are sourced from the Thomson Reuters (TR) mutual fund holdings data (S12), while mutual fund returns and characteristics come from the Center for Research on Security Prices (CRSP) Survivorship Bias-Free Mutual Fund Database. The CRSP database offers comprehensive data on fund returns, along with detailed fund characteristics such as total net assets (TNA), age, expense ratio, turnover, and load.

The analysis is focused on domestic open-end diversified equity funds, as these provide the most complete and reliable holdings data. Consistent with prior research (e.g., Kacperczyk et al., 2008; Evans, 2010; Benos et al., 2010; Huang et al., 2011; Dou et al., 2022), I identify actively managed U.S. equity mutual funds by examining their objective codes and disclosed asset compositions. To ensure accurate classification, I further exclude index funds by cross-referencing their names and the index fund identifiers available in the CRSP data. Additional details on the fund classification process are provided in Appendix Section C. For mutual funds with multiple share classes, I consolidate all observations from different share classes into a single portfolio-level observation, as they share the same portfolio composition.[13]

Once the TR and CRSP mutual fund datasets are filtered and merged, they are linked to the CRSP stock database following the methodology outlined in Kacperczyk et al. (2008). The CRSP stock-level database provides detailed information on individual stock returns and characteristics. The final sample includes 4,143 unique funds and 196,939 fund-report-date observations spanning from March 1980 to December 2023.

Additionally, monthly Carhart factors, including the Fama-French three factors plus momentum, are sourced from Kenneth French's Data Library at Dartmouth, covering the period from 1927 to 2023.

3.2 Mutual Fund Active Exposure to Topics

To evaluate how active equity mutual funds adjust their portfolios in response to media topics, I begin by defining a fund as having exposure to a topic if it overweights stocks that will perform well (or underweights stocks that will perform poorly) when attention to a topic increases. This fund's portfolio will have a positive alpha when attention to the topic rises, and a negative alpha when attention declines. For instance, at the onset of the COVID-19 pandemic in 2020, a fund manager might overweight Pfizer due to anticipated positive returns from vaccine developments, and also underweight Boeing, as the airline industry faced severe disruptions from global travel restrictions.

To measure the mutual fund portfolio exposure, I first estimate a stock i's exposure to a given topic k ($k = 1, \cdots, 59$) in month t, denoted as $\beta_{i,t}^{k}$, on a monthly basis. This is

[13] I aggregate total net assets under management (TNA) by summing across share classes. For qualitative attributes (e.g., fund name, date of origination), I retain the details from the oldest share class. For quantitative attributes (e.g., returns, expense ratios, and loads), I compute a weighted average, using the lagged TNA of each share class as the weighting factor.

estimated by regressing the stock's monthly excess returns on the changes in topic attention using a T-month rolling window:

$$R_{i,t-\tau} = a_{i,t} + \beta^k_{i,t}\Delta\text{Attention}_{k,t-\tau} + \epsilon_{i,t-\tau}, \quad \text{where } \tau = 0, 1, \ldots, T, \tag{2}$$

where $R_{i,t-\tau}$ represents the excess returns of stock i in month $t-\tau$. $\Delta\text{Attention}_{k,t}$ represents the innovation in topic k's attention in month t, defined as the difference in attention between two consecutive periods: $\text{Attention}_{k,t} - \text{Attention}_{k,t-1}$. For each stock, I run (2) for all 59 topics. I estimate the exposure using a rolling window of up to 48 months. When there are fewer than 48 months available, I use an expanding window starting from a minimum of 32 months. However, the results are robust to alternative window lengths, such as 24, 36, and 60 months.

The stock exposure, $\beta^k_{i,t}$, measures stock i's performance when attention to topic k increases. For instance, during the COVID-19 pandemic in 2020, we would expect Pfizer to have a positive $\beta^k_{i,t}$, indicating that its returns increase as attention to the pandemic rises. Conversely, Boeing would likely exhibit a negative $\beta^k_{i,t}$, reflecting declining returns as attention to the pandemic intensifies. Figure 6 illustrates the $\beta^k_{i,t}$ values for Pfizer and Boeing from June 2022 to December 2023. During this period, Pfizer's $\beta^k_{i,t}$ remains around 0.25, while Boeing's $\beta^k_{i,t}$ is approximately -1.17.

I then define an active fund's portfolio exposure to each topic as the difference between the average stock exposure of the fund's portfolio and the average stock exposure of the market portfolio. Intuitively, a fund has a high exposure to a topic if it overweights stocks that will perform well when the topic grows in importance.

For fund f at time t, the active exposure of the mutual fund to topic k is calculated as the weighted average of the stock-topic exposures relative to the market-weighted average exposure:

$$\text{Exposure}^{f,k}_t = \sum_{i=1}^{N} (w^f_{i,t} - w^m_{i,t})\beta^k_{i,t-1}, \tag{3}$$

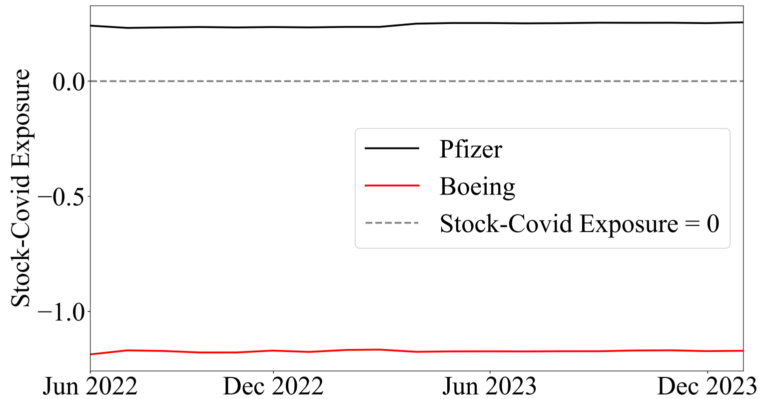

Figure 6: Stock-Topic Exposure $\beta^k_{i,t}$ of Pfizer and Boeing

Note: This figure presents the stock-topic exposure $\beta^k_{i,t}$ for Pfizer and Boeing, calculated using (2).

where $i = 1, \ldots, N$ represents all stocks held by active mutual funds. The portfolio weight $w^f_{i,t}$ is the proportion of fund f's total assets invested in stock i, while the market weight $w^m_{i,t}$ is the proportion of the total market capitalization held in stock i, accounting for all stocks held by active mutual funds. The term $w^f_{i,t} - w^m_{i,t}$ captures fund f's active tilts toward stock i relative to the market benchmark. $\beta^k_{i,t-1}$ is the lagged one-month stock-topic exposure of stock i, ensuring that the topic exposure is observable to fund managers one month prior to the fund's holdings report date.

The quantity Exposure$^{f,k}_t$ measures how a fund manager adjusts the portfolio's exposure to topic k relative to the market. A high Exposure$^{f,k}_t$ indicates that fund f is overweighting stocks with high stock-topic betas and underweighting those with low betas. In other words, a fund has high exposure to a topic if it overweights stocks that will perform well, or underweights stocks that will perform poorly, when attention to a topic increases.

I define exposure based on changes in attention. The reason is that, in the reports that mutual funds write for their shareholders, fund managers often discuss which topics will grow in importance, which is related to media attention. There are many such examples in mutual fund reports. Detailed examples from N-CSR filings are provided in Appendix Section D.

I do not define exposure based on changes in sentiment because these changes may have only a limited impact on prices when attention is low. Attention is a more direct factor for mutual funds to form their strategies on, compared to sentiment.

3.3 Increased Exposure to High-Sentiment Topics

In this subsection, I examine what kinds of topics mutual funds choose to have high exposure to. Do they increase their portfolio exposure to topics that have high sentiment, high attention, or a high sentiment-attention interaction? The answer is not clear, ex-ante. I find that the topics that funds have high exposure to are high-sentiment topics, but not topics with high attention or a high combination of sentiment and attention.

To analyze this issue, I regress the fund's active portfolio exposure on topic sentiment, topic attention, and their interaction:

$$\text{Exposure}_t^{f,k} = b_0 + b_1 \text{Sentiment}_t^k + b_2 \text{Attention}_t^k + b_3(\text{Sentiment}_t^k \times \text{Attention}_t^k) + \mathbf{b_4 X_t^f} + \epsilon_t^{f,k}, \quad (4)$$

where $\mathbf{X_t^f}$ is a vector of fund-specific control variables, including seven fund characteristics. The first characteristic is fund net return, defined as the fund's total monthly return per share minus the expense ratio. The second is fund flow, which measures the percentage growth in new money for the fund, calculated as:

$$\text{Flow}_t^f = \frac{\text{TNA}_t^f - \text{TNA}_{t-1}^f(1 + R_t^f)}{\text{TNA}_{t-1}^f}, \quad (5)$$

where TNA_t^f represents the total net assets, and R_t^f is the net return for fund f in month t. Following Elton et al. (2001), I exclude observations where the previous month's TNA (TNA_{t-1}^f) is below 15 million to ensure data quality. Additionally, following Kacperczyk et al. (2008) and Kacperczyk et al. (2014), fund flows are winsorized at the 1% level within each period to reduce the influence of extreme outliers.

The other control variables include the fund's expense ratio (the ratio of total investment that shareholders pay for the fund's operating expenses), age (the age of the fund in days), TNA (total net assets), turnover (the fund's turnover ratio), and load (the sum of front load and rear load). All variables on the right-hand side of equation (4) are standardized by their standard deviation, ensuring that the coefficients are comparable across variables.

The dataset spans from 1984 to 2023, with average attention and sentiment estimated on a monthly basis. Fund-topic exposure ($\text{Exposure}_t^{f,k}$) is calculated at the holdings report date for each fund f.

Table 2 presents the estimated coefficients and t-statistics from regression (4). In the univariate regression shown in column (1), the coefficient for sentiment is 0.09 with a t-statistic of 2.91. When controlling for attention, sentiment-attention interaction, and other fund-level variables in columns (4) and (5), the sentiment coefficient slightly increases to 0.10 with a t-statistic of 2.48. The significantly positive coefficient of 0.1 indicates that the fund exposure to a topic increases by 118% relative to the average fund's active exposure of 0.08 when the topic sentiment increases by one standard deviation during the same quarter. All three coefficients on sentiment are significantly positive at the 95% confidence level. This indicates that active equity mutual funds tend to increase their portfolio exposure to topics with high sentiment. In contrast, the coefficients for attention and the sentiment-attention interaction are not statistically significant.

One concern is that the fund-level regression in (4) might overestimate the t-statistics because the number of observations for $Exposure_t^k$ is significantly higher than the number of observations for topic attention and sentiment: topic attention and sentiment do not vary by fund. To mitigate this concern, I run a regression where the dependent variable is the average portfolio exposure to each topic across all funds, and the independent variables are the topic's sentiment, attention, and their interaction:

$$\text{Exposure}_t^k = b_0 + b_1\text{Sentiment}_t^k + b_2\text{Attention}_t^k + b_3(\text{Sentiment}_t^k \times \text{Attention}_t^k) + \epsilon_t^k. \quad (6)$$

In this approach, both the left-hand-side and right-hand-side variables have the same number

Table 2: Regression of Fund Exposure on Topic Sentiment and Attention

Note: This table presents the coefficients and t-statistics from a regression of a fund's active portfolio exposure on topic sentiment, attention, and their interaction, as specified in (4). The dependent variable is the fund-topic "Exposure," defined in equation (3), where each stock's topic exposure, $\beta^k_{i,t-1}$, is calculated using a 48-month rolling window. Sentiment^k_t refers to the average sentiment of articles related to topic k during month t, and Attention^k_t measures the attention topic k receives in month t, as defined in equation (1). "Net Return" represents the fund's total monthly return per share minus the expense ratio. "Flow" captures the percentage growth in a fund's new money defined in (5). "Expense Ratio" reflects the percentage of total investment that shareholders pay for the fund's operating expenses. "Age" is the fund's age, measured in days. "TNA" refers to the fund's total net assets. "Turnover" denotes the fund's turnover ratio. "Load" is the total fund load, which is the sum of front load and rear load. "Flow" is winsorized at the 1% level to mitigate the impact of outliers. All right-hand-side variables are standardized by their standard deviation to make the coefficients comparable. The data are monthly and span the period from 1984 to 2023. t-statistics are shown in parentheses, with standard errors clustered by fund, topic, and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exposure				
	(1)	(2)	(3)	(4)	(5)
Sentiment	0.09***			0.10**	0.10**
	(2.91)			(2.48)	(2.48)
Attention		-0.02		-0.01	-0.01
		(-0.88)		(-0.45)	(-0.45)
Sentiment × Attention			0.02	-0.02	-0.02
			(1.39)	(-0.95)	(-0.97)
Net Return					-0.01
					(-0.92)
Flow					0.01
					(1.65)
Expense Ratio					0.03**
					(2.02)
Age					-0.01*
					(-1.90)
TNA					-0.00
					(-0.31)
Turnover					-0.00
					(-0.18)
Load					-0.01**
					(-2.18)
Constant	0.03	0.09**	0.07**	0.04	-0.00
	(1.00)	(2.06)	(2.00)	(0.93)	(-0.10)
Observations	9,782,503	9,782,503	9,782,503	9,782,503	9,782,503
R^2	0.16%	0.01%	0.01%	0.17%	0.20%

Table 3: Regression of Average Fund Exposure on Topic Sentiment and Attention

Note: This table reports the coefficients and t-statistics from a regression of a fund's active portfolio exposure on topic sentiment, attention, and their interaction, as specified in equation (6). The dependent variable is the average fund-topic "Exposure" (defined in (3)) across funds, where $\beta^k_{i,t-1}$, is calculated using a 48-month rolling window. Sentiment^k_t refers to the average sentiment of articles related to topic k during month t, and Attention^k_t measures the attention topic k receives in month t, as defined in equation (1). The data are monthly and cover the period 1984 to 2023. t-statistics are shown in parentheses, with standard errors clustered by topic and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Exposure			
	(1)	(2)	(3)	(4)
Sentiment	0.39***			0.46***
	(3.75)			(3.41)
Attention		-1.11		-0.09
		(-1.08)		(-0.11)
Sentiment × Attention			2.64	-5.41*
			(1.12)	(-1.79)
Constant	0.02	0.10**	0.08*	0.02
	(0.54)	(2.04)	(1.93)	(0.53)
Observations	23,890	23,890	23,890	23,890
R^2	0.95%	0.04%	0.03%	1.07%

of observations. The results of this regression, shown in Table 3, are consistent with the main findings in Table 2.

To determine which categories of topics contribute to the positive sentiment coefficient, I estimate the following regression for each of the 14 metatopics shown in Figure 3:

$$\text{Exposure}^k_t = b_0 + b_1\text{Sentiment}^k_t + \epsilon^k_t. \tag{7}$$

The regression results for each metatopic are presented in Table 4. The findings reveal that the positive sentiment coefficient is primarily driven by topics associated with economic growth, including *Financial Markets*, *Economic Outlook*, *Labor/Income*, *Economic Stimulus*, and *Financial Stability*. Interestingly, the metatopic *ESG* has the highest sentiment coefficient.

Table 4: Regression of Fund Exposure on Topics

Note: This table reports the coefficients and t-statistics of regressing average fund portfolio active exposure on topic sentiment, attention, and their interaction in (7). The dependent variable is the average fund-topic *Exposure* (defined in (3)) across funds. $Sentiment_t^k$ is the average sentiment of articles related to topic k in month t. $Attention_t^k$ is the topic attention of topic k in month t, defined in (1). The data are monthly and cover the period 1984 to 2023. The t-statistics are in parentheses. Standard errors are clustered by topic and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Metatopic	Sentiment	t-statistics	Observations	R^2
ESG	1.33***	3.59	1,691	9.74%
Financial Markets	0.90***	11.28	1,274	12.10%
Economic Outlook	0.87***	5.71	1,700	10.46%
Economic Policy	0.83	1.46	1,469	0.16%
Labor/Income	0.72***	2.00	850	2.49%
Economic Stimulus	0.69***	3.45	1,253	5.58%
Financial Stability	0.58***	6.12	2,144	4.47%
Consumer Behavior	0.25	1.38	2,094	0.33%
Political/Social/Cultural	0.24	1.36	2,125	2.04%
Corporate Finance	0.07	0.50	2,964	0.21%
Technology	0.00	0.02	1,653	0.00%
Healthcare	-0.18	-0.70	2,133	0.17%
International Affairs	-0.20	-1.40	1,690	0.92%
Oil & Energy	-0.84	-1.11	850	5.27%

3.4 Performance of Funds with Increased Exposure to High-Sentiment Topics

After showing that mutual funds have high portfolio exposure towards high-sentiment topics, a key question arises: Are these funds profiting from this strategy? The answer is no. The empirical results show that the more a fund is exposed to high-sentiment topics, the lower its Carhart alpha.

To evaluate fund returns based on increased exposure to high-sentiment topics, I sort funds according to their sentiment-weighted portfolio exposure. Specifically, given that sentiment ranges from $[-1, 1]$, I first rescale sentiment for each topic k to fall between 0 and 1 as follows:

$$\text{ScaledSentiment}_t^k = \frac{\text{Sentiment}_t^k + 1}{2}.$$

Next, I calculate the sentiment-weighted exposure (SWE) for each fund f at the end of month t, which is the average fund-topic exposure weighted by the scaled sentiment of each topic:

$$\text{SWE}_t^f = \sum_k \text{ScaledSentiment}_t^k \text{Exposure}_t^{f,k}, \tag{8}$$

where $\text{Exposure}_t^{f,k}$ is standardized to have a cross-sectional standard deviation of one for each topic k and month t. Intuitively, funds with high SWE have high exposure to high-sentiment topics.

It is crucial to highlight that, to sort all funds at the end of each month, I estimate $\text{Exposure}_t^{f,k}$ for each fund based on the most recent $\beta_{i,t}^k$, rather than relying solely on holdings report dates.

The sentiment of low-attention topics may be subject to noise due to there being insufficient articles to compute an accurate average sentiment. To mitigate this, I exclude the 10% of topics with the least attention in each period.

At the end of each month, I categorize mutual funds into 10 deciles based on their SWE and calculate the average Carhart alpha for each decile. Three types of fund returns are used in the Carhart alpha calculation. The first is the holdings return, constructed from TR S12 mutual fund holdings following Kacperczyk et al. (2008). The second is the raw return, representing the fund's total monthly return per share, sourced from the CRSP Survivorship Bias-Free Mutual Fund Database. The third is the net return, calculated by subtracting the expense ratio from the raw return.

Table 5 presents the TNA-weighted and equal-weighted Carhart alphas in the month after portfolio formation for all three return types. Across both TNA-weighted and equal-weighted portfolios, and for all return types, Decile 10 shows a significantly lower alpha than Decile 1, as indicated by the significantly negative alpha in the "Decile 10 - Decile 1" row. In terms of Carhart alpha based on fund net returns in a one-month out-of-sample period, high-SWE funds (Decile 10) underperform low-SWE funds (Decile 1) by 39 basis points (bps) per month (4.68% annually) in TNA-weighted portfolios and by 32 bps per month (3.84%

Table 5: Carhart alphas of Sentiment-Weighted Exposure Fund Portfolio Sorts

Note: Each month, I sort mutual funds into ten deciles based on their sentiment-weighted exposure (SWE), as defined in (8), ranging from the lowest values (Decile 1) to the highest (Decile 10). This table presents the Carhart alpha along with alpha *t*-statistics (in parentheses) for both TNA-weighted and equal-weighted portfolios, measured one month after portfolio formation. The holdings return is constructed using TR S12 mutual fund holdings, following Kacperczyk et al. (2008). The raw return represents the total monthly return per share from the CRSP Survivorship Bias-Free Mutual Fund Database. The net return is calculated by subtracting the expense ratio from the raw return. The portfolio period spans from 1988 to 2023. All reported alphas are monthly values expressed in percentage terms. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	TNA-weighted Carhart alpha			Equal-weighted Carhart alpha		
Decile	Holdings return	Raw return	Net return	Holdings return	Raw return	Net return
1 (Lowest SWE)	0.20**	0.17**	0.10	0.18**	0.18**	0.09
	(2.26)	(2.23)	(1.26)	(2.15)	(2.34)	(1.12)
2	0.07	0.07	0.00	0.07	0.05	-0.03
	(1.29)	(1.44)	(0.03)	(1.30)	(1.15)	(-0.65)
3	0.04	0.00	-0.06*	0.03	0.02	-0.06*
	(1.03)	(0.03)	(-1.80)	(0.73)	(0.55)	(-1.75)
4	-0.01	-0.02	-0.08***	0.00	-0.01	-0.09 ***
	(-0.42)	(-0.55)	(-2.61)	(-0.01)	(-0.37)	(-3.33)
5	-0.03	0.01	-0.06	0.00	-0.02	-0.10***
	(-0.89)	(0.22)	(-1.16)	(-0.07)	(-0.68)	(-3.71)
6	-0.02	-0.01	-0.08**	0.00	0.01	-0.07**
	(-0.46)	(-0.23)	(-2.40)	(0.09)	(0.44)	(-2.20)
7	-0.01	0.01	-0.06	0.01	0.04	-0.04
	(-0.13)	(0.15)	(-1.53)	(0.31)	(1.05)	(-1.11)
8	-0.04	-0.04	-0.11**	-0.04	-0.03	-0.11***
	(-0.77)	(-0.79)	(-2.24)	(-0.81)	(-0.60)	(-2.68)
9	-0.08	-0.05	-0.12*	-0.07	0.07	-0.02
	(-1.07)	(-0.67)	(-1.76)	(-1.09)	(0.52)	(-0.13)
10 (Highest SWE)	-0.25**	-0.21**	-0.30***	-0.18*	-0.13	-0.23***
	(-2.41)	(-2.26)	(-3.15)	(-1.90)	(-1.59)	(-2.83)
Decile 10 - Decile 1	-0.45***	-0.39***	-0.39***	-0.35**	-0.31**	-0.32**
	(-2.82)	(-2.74)	(-2.80)	(-2.47)	(-2.43)	(-2.48)

annually) in equal-weighted portfolios. This performance gap is robust to other fund return measures, including fund raw returns and returns constructed from fund holdings.

To visualize the trend in portfolio Carhart alpha as SWE increases, I plot the alpha for

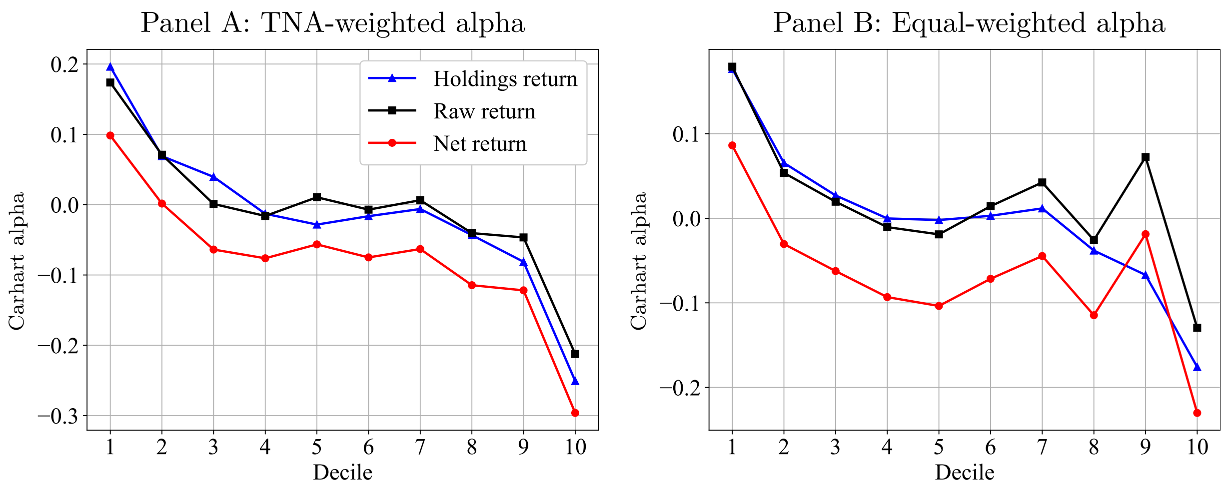

Figure 7: Carhart alphas of Funds Sorted by Sentiment-Weighted Exposure

Note: This table reports the Carhart alpha for both TNA-weighted and equal-weighted portfolios, measured in the month after portfolio formation. Each month, mutual funds are sorted into ten deciles based on their sentiment-weighted exposure (SWE), as defined in (8), with Decile 1 representing the lowest values and Decile 10 the highest. The holdings return is constructed using TR S12 mutual fund holdings, following Kacperczyk et al. (2008). The raw return refers to the fund's total monthly return per share from the CRSP Survivorship Bias-Free Mutual Fund Database. The net return is calculated by subtracting the expense ratio from the raw return. The portfolio period spans from 1988 to 2023, and all alphas are expressed as monthly percentages.

each decile in Figure 7. This decreasing trend remains consistent when the portfolios are sorted into five quintiles, as shown in Figure A.16.

3.5 Fund Flow Responses to Increased Exposure to High-Sentiment Topics

It seems counterintuitive that mutual fund managers would increase their portfolio exposure to high-sentiment topics, given that this leads to lower alpha. So, why do they make this decision? One possible explanation is that they are motivated by the potential to attract higher inflows. Given that funds earn a fee as a percentage of total net assets (TNA), larger inflows would translate into higher profits.

To test this hypothesis, fund flows are calculated using (5). As in Section 3.3, I ex-

Table 6: Flows to Funds Sorted by Sentiment-Weighted Exposure

Note: Each month I sort mutual funds into ten deciles based on their SWE, defined in (8), from lowest values (Decile 1 or Quintile 1) to highest values (Decile 10 or Quintile 5). This table reports the average flows and their t-statistics (in parentheses) for both TNA-weighted and equal-weighted portfolios in the month after portfolio formation. Flows are constructed as in (5). The portfolio period is from 1988 to 2023. All flow numbers represent monthly flows in percentage terms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	10 Deciles		5 Quintiles	
Decile/Quintile	TNA-weighted	Equal-weighted	TNA-weighted	Equal-weighted
Lowest SWE	-0.06	0.24***	-0.07	0.19**
	(-0.62)	(2.63)	(-0.87)	(2.38)
Highest SWE	0.25**	0.55***	0.19*	0.49***
	(2.04)	(3.84)	(1.71)	(3.92)
Highest - Lowest	0.31***	0.31***	0.25***	0.30***
	(3.14)	(2.72)	(3.52)	(3.72)

clude observations where the previous month's TNA is below \$15 million and apply a 1% winsorization to fund flows within each period to account for extreme outliers.

Next, I sort mutual funds into deciles based on their SWE at the end of each month and calculate both TNA-weighted and equal-weighted average fund flows for the following month. The average flows, along with their t-statistics (obtained by regressing fund flows on a constant), for the highest and lowest SWE deciles are presented in Table 6. For robustness, I also report results for funds sorted into quintiles. In both cases, funds with the highest SWE exhibit significantly higher average flows than those with the lowest SWE.[14]

To examine the trend of portfolio average flows as SWE increases, I plot the average flow for each decile or quintile in Figure 8. The results show that both TNA-weighted and equal-weighted flows exhibit an upward trend with increasing SWE.

Mutual fund flows can be influenced by various factors, such as past net returns and previous flows. To account for these, I perform a panel regression of future fund flows on SWE, controlling for other fund characteristics:

$$\text{Flow}_{t+1}^{f} = b_0 + b_1 \text{SWE}_t^f + \mathbf{b_2 X_t^f} + a_t + \varepsilon_t^{f,k}, \tag{9}$$

[14] Table A.3 in the Appendix contains detailed results for all deciles.

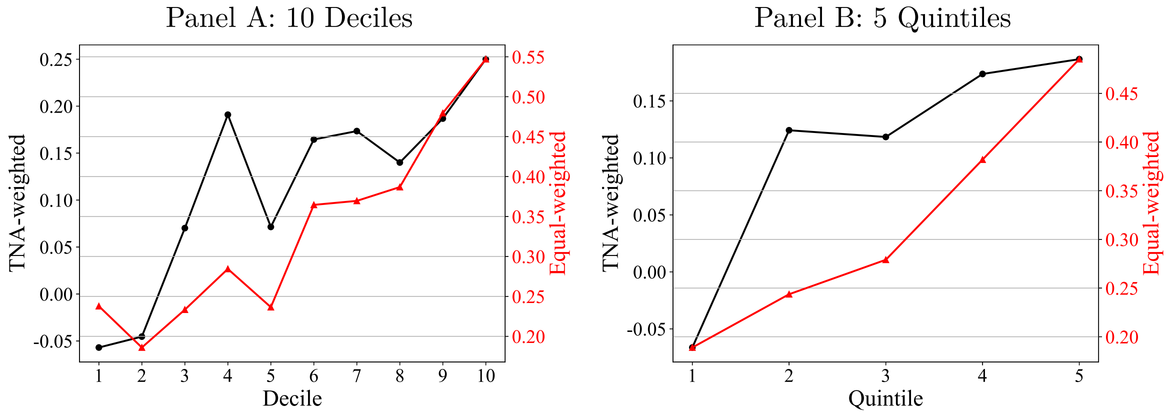

Figure 8: Average Flows of SWE Fund Sorts

Note: The TNA-weighted and equal-weighted average flows are calculated for the month following portfolio formation. Mutual funds are sorted each month into ten deciles based on their SWE (as defined in equation (8)), with Decile 1 (or Quintile 1) representing the lowest SWE values and Decile 10 (or Quintile 5) representing the highest. The portfolio formation period spans from 1988 to 2023, and all flow values are expressed as percentages of monthly fund flows.

where $\mathbf{X_t^f}$ represents a vector of fund-specific control variables, as defined in (4). Both SWE_t^f and $\mathbf{X_t^f}$ are standardized to have a standard deviation of one to ensure comparability across coefficients. Standard errors are clustered by both fund and month.

The regression results, shown in Table 7, indicate that funds tend to attract higher flows by increasing their portfolio exposure to high-sentiment topics. Since fund fees are calculated as a fraction of TNA, larger flows ultimately lead to higher profits.

If mutual funds increase their exposure to high-sentiment topics to attract more inflows, funds with higher expense ratios should be more incentivized to pursue this strategy, as higher inflows directly boost their profits. Therefore, I test the hypothesis that a fund's expense ratio positively predicts its next-month SWE. Specifically, I run the following panel regression, where SWE at time $t+1$ is regressed on the expense ratio at time t:

$$\text{SWE}_{t+1}^f = b_0 + b_1 \text{Expense Ratio}_t^f + \mathbf{b_2 X_t^f} + a_t + \varepsilon_t^{f,k}. \tag{10}$$

Table 7: Regressing Future Fund Flows on SWE

Note: This table reports the coefficients and t-statistics of a panel regression of future fund flows (one month ahead) on SWE, as defined in (9). The dependent variable is the monthly fund flow. SWE is defined in (8). "Net Return" represents the fund's total monthly return per share minus the expense ratio. "Flow" captures the percentage growth in a fund's new money defined in (5). "Expense Ratio" reflects the percentage of total investment that shareholders pay for the fund's operating expenses. "Age" is the fund's age, measured in days. "TNA" refers to the fund's total net assets. "Turnover" denotes the fund's turnover ratio. "Load" is the total fund load, which is the sum of front load and rear load. "Flow" is winsorized at the 1% level to mitigate the impact of outliers. All right-hand-side variables are standardized by their standard deviation to make the coefficients comparable. The data are monthly and span the period from 1984 to 2023. t-statistics are shown in parentheses, with standard errors clustered by topic and month. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Flow	
	(1)	(2)
SWE	0.09***	0.05**
	(3.30)	(2.25)
Net Return		0.33***
		(5.24)
Flow		0.38*
		(1.71)
Expense Ratio		0.02
		(0.35)
Age		-1.65***
		(-13.29)
TNA		-0.02
		(-0.98)
Turnover		0.06
		(1.08)
Load		0.07
		(1.05)
Constant	0.18	1.89***
	(3.24)	(7.84)
Time Effects	Yes	Yes
Observations	606,419	606,419
R^2	0.01%	2.13%

In this specification, SWE_{t+1}^{f}, Expense Ratio_{t}^{f}, and the control variables $\mathbf{X_t^f}$ are standardized to have a standard deviation of one to allow for direct comparison of coefficient magnitudes.

The regression results, presented in Table 8, show that the expense ratio has a positive and statistically significant coefficient of 0.05, with a t-statistic of 3.51, even after controlling for other fund characteristics. This suggests that funds with higher expense ratios are more

Table 8: Regressing SWE on Expense Ratio

Note: This table reports the coefficients and t-statistics of a panel regression of fund SWE (defined in (8)) on its expense ratio in (10). The dependent variable is the fund's "Expense Ratio", which is the ratio of total investment that shareholders pay for the fund's operating expenses. "Net Return" represents the fund's total monthly return per share minus the expense ratio. "Flow" captures the percentage growth in a fund's new money defined in (5). "Age" is the fund's age, measured in days. "TNA" refers to the fund's total net assets. "Turnover" denotes the fund's turnover ratio. "Load" is the total fund load, which is the sum of front load and rear load. "Flow" is winsorized at the 1% level to mitigate the impact of outliers. All right-hand-side variables are standardized by their standard deviation to make the coefficients comparable. The data are monthly and span the period from 1984 to 2023. t-statistics are shown in parentheses, with standard errors clustered by topic and month. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	SWE	
	(1)	(2)
Expense Ratio	0.05***	0.05***
	(3.52)	(3.51)
Net Return		0.01*
		(1.68)
Flow		0.00
		(1.40)
Age		0.00
		(-0.23)
TNA		0.00
		(-0.67)
Turnover		0.05***
		(4.21)
Load		-0.05***
		(-4.01)
Constant	-0.12***	-0.11***
	(-3.52)	(-2.71)
Time Effects	Yes	Yes
Observations	606,419	606,419
R^2	0.07%	0.27%

likely to increase their exposure to high-sentiment topics in the following month, supporting the hypothesis that higher expenses motivate funds to adopt strategies that attract greater inflows and, consequently, higher profits.

4 Stock-Level Active Tilts and Media Topics

In this section, I examine how much media topics can explain mutual fund tilts away from the market portfolio. Using an instrumented regression approach, I show that the topic-oriented behavior explains a large fraction, specifically 37%, of the aggregate active mutual fund tilt to stocks. Furthermore, the analysis reveals that the negative Carhart alpha associated with the aggregate active mutual fund tilt is entirely attributable to the topic-driven component. After isolating and removing the component, the residuals exhibit no significant alpha, suggesting that the underperformance of the active tilts is entirely due to topic-driven behavior.

4.1 Instrumented Regression

To investigate how much mutual fund tilts are influenced by the topic information, I first define the aggregate active equity mutual fund tilt (referred to as "active tilt") towards stock i at time t as:

$$\text{Tilt}_{i,t}^{MF} = w_{i,t}^{MF} - w_{i,t}^{m}, \tag{11}$$

where $w_{i,t}^{MF}$ represents the weight of asset i in the aggregate active equity mutual fund portfolio at time t, and $w_{i,t}^{m}$ denotes the market weight, which is the fraction of total market capitalization in asset i based on the stock pool held by the active equity mutual funds.[15]

To assess how much of this stock-level active tilt is driven by media topics, the ideal regression model would be:

$$\frac{\text{Tilt}_{i,t}^{MF}}{w_{i,t}^{m}} = \alpha + \sum_{k=1}^{K} \left(b_{i,t}^{k,S}\, \text{Sentiment}_t^k + b_{i,t}^{k,A}\, \text{Attention}_t^k + b_{i,t}^{k,SA}\, \text{Sentiment}_t^k \times \text{Attention}_t^k \right) + e_{i,t}, \tag{12}$$

where $b_{i,t}^{k,S}$, $b_{i,t}^{k,A}$, and $b_{i,t}^{k,SA}$ capture the sensitivity of the active tilt in asset i to the sentiment,

[15]I conduct the analysis at the stock level by aggregating fund tilts rather than using individual fund tilts to allow for an examination of the alpha of stock portfolios sorted by aggregating fund tilts in Section 4.2.

attention, and their interaction for topic k, respectively. To control for the effect of stock size, the left-hand-side variable, $\text{Tilt}_{i,t}^{MF}$, is standardized by the market weight of stock i.

However, estimating (12) for each stock i poses a challenge due to data limitations. For each stock, the quarterly holdings data spans 40 years from 1984 to 2023, which yields 160 observations. Unfortunately, the number of parameters on the right-hand side of the equation exceeds the number of observations ($3 \times 59 + 1 = 178$), rendering the regression infeasible.

To address this issue, I employ two strategies. First, instead of using all 59 topics on the right-hand side, I reduce the dimensionality by using the 14 metatopics instead, thereby decreasing the number of parameters. Despite this reduction, the observation-to-parameter ratio remains low:

$$\frac{\text{observations}}{\text{parameters}} = \frac{T}{3K+1} = \frac{40 \times 4}{3 \times 14 + 1} = 3.7,$$

which suggests that the regression may still be unstable.

The second strategy involves using stock characteristics as instruments for parameter estimation. Let N represent the number of stocks, M the number of stock characteristics, K the number of metatopics, and T the number of quarters in the estimation. The instrumented regression model is specified as follows:

$$\underbrace{\frac{\text{Tilt}_{i,t}^{MF}}{w_{i,t}^{m}}}_{N\times 1} = c + \underbrace{X_{i,t-1}}_{N\times M} \underbrace{\Gamma}_{M\times 3K} \underbrace{S_t}_{3K\times 1} + e_{i,t}, \tag{13}$$

where $X_{i,t-1}$ is a $N \times M$ instrument matrix containing asset characteristics. The topic signals S_t is a $3K \times 1$ vector consisting of Sentiment_t^k, Attention_t^k, and their interaction $\text{Sentiment}_t^k \times \text{Attention}_t^k$. The $M \times 3K$ matrix Γ captures the sensitivity of stock active tilt to the interaction between topic signals and stock characteristics. For the instrumented regression in equation (13), the observation-to-parameter ratio is given by:

$$\frac{\text{observations}}{\text{parameters}} = \frac{N \times T}{M \times 3K + 1}, \tag{14}$$

which is notably larger than the OLS observation-to-parameter ratio of $\frac{T}{3K+1}$, as $N \gg M$. This approach effectively addresses the data limitation issue.

For the stock characteristic data, following Jensen et al. (2024), I use 115 stock characteristics examined in Jensen et al. (2023) and one-month lagged excess returns.[16] Each characteristic is standardized each quarter by mapping the cross-sectional rank onto the $(0, 1]$ interval. Missing values are set to 0 to ensure that they do not influence the coefficient estimates.

The expanding window starts with 100 quarters, meaning the last date of the window ranges from December 2008 to December 2023. In the initial window, the observation-to-parameter ratio is 92.72 with 451,801 observations and 4,873 observations.[17] For the full sample, the observation-to-parameter ratio increases to 137.71 with 671,078 observations.[18] With the number of observations being approximately 100 times larger than the number of parameters, the risk of overfitting is substantially mitigated.

To assess the extent to which topic information explains the aggregate active equity mutual funds tilt, I analyze two types of R^2 values. The first is the adjusted full-sample R^2 for the period 1984 to 2023:

$$\text{Adjusted } R^2_{full} = 1 - \frac{(1 - R^2_{full})(n-1)}{n-p-1}, \tag{15}$$

where n represents the number of observations, p is the number of independent variables in the model, and R^2_{full} is the unadjusted full-sample R^2. The second measure is the expanding

[16] Jensen et al. (2023) investigates 153 stock characteristics from 1984 to 2023. However, characteristics with poor coverage are excluded in this analysis. Table A.2 in the Appendix provides an overview of the selected characteristics.

[17] According to (14), $\frac{\text{observations}}{\text{parameters}} = \frac{451{,}801}{116 \times 3 \times 14 + 1} = 92.72$.

[18] According to (14), $\frac{\text{observations}}{\text{parameters}} = \frac{671{,}078}{116 \times 3 \times 14 + 1} = 137.71$.

window R^2, calculated from December 2008 to December 2023. This approach uses the final observation in each expanding window to compute R^2:

$$R^2_{expanding} = 1 - \frac{\sum_i \sum_t \left(y_{i,t} - X_{i,t-1}\hat{\Gamma}_t S_t\right)}{\sum_i \sum_t \left(y_{i,t} - \bar{y}\right)^2}, \tag{16}$$

where $y_{i,t} = \frac{\text{Tilt}^{MF}_{i,t}}{w^m_{i,t}}$, and $\bar{y}$ is the mean of $y_{i,t}$. $\hat{\Gamma}_t$ represents the estimated parameter Γ from the instrumented regression in (13), with the training window ending in quarter t. The $R^2_{expanding}$ evaluates the proportion of the active tilts that can be attributed to topic information from 2008 to 2023.

The estimated values for Adjusted R^2_{full} and $R^2_{expanding}$ are reported in Table 9. The first three columns present the results for each of the topic signals S_t: Sentiment^k_t, Attention^k_t, and the interaction term $\text{Sentiment}^k_t \times \text{Attention}^k_t$ individually. The final column includes all three topic signals simultaneously.

The Adjusted R^2_{full} is approximately 10% for each of the first three columns and increases slightly to around 11% when all topic signals are included together. This suggests that the explanatory power of topic sentiment, topic attention, and their interaction overlaps to some extent.

The $R^2_{expanding}$ values exceed 30% for each column, with topic attention exhibiting the highest explanatory power at 36.51% among the individual signals. When all three topic signals are combined, the $R^2_{expanding}$ reaches 36.73%.

Both Adjusted R^2_{full} and $R^2_{expanding}$ indicate that topic attention has the strongest influence on the aggregate active equity fund tilt. It is important to note that this finding does not conflict with previous results showing that active mutual funds increase their exposure to high-sentiment topics rather than high-attention topics. This difference arises because the fund portfolio exposure is calculated based on topic attention, meaning the two comparisons address different aspects.

Table 9: Adjusted R^2_{full} and $R^2_{expanding}$ of Instrumented Regression

Note: This table presents the Adjusted R^2_{full} for the full sample and the expanding-window $R^2_{expanding}$ for the instrumented regression in (13). The full-sample Adjusted R^2_{full} is calculated using equation (15) for the period from January 1984 to December 2023. The expanding-window $R^2_{expanding}$ is similarly calculated using equation (15) for the period from December 2008 to December 2023. Columns (1), (2), and (3) report results for each of the individual topic signals—Sentiment^k_t, Attention^k_t, and the interaction term Sentiment^k_t $\times$ Attention^k_t. Column (4) includes all topic signals simultaneously.

Topic Signal S_t	(1)	(2)	(3)	(4)
Sentiment	Y			Y
Attention		Y		Y
Sentiment $\times$ Attention			Y	Y
Adjusted R^2_{full} (Jan 1984 – Dec 2023)	9.71%	9.83%	9.62%	10.98%
$R^2_{expanding}$ (Dec 2008 – Dec 2023)	32.42%	36.51%	31.32%	36.73%

4.2 Stock Portfolio Construction

In this subsection, I investigate whether the Carhart alpha of the aggregated active equity fund tilt can be attributed to the topic-driven component.

To test this hypothesis, I construct three portfolios. In each case, I sort stocks into ten deciles and compute the monthly Carhart alpha by subtracting the returns of the bottom decile from the top decile. The first portfolio is based on the size-standardized aggregated active equity fund tilt, defined as $\frac{Tilt^{MF}_{i,t}}{w^m_{i,t}}$. The second portfolio is sorted by the topic-driven tilt, $X_{i,t-1}\hat{\Gamma}_t S_t$, estimated at the end of each expanding window. The third portfolio is constructed using the residual from the instrumented regression (13):

$$\hat{e}_{i,t} = \underbrace{\frac{w^{MF}_{i,t} - w^m_{i,t}}{w^m_{i,t}}}_{\text{Active Tilt}} - \underbrace{X_{i,t-1}\hat{\Gamma}_t S_t}_{\text{Topic-Driven Tilt}}, \tag{17}$$

which represents the difference between the size-standardized active tilt and the topic-driven tilt in each expanding window, ending at quarter t.

This analysis aims to determine how much of the Carhart alpha of the active tilts can be explained by the topic-driven tilts. If the topic information primarily drives the alpha of the active tilts, we would expect the topic-driven tilts to exhibit similar alpha to the active tilts, while the residual tilts would have no significant alpha.

Figure 9 presents the Carhart alpha with 95% confidence intervals for the active tilts, topic-driven tilts, and residual tilts across three weighting methods. The "Equal-W" portfolio is equal-weighted within each decile, the "Value-W" portfolio is weighted by market equity, and the "Holdings-W" portfolio is weighted by the holdings of aggregated active equity mutual funds in each decile.

Starting with the equal-weighted active tilt portfolio, we observe a significantly negative alpha of approximately -1.86% per month with a t-statistic of -2.24. This suggests that, on average, the stocks in the top active tilt decile underperform those in the bottom decile out-of-sample. By contrast, the value-weighted and holdings-weighted portfolios exhibit no significant alpha, which aligns with previous literature, such as Cremers and Petajisto (2009) and Chen et al. (2000), where holdings-weighted portfolios generally show no alpha. This difference in performance between the equal-weighted and other portfolios can be interpreted as a concentration of underperformance among smaller stocks, which tend to have higher weight in equal-weighted portfolios.

Next, we turn to the topic-driven tilt portfolio. For the equal-weighted portfolio, the Carhart alpha of the topic-driven tilts is also significantly negative at -2.23% with a t-statistic of -2.40, whose magnitude is comparable to that of the active tilt portfolio. This suggests that the topic-driven component explains much of the underperformance in the active tilt portfolio. In other words, the negative alpha observed in the active tilts can largely be attributed to the topic-related factors driving stock selection.

Finally, the residual tilts, which represent the portion of active tilts unexplained by the topic-driven component, show no significant alpha across all weighting methods. This absence of alpha in the residual tilts suggests that, after accounting for the topic-driven tilts, there is no remaining evidence of persistent underperformance or outperformance in the active tilt portfolio. The results imply that the topic-driven tilts fully explain the negative alpha in the equal-weighted active tilt portfolio.

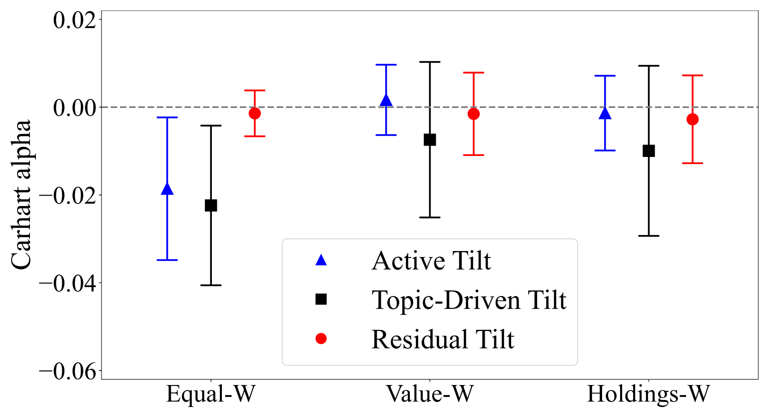

Figure 9: Carhart alpha of Active Tilt, Topic-Driven Tilt, and Residual Tilt Portfolios

Note: This figure shows the monthly Carhart alpha along with the 95% confidence interval for portfolios sorted by active tilts, topic-driven tilts, and residual tilts. The portfolios are constructed by sorting stocks into ten deciles based on each type of tilt, and the Carhart alpha is calculated as the difference between the top and bottom decile returns over the month following portfolio construction at each quarter's end. The "Active Tilt" portfolio is sorted using the size-standardized aggregated active equity fund tilt $\frac{Tilt_{i,t}^{MF}}{w_{i,t}^{m}}$. The second "Topic-Driven Tilt" portfolio is sorted based on the topic-driven tilt, $X_{i,t-1}\hat{\Gamma}_t S_t$, estimated at the end of each expanding window. The "Residual Tilt" portfolio is sorted by the residual from the instrumented regression (13). The portfolios are further categorized by three weighting methods: "Equal-W," which represents equal-weighted portfolios, "Value-W," where portfolios are weighted by market equity, and "Holdings-W," where the portfolio is weighted by the holdings of aggregated active equity mutual funds.

The fact that the value-weighted and holdings-weighted portfolios for both the active tilts and topic-driven tilts exhibit no significant alpha indicates that the topic's impact on performance is more pronounced in smaller stocks. The equal-weighted portfolio, with its larger exposure to smaller-cap stocks, captures this underperformance more directly. This suggests that topic-driven tilts are more concentrated among smaller stocks, where active mutual funds tend to face greater challenges in delivering consistent excess returns.

In summary, the results indicate that the negative alpha in active equity fund tilts can be attributed to the topic-driven tilts, particularly in portfolios with a higher weight on smaller stocks.

4.3 Reconciliation with the Active Share Literature

The literature on mutual fund active share finds that stocks overweighted by active mutual funds tend to outperform underweighted stocks, as shown by Jiang et al. (2014). At first glance, this might conflict with the negative alpha observed in the equal-weighted active tilt portfolio. However, the key to resolving this apparent contradiction lies in understanding the choice of benchmark.

The active share literature typically evaluates performance relative to individual mutual fund benchmarks, such as those self-declared by the funds themselves. Under this framework, stocks that are overweighted by mutual funds do tend to show outperformance. However, this does not necessarily imply that the outperformance is driven by the mutual funds' skill in stock selection. Instead, as Cremers and Petajisto (2009) point out, the outperformance relative to fund-specific benchmarks is often due to the underperformance of the benchmarks themselves, rather than to the outperformance of the funds with high active share.

When we switch from individual fund benchmarks to a common market benchmark, as is the case in studies such as Chen et al. (2000), there is no evidence of outperformance driven by the active tilts. In fact, the zero alpha observed in the holdings-weighted active tilt portfolio in Figure 9 mirrors the findings in Chen et al. (2000), reinforcing that, when measured against a universal market benchmark, mutual funds' active tilts do not generate excess returns in the holdings-weighted portfolio.

5 Conclusion

This paper addresses the question of how professional investors adjust their portfolio strategies in response to media topics. It has three sets of results.

First, I develop a novel prompt-based methodology that uses ChatGPT and WSJ news articles to quantify media topics. I use this approach to distill media topics into 59 topics, and then quantify each topic's time-varying share of news attention and sentiment.

Second, I analyze how active equity mutual funds adjust their portfolio exposure in response to media topics. I find that the topics that funds have high exposure to are high-sentiment topics, but not topics with high attention or a high combination of sentiment and attention. While this strategy results in mutual fund underperformance, it attracts investor flows, which explains its use.

Third, the paper shows that topic-oriented behavior accounts for a significant portion, namely 37%, of the aggregate mutual fund tilt away from the market portfolio. It is also a major contributor to the negative alpha associated with the active tilt.

Stepping back from these three specific results, the broader contribution of this paper is to offer a new perspective on investors' portfolios – not in terms of industry tilts or tilts toward other stock characteristics, but in terms of exposure to various media topics. AI tools play a crucial role in this approach, allowing me to summarize the complex information set investors consider when making portfolio decisions.

This paper also has important implications for practitioners. For asset managers, the results highlight the risks of catering to high-sentiment topics that prioritize short-term inflows over long-term performance. While this strategy may attract investor capital in the short run, it is associated with lower alpha. For investors, the research underscores the importance of being mindful of how the attention and sentiment of media topics can influence fund performance.

The paper also points to several interesting directions for future research, including exploring the influence of media topics on the heterogeneous behavior of retail investors and other types of institutional investors, as well as investigating the role of these topics in investor belief formation.

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INTERNET APPENDIX

A Examples of *WSJ* Articles on SARS

In 2003, attention of *Pandemic and Vaccine Development* increased moderately due to the severe acute respiratory syndrome (SARS) outbreak. Initially, sentiment was negative, with airline operations being suspended during the outbreak. Sentiment gradually shifted to positive as the airline industry began to recover. This section provides several examples of news articles illustrating this change in sentiment.

On May 27th, 2003, a news article titled "Air Traffic Shows a 19% Decline" reported:

> "Global air-passenger traffic fell about 19% on the year in April, preliminary data from the International Air Transport Association show. Asian-Pacific carriers experienced a 45% drop in passenger traffic, as severe acute respiratory syndrome took its toll on air-travel demand, the IATA said. ⋯ North American carriers showed a 24% decline in April, while European carriers had a 4.8% decline."

ChatGPT assigns this article to the topic *Pandemic and Vaccine Development* with a confidence score of 0.9. The rationale is: "The article discusses a significant decline in air traffic, which is directly related to the impact of the pandemic, particularly the severe acute respiratory syndrome (SARS) mentioned as a factor affecting air travel demand."

In addition, the article is assigned a sentiment score of -0.7, with the explanation: "The article conveys a negative sentiment due to the reported drastic decline in air traffic, which indicates severe challenges for the airline industry and broader economic implications."

Another example is from July 31, 2003, in an article titled "Travel Brief: Singapore Airlines," which reported:

> "Singapore Airlines reported a net loss for the first quarter of its fiscal year, but said the worst of the SARS-related damage appears to be over amid growing signs of a rebound in Asia's battered aviation sector. In the wake of the outbreak

> of severe acute respiratory syndrome, or SARS, the airline slashed a third of its capacity and cut 600 jobs, the most layoffs in its history."

ChatGPT assigns this article a topic confidence score of 0.9, reasoning: "The article discusses the impact of the SARS outbreak on Singapore Airlines, highlighting the financial losses and operational changes due to the pandemic. This aligns with the topic of COVID-19 and its effects on the aviation sector."

In addition, the article is assigned a sentiment score of -0.5, with the explanation: "The article conveys a negative sentiment due to the reported significant financial losses and job cuts at Singapore Airlines, indicating a challenging situation for the airline amidst the pandemic's aftermath."

These two examples demonstrate that the initial negative sentiment during the SARS outbreak stemmed from the suspension of airline operations. In the later stages of the outbreak, sentiment shifted to positive, primarily driven by the recovery of airlines as they resumed normal operations and restored capacity.

Following the example of Singapore Airlines on July 31st, a September 25, 2003, article titled "Singapore Airlines Lifts Capacity" illustrates the airline's recovery from the SARS outbreak:

> "Singapore Airlines said its passenger capacity is almost back to 2002 levels, and that its northern winter schedule reflects a restoration of many of the flights suspended during the outbreak of severe acute respiratory syndrome in April and May. The airline had cut routes by as much as one-third during the height of the SARS outbreak in April and May. The carrier said it will monitor the industry's trend toward recovery and will adjust capacity to meet demand. Singapore Airlines also said it will fly to Shenzhen, China, three times weekly starting Jan. 16. Shenzhen will be the airline's second new destination since the SARS outbreak."

The article is assigned a sentiment score of 0.6, with the rationale: "The article conveys a positive sentiment as it highlights the recovery of Singapore Airlines' capacity and the resumption of flights, indicating a rebound in the travel industry. The tone is optimistic about the airline's future operations, reflecting a sense of recovery and growth."

B Topics Overview in Figure 4

This section presents an overview of the final four topics in Figure 4, validating the assigned attention and sentiment for each.

The fifth topic, *Economic Stimulus and Government Interventions*, reveals four prominent peaks in attention around 1993, 2002, 2009, and 2021. The first peak in 1993 reflects President Bill Clinton's major economic stimulus plan, aimed at reducing the federal deficit while promoting economic growth. The second peak in 2002 corresponds to President George W. Bush's "Job Creation and Worker Assistance Act," implemented in response to the 2001 recession and the September 11 attacks to facilitate economic recovery. The third peak in 2009 arises from President Barack Obama's signing of the American Recovery and Reinvestment Act (ARRA), enacted to combat the Great Financial Crisis. Similarly, the final peak in 2021 aligns with President Joe Biden's American Rescue Plan Act, designed to mitigate the economic fallout from the COVID-19 pandemic. Each peak reflects a period of heightened government intervention aimed at stabilizing the economy during significant downturns.

The sixth topic, *International Trade Relations and Economic Policies*, highlights significant trade tensions between the United States and other global economies, particularly China and Japan. In the 1980s and early 1990s, the focus was on the U.S.-Japan trade war, primarily driven by disputes in the automotive and electronics sectors. The conflict reached a critical point in 1986 with the Semiconductor Agreement, when the U.S. accused Japan of engaging in unfair trade practices in the semiconductor industry. Fast-forwarding to more recent times, the U.S.-China trade war began in 2018, reflecting concerns over trade deficits, intellectual property theft, and market access. The trade war temporarily eased in January

2020 with the signing of the Phase One Trade Agreement, under which China agreed to increase purchases of U.S. goods and services.

The topic of *Cryptocurrency and Financial Market Regulations* gained prominence in 2013 as Bitcoin experienced its first major price rally, climbing from around $13 to over $1,100 by December. This rise in value marked the beginning of growing attention on cryptocurrencies. In 2017, Bitcoin surged again, increasing from around $1,000 in January to nearly $20,000 by December, driven by retail speculation and media hype. Simultaneously, the Initial Coin Offering (ICO) market boomed, raising billions through the creation of new cryptocurrencies, and leading to peaks in both attention and sentiment. However, in 2018, the cryptocurrency market faced a significant downturn after the ICO bubble burst, with many projects collapsing or being exposed as scams. Bitcoin fell from its near $20,000 high to around $3,000 by year-end, with many other coins losing over 90% of their value, resulting in a sharp decline in topic sentiment. In 2019, stablecoins like Tether (USDT) and USD Coin (USDC) saw increased adoption, particularly for transferring funds between exchanges, generating a modest rise in the topic attention. Between 2020 and 2021, cryptocurrency prices surged once again, with Bitcoin reaching all-time highs of $64,000 in April 2021 and $69,000 in November. Ethereum also peaked, hitting $4,800 by the end of the 2021. The same period saw the explosion of non-fungible tokens (NFTs), with projects like CryptoPunks and Bored Ape Yacht Club gaining widespread recognition. By 2022, market sentiment shifted from positive to negative as a prolonged bear market set in, driven by macroeconomic concerns and rising interest rates. Bitcoin fell below $20,000. The collapse the FTX exchange, due to mismanagement and fraud, further eroded confidence in the cryptocurrency industry.

The last topic, *Digital Economy Growth and E-commerce Trends*, peaks in 2000, closely tied to the rise and collapse of the dot-com bubble.

C Classification of Active and Index Funds

I employ the following methodology when screening for domestic equity mutual funds in both CRSP and Thomson Reuters (TR) mutual fund holdings data (S12):

1. Following Kacperczyk et al. (2008), I exclude funds in TR mutual fund holdings data (S12) with Investment Objective Codes (IOC) categorized as International (ioc=1), Municipal Bonds (ioc=5), Bond and Preferred (ioc=6), or Balanced (ioc=7).

2. I remove all funds where the "policy" variable is categorized as C & I, Bal, Bonds, Pfd, B & P, GS, MM and TFM, as outlined in the CRSP Survivor-Bias-Free US Mutual Fund Guide documentation (p. 20). This approach is consistent with Kacperczyk et al. (2008) and Evans (2010).

3. After the "policy" screen, I include funds with a Lipper Class (Lipper_Class, if available) that match the following: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE (as per Benos et al. (2010)).

4. If Lipper Class is unavailable, I use the Strategic Insight Objective Code (si_obj_cd) and include funds with SIOC codes: AGG, GMC, GRI, GRO, ING, or SCG.

5. If neither Lipper Objective Code nor Strategic Insight Objectives are available, I refer to the Wiesenberger Fund Type Code, selecting funds with the following objectives: G, GI, AGG, GCI, GRI, GRO, LTG, MCG, or SCG.

6. If none of these objective codes are available but the fund has a CS policy (indicating that common stocks are the fund's primary holdings), the fund is included.

7. If none of the above objective criteria are met, I exclude funds that hold, on average, less than 80% or more than 105% of their assets in stocks, following the methodology of Kacperczyk et al. (2008).

8. I also exclude funds holding fewer than 10 stocks or managing less than $5 million in the previous month, as per Kacperczyk et al. (2008).

9. Finally, I identify and exclude index funds based on both their names and the index fund identifiers in the CRSP data. A fund is classified as an index fund if its index fund flag is set to B (index-based), D (pure index), or E (enhanced index). Additionally, consistent with previous studies (e.g., Busse and Tong (2012); Ferson and Lin (2014); Busse et al. (2021); Jones and Mo (2021); Dou et al. (2022)), I define a fund as an index fund if its name contains any of the following strings: Index, Inde, Indx, Inx, Idx, Exchange-traded, Exchange traded, ETF, DFA, Dow Jones, iShare, S&P, S &P, S& P, S & P, 500, Wilshire, Russell, Russ, MSCI.

D N-CSR Filing Examples

In the N-CSR filing of the John Hancock Investment Trust for the reporting period ending April 30, 2018, the fund adjusted its portfolio exposure, anticipating that the US-China trade war would maintain at least the same level of importance in the future:

> "Although we do not expect a full-blown trade war, we do anticipate an extended period of negotiation between the two countries. Consequently, we are reducing our exposure to companies and industries, such as textiles and selected technology hardware, that are more reliant on trade with the United States, and increasing our holdings of companies poised to benefit from the economic recovery story in China. "

Another example is found in the N-CSR filing of the Adirondack Small Cap Fund for the reporting period ending March 31, 2020. The fund increased its portfolio exposure to natural gas, anticipating that U.S.-based export capacity for natural gas would become increasingly important in the future:

"We made some changes to the Fund's energy exposure. We exited two exploration and production investments challenged by the dramatic drop in oil/liquids prices (Callon Petroleum(CPE) and Southwest Energy (SWN)). Instead, we added Cabot Oil & Gas Corp (COG .84%) the strongest and lowest cost independent natural gas producer in the United States. (As of 3/31/2020, COG represented 0.84% of the portfolio.) There are a number of factors that should benefit U.S. natural gas prices going forward. Most important for gas is the substantial U.S. based export capacity that continues to come online."

E Topic List with Descriptions

Table A.1: Topic List with Descriptions

Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
Economic Outlook	Economic Growth and Recovery Outlook	Indicators suggesting potential economic recovery emerge from various sources, including consumer confidence reports, job growth trends, and corporate earnings. While positive signals contribute to optimistic investor outlooks, ongoing challenges like inflation and employment hurdles remain pressing concerns.	0.024	0.477
	U.S. Economic Data and Job Market Challenges	Sluggish job growth and declining manufacturing output in the U.S. spur market caution, highlighting persistent issues like high unemployment and conservative hiring practices despite some recovery signs. Labor market reports significantly influence market sentiment and investor confidence.	0.009	-0.121
	Federal Reserve Policies and Economic Outlook	The Federal Reserve's policies on interest rates and quantitative easing significantly influence market expectations and economic growth. Anticipated changes can lead to market volatility and impact investment strategies.	0.025	0.191
	Consumer Price Index and Inflation Trends	Increases in consumer prices, potential inflationary trends, and their implications for stock markets and economic strategies are highlighted through various economic indicators. The central banks proactively respond to these indicators to maintain economic stability.	0.009	0.084

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Metatopic Label	**Topic Label**	**Description**	**Average Attention**	**Average Sentiment**
Economic Policy	Debt Ceiling Negotiations and Economic Policies	Discussions surrounding the U.S. debt ceiling involve critical negotiations that influence government spending and broader economic policy, impacting market confidence and stock trends. Investors closely monitor these negotiations due to potential fiscal implications.	0.001	0.154
	Tax Reform Legislation and Economic Implications	Debates around proposed tax reforms reflect differing views on stimulating economic growth, with tax cuts or increases significantly influencing corporate decision-making and market reactions.	0.011	0.187
	Legislative and Government Policy Changes	Ongoing budget negotiations and policy debates highlight key economic strategies influencing market expectations. Legislative reforms impact sectors like healthcare and taxation, affecting corporate strategies.	0.031	0.141
	Industrial Policy and Market Implications	Shifts in industrial policy impact company operations and market competitiveness, prompting strategic adjustments in various sectors.	0.001	0.269
Economic Stimulus	Infrastructure Development and Economic Revitalization	Discussions on infrastructure funding proposals concentrate on their vital role in economic recovery and job creation. These initiatives signify broader strategies for revitalizing economies, enhancing market confidence, and cultivating an environment conducive to investment, thereby influencing equity trading.	0.007	0.467
	Federal Budget Deficits and Economic Pressure Responses	Rising federal budget deficits prompt discussions on fiscal responsibility and possible responses, such as tax policy adjustments or spending cuts.	0.003	-0.006

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
	Economic Stimulus and Government Interventions	Government initiatives to stimulate economic recovery and support various industries reflect efforts to combat downturns. These measures include fiscal policies and stimulus packages aimed at boosting job creation and financial stability.	0.004	0.336
Financial Stability	Financial Crises and Investor Confidence	Increased bankruptcy filings and financial restructuring underscore broader instability in the financial sector. Investor confidence and market stability are impacted by difficulties in managing debts and restructuring efforts.	0.011	-0.294
	Financial Sector Instability and Job Cuts	The banking sector faced significant job cuts and financial struggles amid the recession, with notable banks reflecting deeper financial crises. Failures prompt regulatory scrutiny and investor concern over stability.	0.003	-0.367
	Cryptocurrency and Financial Market Regulations	The integration of cryptocurrencies into traditional finance and evolving regulatory frameworks highlight ongoing discussions on market stability and investor confidence in the financial sector.	0.002	0.170
	U.S. Housing Market Trends and Economic Indicators	The U.S. housing market faces ongoing challenges with fluctuating mortgage rates and consumer confidence, impacting home sales and construction sectors. Economic health is reflected in housing market dynamics, which influence broader market conditions.	0.021	0.302

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Metatopic Label	**Topic Label**	**Description**	**Average Attention**	**Average Sentiment**
Financial Stability	Banking Sector Challenges and Regulatory Scrutiny	High-profile bank failures, regulatory scrutiny, and loan issues highlight instability within the banking sector. Changes in banking regulations indicate shifts in practices amid increased scrutiny. This also includes growing concerns about bank failures and their impact on financial stability.	0.037	-0.015
	Emerging Market Financial Instability	Emerging markets face significant strains due to currency devaluations and economic pressures, impacting global trade and investments. These conditions influence stock market performance and investment strategies.	0.002	-0.434
Financial Markets	Emerging Markets and Investment Opportunities	Investment in emerging markets increases as investors look for new opportunities amid shifting global economic conditions. Regional financial instability impacts international markets due to interconnections.	0.006	0.513
	Stock Market Volatility and Economic Indicators	The stock market experiences increased volatility driven by economic data releases, consumer spending metrics, and corporate earnings reports. Mixed signals from these indicators prompt varied investor responses, reflecting uncertainty in market conditions.	0.009	-0.029
	Market Activity and Financial Performance	Post-earnings reports indicate positive stock market activity influenced by firm performances across various sectors, signaling broader economic trends. Disappointing earnings reports lead to cautious investor sentiments.	0.054	0.377

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
Corporate Finance	Corporate Profit Declines and Market Reactions	Numerous companies report declines in profits amid high costs and weak pricing, which impacts investor sentiment and reflects pressures affecting stock market performance.	0.020	-0.476
	Corporate Debt Management and Economic Forecasts	Rising corporate debt levels contribute to concerns about financial health among companies and influence market perceptions. Corporate strategies for managing debt, coupled with interest rate adjustments, significantly impact equity trading and investment decisions.	0.006	0.102
	Corporate Earnings Reports and Market Responses	Earnings reports from major firms lead to varied stock price reactions and investor sentiment. Positive results drive market rallies while disappointing earnings contribute to declines, reflecting investor sentiment.	0.029	0.410
	Corporate Philanthropy and Market Perception	Increased corporate philanthropic efforts reflect a growing trend toward corporate social responsibility, influencing investor perceptions and market behavior.	0.003	0.621
	Corporate Layoffs and Economic Downturn	U.S. firms announce significant layoffs and cost-cutting initiatives in response to declining revenues and economic pressures during a downturn. These actions reflect broader economic challenges influencing market dynamics.	0.011	-0.430
	Corporate Mergers and Acquisitions Activity	The trend of corporate mergers and acquisitions reflects consolidation efforts across various sectors, driven by strategic positions amid economic pressures. Regulatory scrutiny and market reactions to these activities underscore their significance.	0.087	0.394

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
	Corporate Governance and Shareholder Activities	Increased scrutiny and regulatory changes highlight corporate governance practices impacting market perceptions. Shareholder activism indicates evolving control dynamics and investor influence in companies. This includes legal challenges and high-profile scandals that emphasize the importance of ethical operations and transparency.	0.059	0.133
ESG	Impact of Natural Disasters on Economy	Natural disasters significantly disrupt economies, leading to discussions surrounding recovery efforts and infrastructure investments that can shape market dynamics.	0.008	-0.147
	Investment Trends in Renewable Energy	Growing investments in renewable energy sources reflect shifts in corporate strategies towards sustainability, influencing market expectations and economic projections.	0.003	0.508
	Automotive Industry Trends and Market Impact	The automotive sector experiences significant changes driven by shifts in consumer preferences towards electric vehicles and sustainable practices, along with production challenges. Industry trends directly influence stock performance and market strategies.	0.025	0.274
	Environmental Regulations and Corporate Compliance	Stricter environmental regulations impact corporate operations and investment strategies, reflecting broader trends toward sustainability. Compliance efforts across industries illustrate growing corporate responsibility. This also includes legislative actions on climate change and sustainability initiatives.	0.009	0.132

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Metatopic Label	**Topic Label**	**Description**	**Average Attention**	**Average Sentiment**
Labor/Income	Labor Market Trends and Unemployment	Reports on rising unemployment and labor disputes reflect broader economic pressures. Corporate responses to economic pressures through restructuring and workforce evaluations significantly affect consumer confidence and market trends.	0.006	0.124
	Labor Strikes and Negotiations in Major Industries	Labor disputes and negotiations, especially in major industries, highlight tensions over wages and job security. These tensions impact production and overall profitability, with significant implications for their respective markets.	0.008	0.057
Technology	Technological Shifts in Media, Finance, and Transportation	The move towards on-demand distribution in media and the adoption of technological advancements in various sectors reshape industry practices and consumer preferences, leading to market adjustments and regulatory discussions.	0.007	0.416
	Digital Economy Growth and E-commerce Trends	The rise of e-commerce and digital businesses shifts traditional retail dynamics, influencing market strategies and investment behaviors significantly.	0.011	0.500
	Cybersecurity Threats and Industry Preparedness	Recent cyberattacks and rising cybersecurity concerns have heightened awareness of vulnerabilities across industries, leading to increased investment in security measures. This has implications for regulatory responses and corporate strategies, influencing investor confidence.	0.003	0.138

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
	Technological Innovations and Corporate Strategies	Advancements in the tech sector, including significant product launches and competitive dynamics, illustrate evolving market strategies. Innovations drive competitive strategies and influence stock performance.	0.028	0.504
Healthcare	Pharmaceutical Innovations and Market Responses	Significant advancements and challenges in healthcare include regulatory scrutiny and the approval of new medical technologies and drugs, shaping market dynamics and corporate strategies within the pharmaceutical industry.	0.017	0.377
	Public Health Policies and Corporate Compliance	Public health concerns, like rising healthcare costs and environmental regulations, prompt scrutiny of corporate practices. Compliance with health guidelines significantly influences operational costs and strategic corporate responses.	0.002	0.142
	Healthcare Industry Developments and Legal Scrutiny	The healthcare sector deals with various challenges such as fraud investigations, regulatory scrutiny, and merger impacts. Examples include Columbia/HCA's fraud probes and Cigna's acquisition-related expansion efforts, reflecting ongoing industry transformations. Increased legal actions and regulatory scrutiny, such as class-action lawsuits against Aetna, impact financial performance and corporate practices.	0.019	0.138

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
	Healthcare Costs and Legislative Measures	Rising healthcare costs led to legislative measures aimed at expense control amidst a growing U.S. budget deficit. These pressures significantly affected family incomes and business profitability, further stressing an already strained corporate sector, particularly within healthcare and related industries.	0.003	0.032
	Pandemic and Vaccine Developments	The COVID-19 pandemic has significantly affected health and economic conditions globally. Multiple pharmaceutical companies, including Pfizer, Moderna, and AstraZeneca, have developed COVID-19 vaccines with high efficacy rates. Distribution plans face logistical challenges and vaccine hesitancy. COVID-19 variants have necessitated booster shots and further public health measures.	0.010	0.149
	Public Health Crises and Corporate Responses	Public health challenges involving disease outbreaks lead to increased regulatory scrutiny and corporate adaptations to ensure consumer protection and industry compliance. Corporate actions reflect the evolving landscape of public health.	0.010	0.081
Oil & Energy	Oil Prices and Production Changes	Global oil prices fluctuate due to market pressures and geopolitical tensions, with production strategies by major oil exporters influencing market stability. OPEC decisions impact oil pricing dynamics.	0.015	0.202

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
	Natural Gas and Energy Market Fluctuations	Changes in natural gas production and pricing due to higher demand and geopolitical factors lead to fluctuations in the energy market. These dynamics impact broader economic stability and influence investor strategies.	0.008	0.283
International Affairs	Impact of International Financial Aid	International financial aid and support for struggling economies reflect global efforts to stabilize markets and maintain economic confidence, impacting investment strategies.	0.004	0.175
	International Trade Relations and Economic Policies	Trade tensions between the U.S. and other nations, particularly China and Japan, significantly impact global trade and stability. Negotiations on trade agreements shape market dynamics and influence investor sentiment.	0.016	0.141
	International Trade Agreements and Economic Relations	Trade agreements and international economic relations play critical roles in shaping global trade strategies. Negotiations highlight the interconnectedness of international markets and economic policies, influencing market confidence.	0.006	0.389
	Geopolitical Tensions and Economic Impacts	Rising geopolitical tensions significantly impact stock prices and investor sentiment, emphasizing the interplay between global unrest and market volatility. Political instability can lead to market fluctuations influenced by investor reactions.	0.044	-0.095

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Metatopic Label	**Topic Label**	**Description**	**Average Attention**	**Average Sentiment**
Political/Social/Cultural	Educational Reform and Economic Implications	Ongoing discussions about education reform, access to education, and the impact of student debt reflect broader socioeconomic challenges. These issues influence public policies, related market sectors, and consumer spending.	0.012	0.269
	Political Climate and Economic Strategies	Political developments and election outcomes significantly impact economic policies and strategies, influencing investor strategies and market dynamics.	0.036	0.144
	Social Unrest and Market Reactions	Rising social unrest and movements for justice and equality affect public sentiment and business practices, influencing corporate reputation and market behavior. Companies are increasingly held accountable for their social impacts, affecting investor sentiment.	0.033	-0.203
	Supreme Court Rulings and Their Impact on Business	Recent Supreme Court rulings on civil rights and property rights influence corporate and public sentiment towards inclusivity, non-discrimination, and property ownership. These rulings affect business strategies, market perceptions, and can lead to changes in consumer behavior, which in turn impacts equity trading.	0.014	0.213
	Sports Events and Their Economic and Cultural Impact	Major sports events generate significant economic activity and hold cultural significance, influencing consumer behaviors and advertising expenditures. Innovations in sports marketing reflect broader trends in consumer preferences and economic conditions.	0.029	0.453

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Metatopic Label	Topic Label	Description	Average Attention	Average Sentiment
Consumer Behavior	Advertising Trends and Market Strategies	The advertising industry adapts to changing market dynamics and consumer preferences, impacting brand positioning and financial performance across sectors. Strategic shifts in advertising reflect broader economic conditions.	0.008	0.329
	Consumer Behavior and Marketing Strategies	Understanding shifts in consumer behavior drives marketing strategies that companies adopt to maintain market share during economic fluctuations.	0.003	0.468
	Consumer Behavior Amid Economic Strains	Economic pressures shift consumer spending trends, leading to cautious behavior around discretionary purchases, especially during key spending periods. Retailers adjust strategies to maintain market share amidst rising fuel prices and inflation concerns.	0.002	0.017
	Consumer Confidence and Retail Spending Patterns	Consumer confidence metrics and spending trends reflect economic conditions and potential market performance. Healthy consumer confidence can signal increased spending, directly impacting retail stocks.	0.005	0.363
	Cultural Consumption Trends	Changing consumer behaviors and preferences impact various sectors, including food and retail, as companies adapt strategies to align with evolving cultural expectations.	0.006	0.576

F Topic Attention and Sentiment Time Series

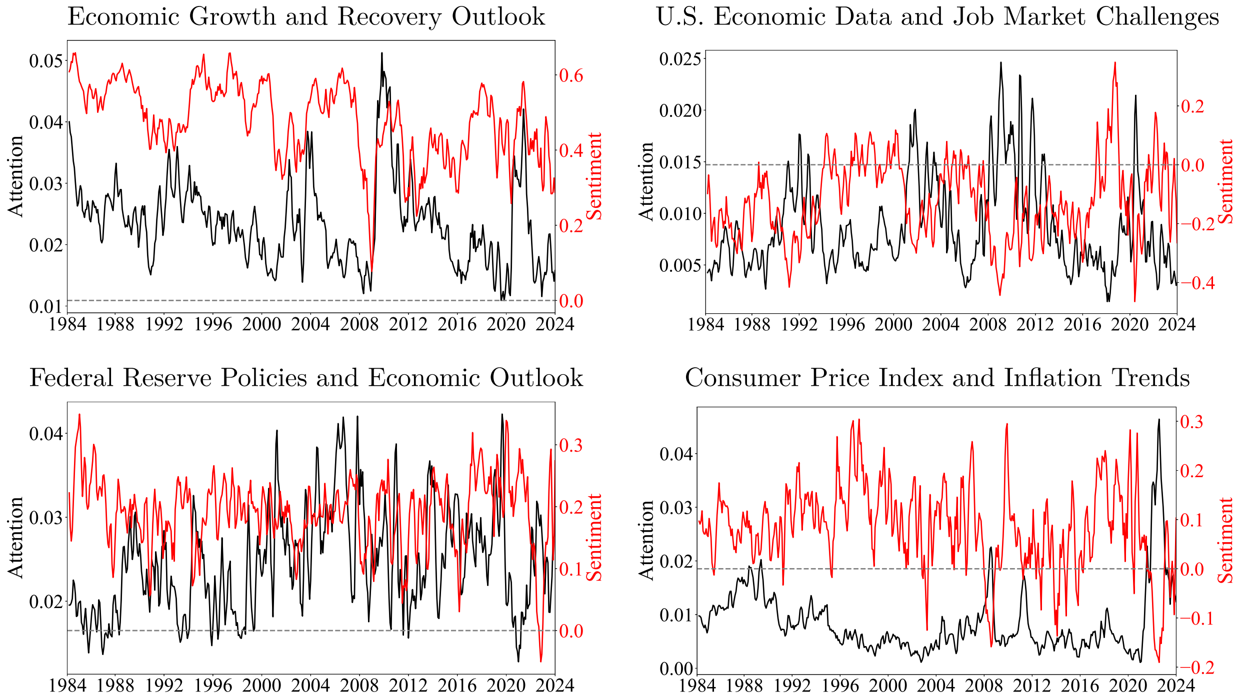

Figure A.1: Topic Attention and Sentiment for Metatopic *Economic Outlook*

Note: Topic attention and sentiment time series for topics within the metatopic *Economic Outlook*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

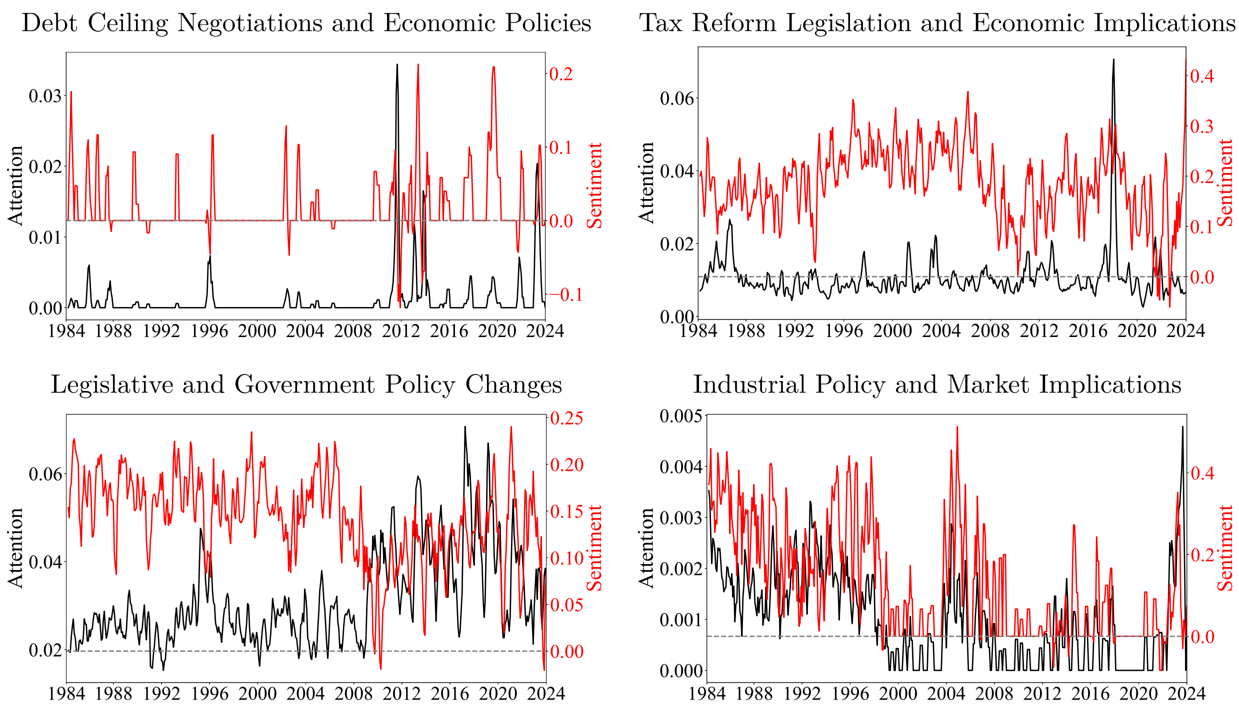

Figure A.2: Topic Attention and Sentiment for Metatopic *Economic Policy*

Note: Topic attention and sentiment time series for topics within the metatopic *Economic Policy*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

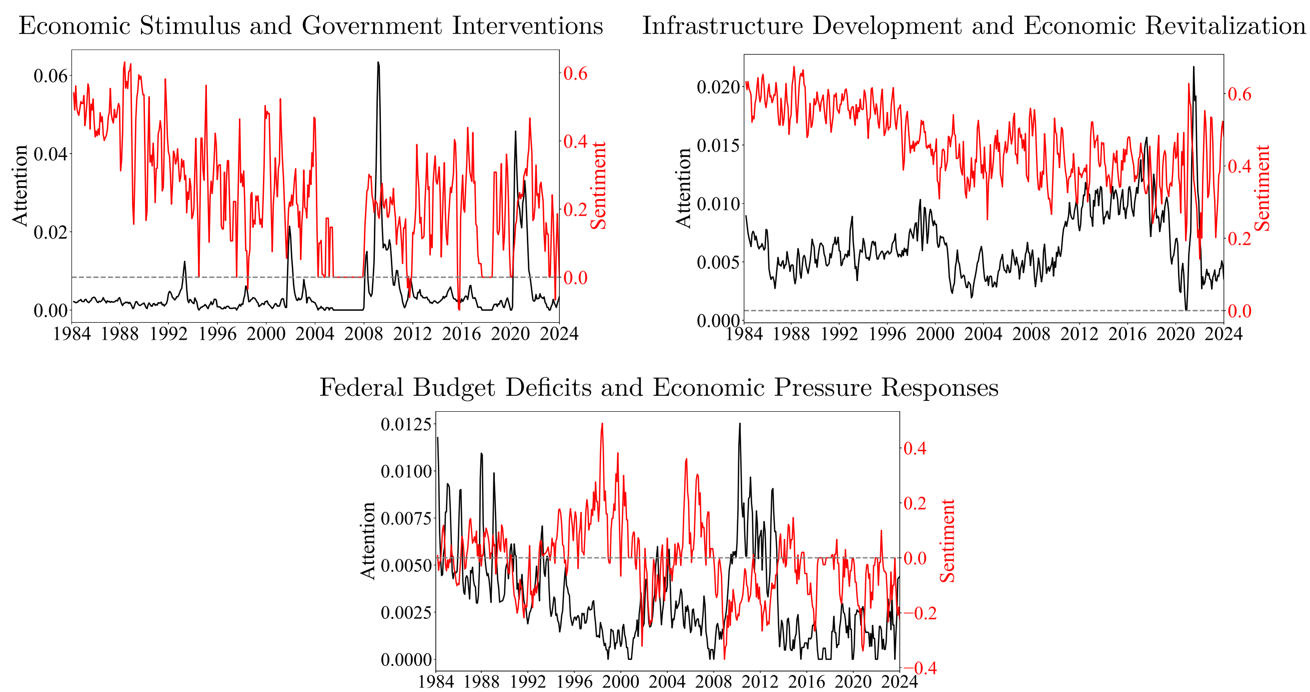

Figure A.3: Topic Attention and Sentiment for Metatopic *Economic Stimulus*

Note: Topic attention and sentiment time series for topics within the metatopic *Economic Stimulus*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

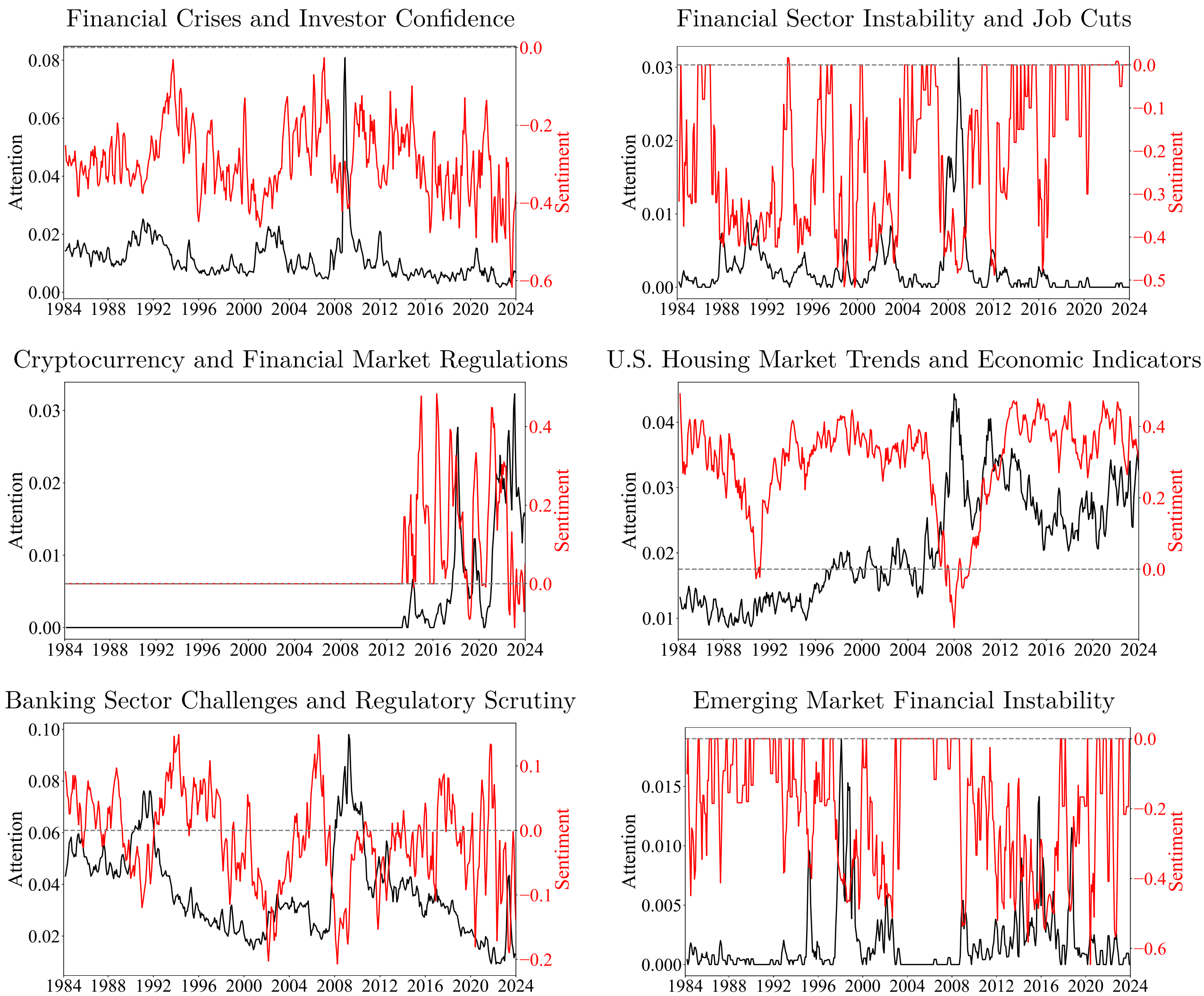

Figure A.4: Topic Attention and Sentiment for Metatopic *Financial Stability*

Note: Topic attention and sentiment time series for topics within the metatopic *Financial Stability*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

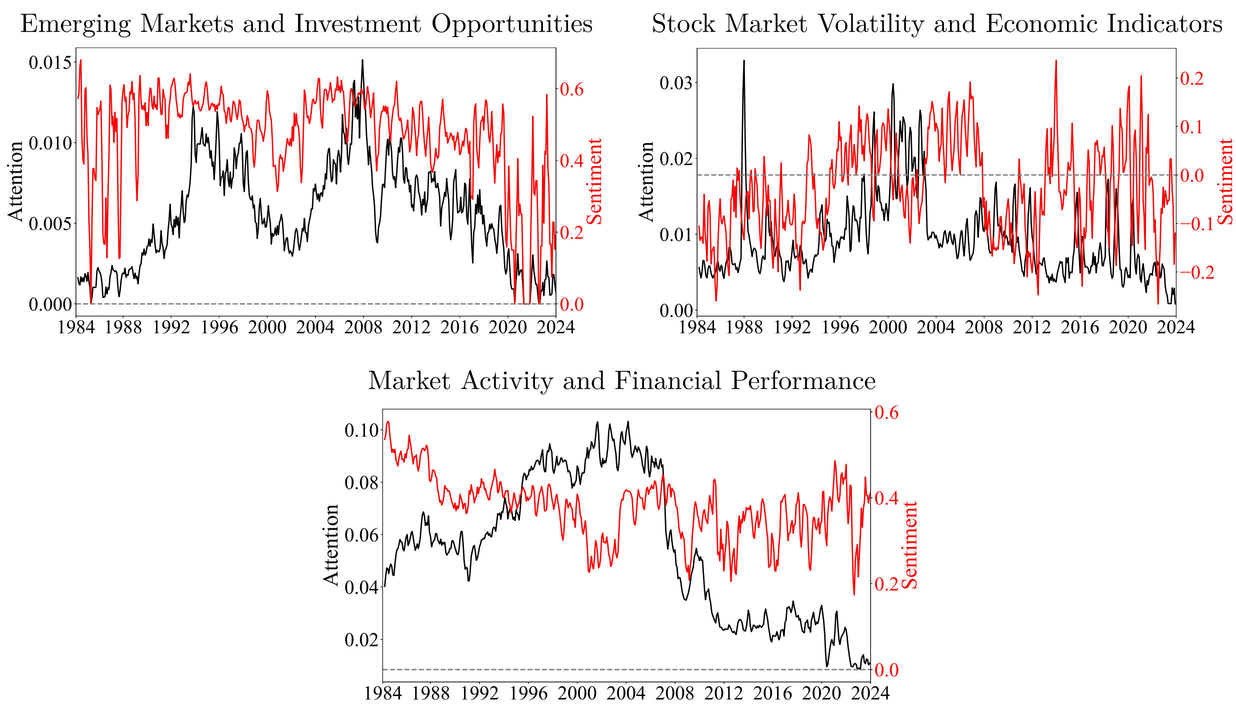

Figure A.5: Topic Attention and Sentiment for Metatopic *Financial Markets*

Note: Topic attention and sentiment time series for topics within the metatopic *Financial Markets*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

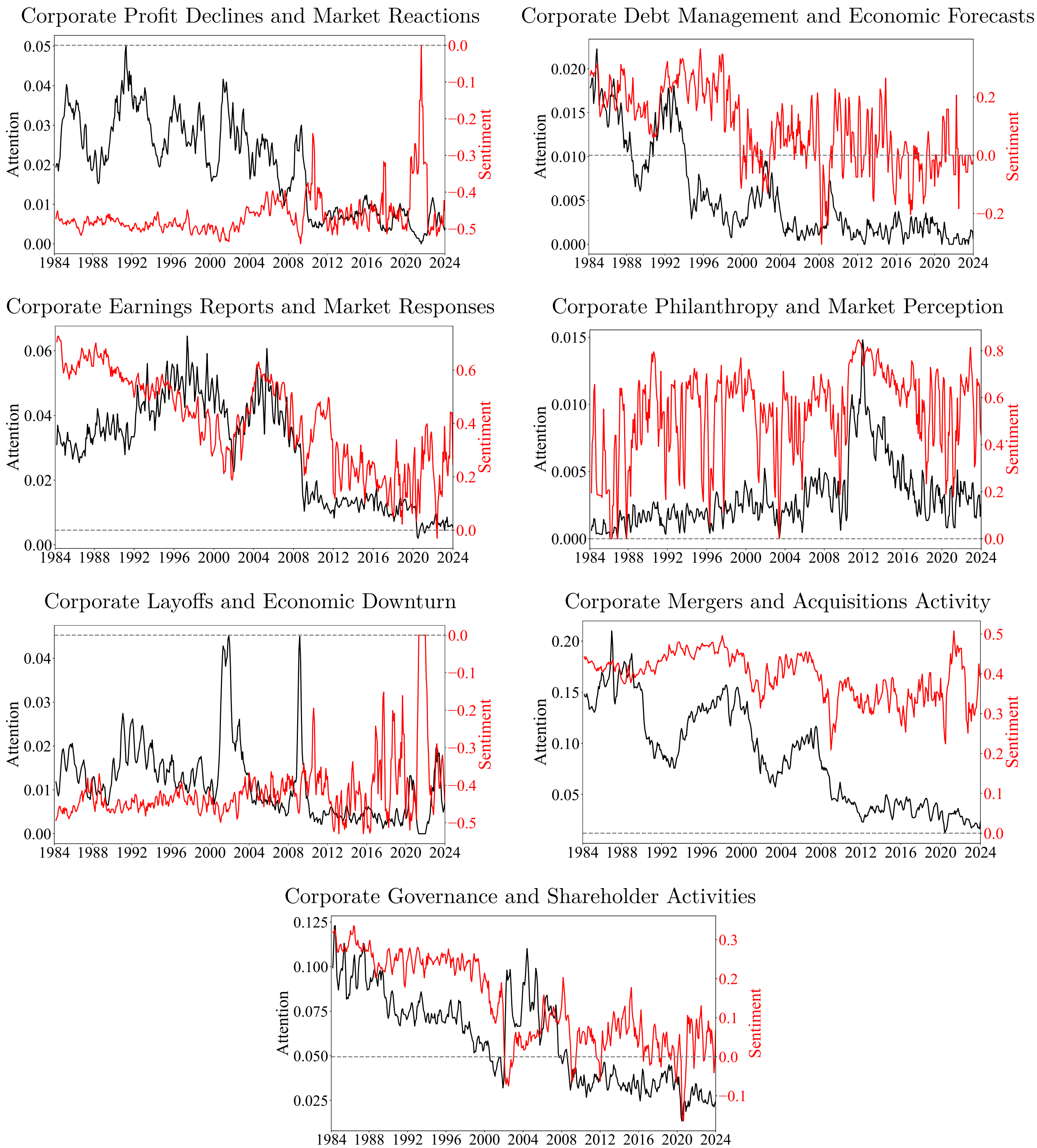

Figure A.6: Topic Attention and Sentiment for Metatopic *Corporate Finance*

Note: Topic attention and sentiment time series for topics within the metatopic *Corporate Finance*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

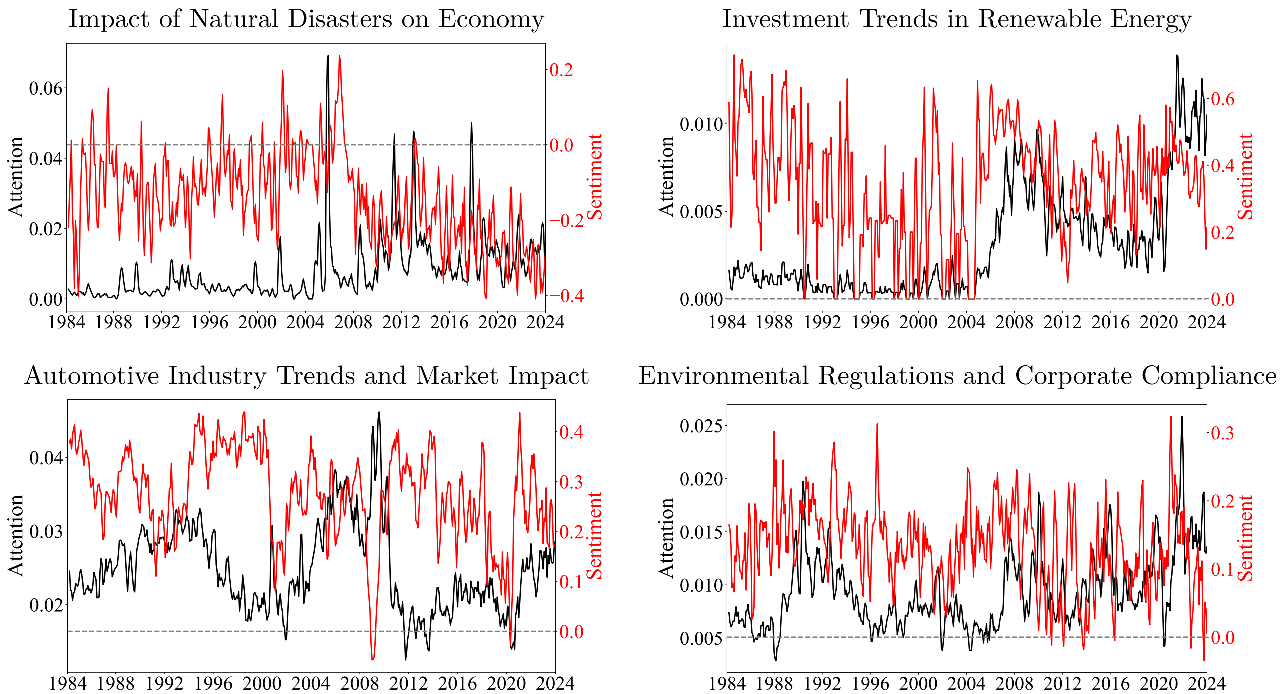

Figure A.7: Topic Attention and Sentiment for Metatopic *ESG*

Note: Topic attention and sentiment time series for topics within the metatopic *ESG*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

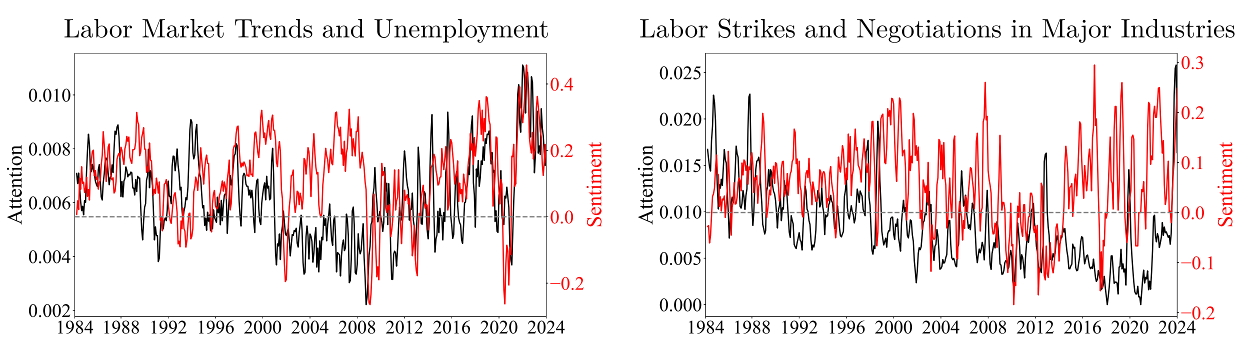

Figure A.8: Topic Attention and Sentiment for Metatopic *Labor/Income*

Note: Topic attention and sentiment time series for topics within the metatopic *Labor/Income*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

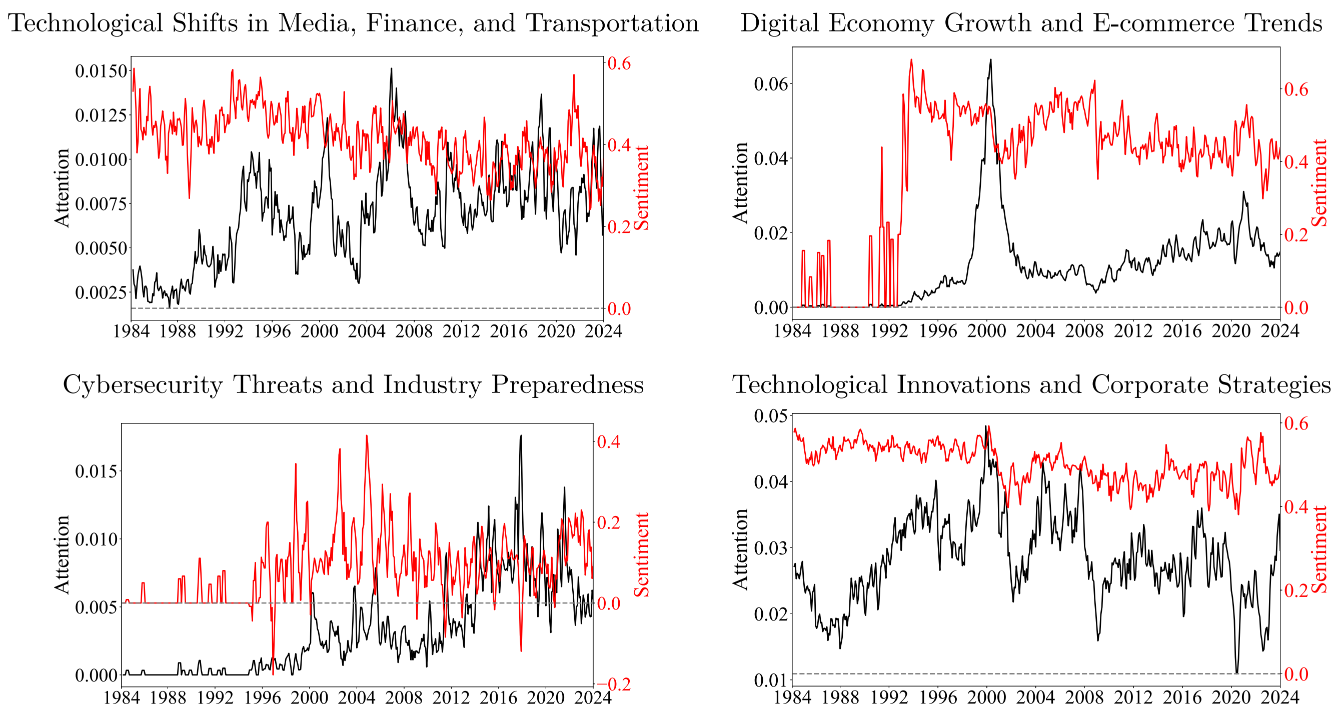

Figure A.9: Topic Attention and Sentiment for Metatopic *Technology*

Note: Topic attention and sentiment time series for topics within the metatopic *Technology*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

Figure A.10: Topic Attention and Sentiment for Metatopic *Healthcare*

Note: Topic attention and sentiment time series for topics within the metatopic *Healthcare*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

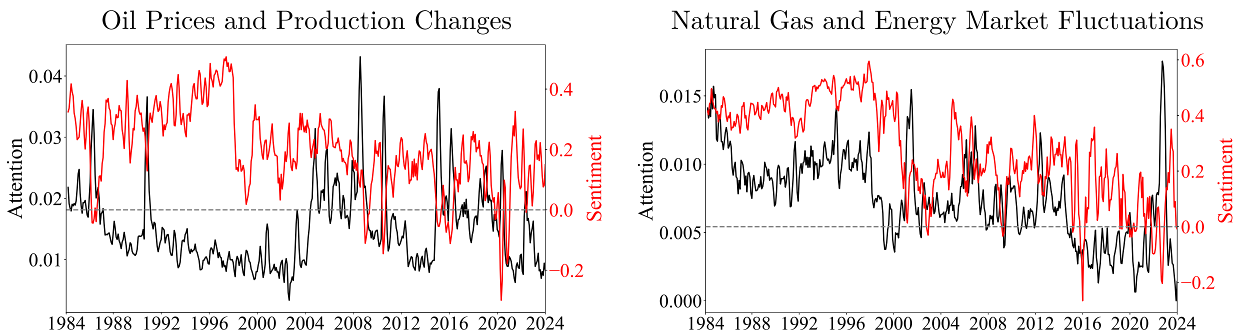

Figure A.11: Topic Attention and Sentiment for Metatopic *Oil & Energy*

Note: Topic attention and sentiment time series for topics within the metatopic *Oil & Energy*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

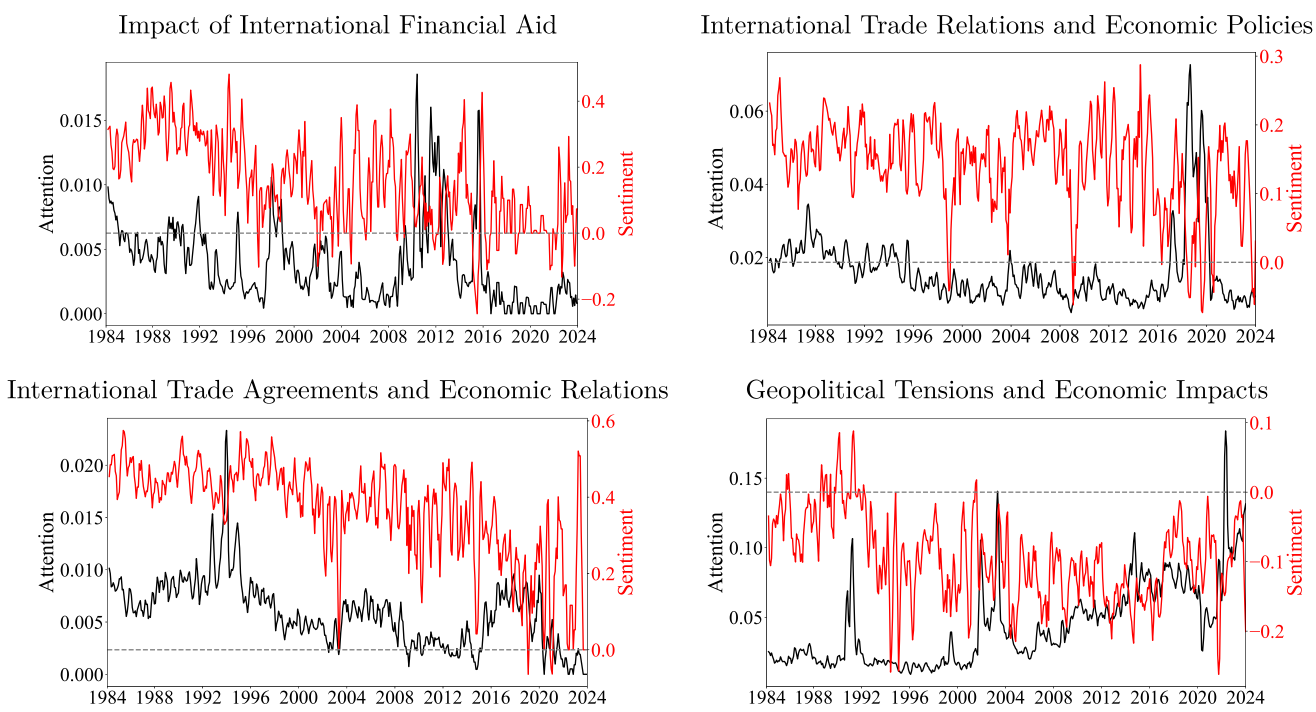

Figure A.12: Topic Attention and Sentiment for Metatopic *International Affairs*

Note: Topic attention and sentiment time series for topics within the metatopic *International Affairs*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

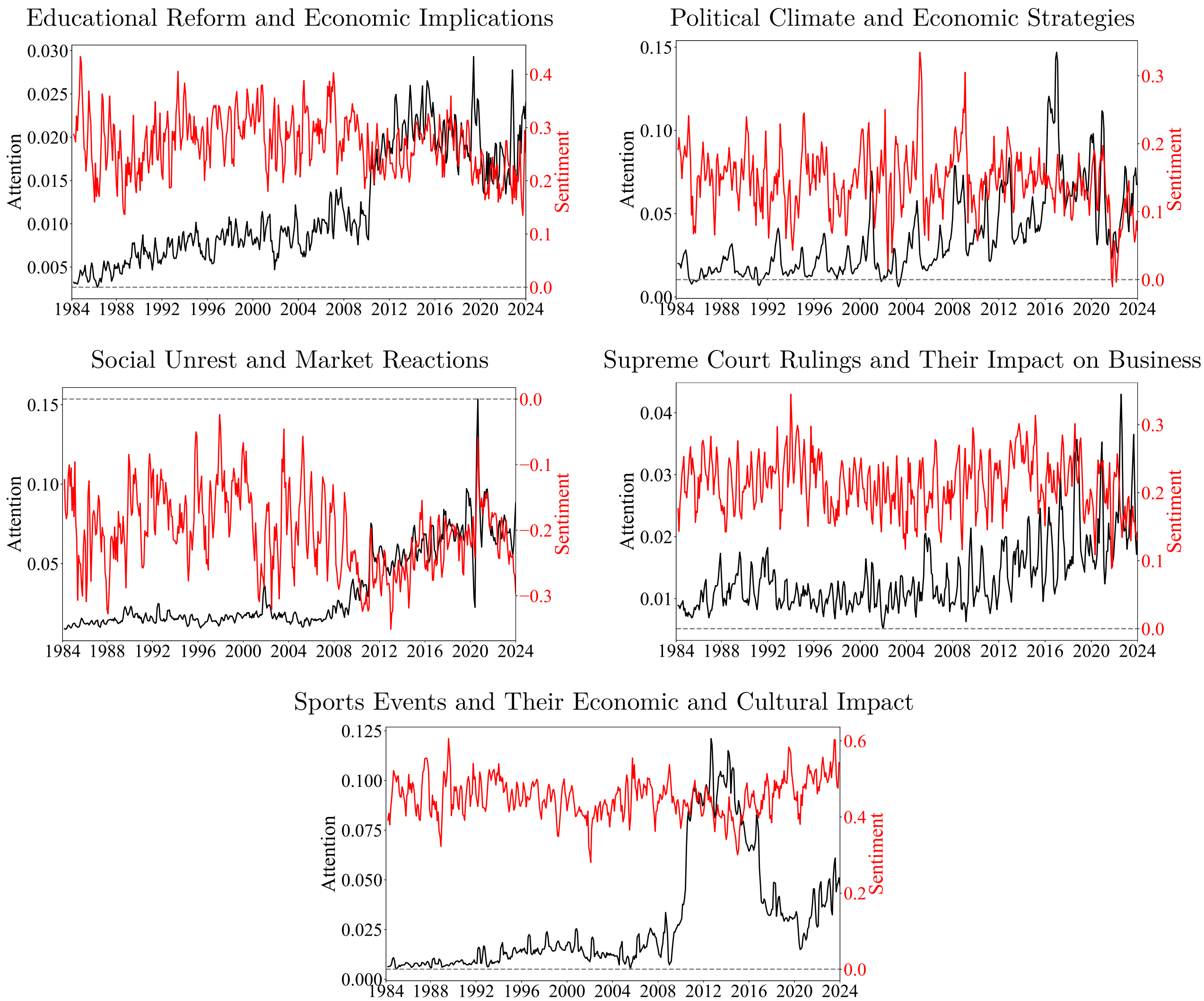

Figure A.13: Topic Attention and Sentiment for Metatopic *Political/Social/Cultural*

Note: Topic attention and sentiment time series for topics within the metatopic *Political/Social/Cultural*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

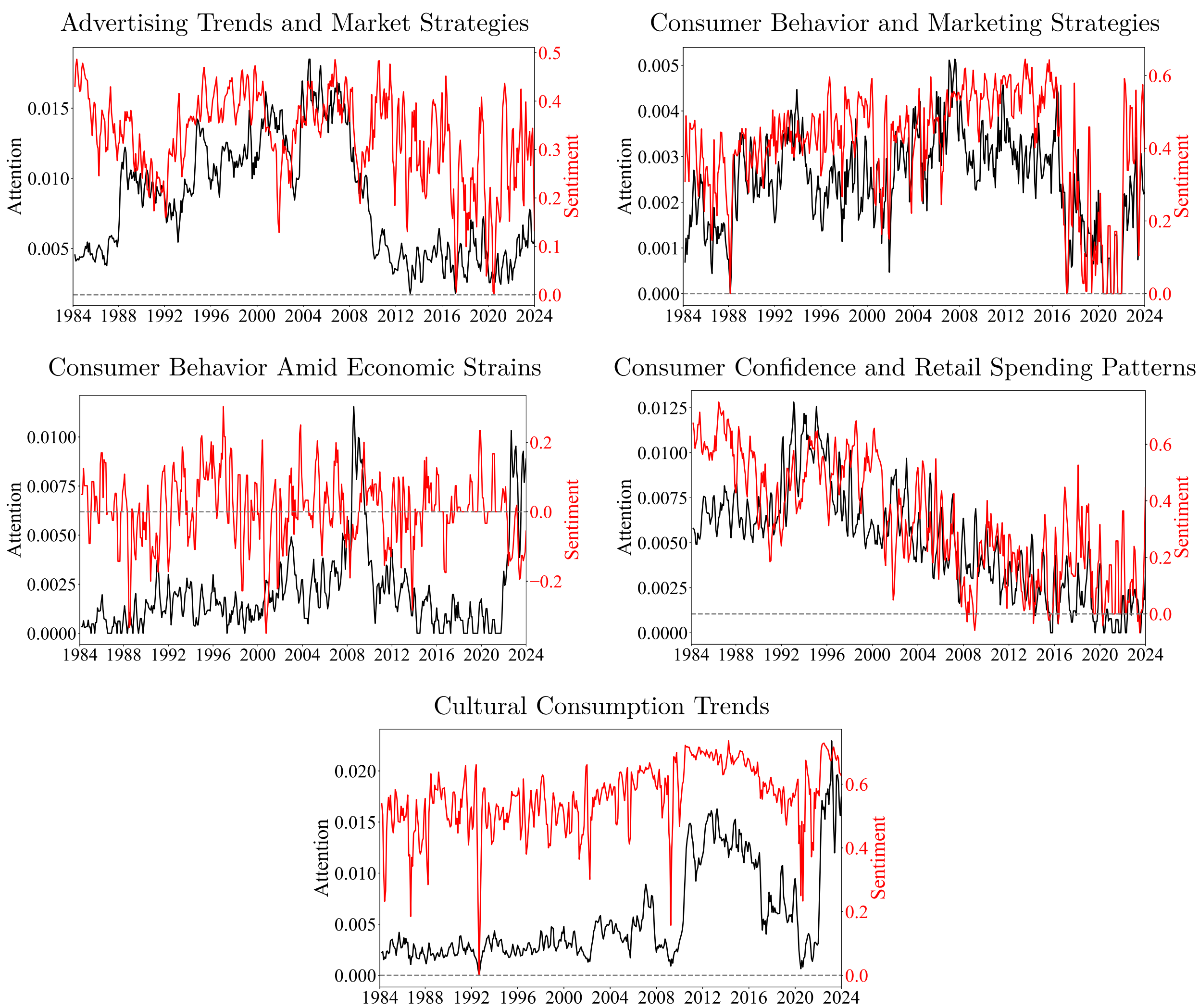

Figure A.14: Topic Attention and Sentiment for Metatopic *Consumer Behavior*

Note: Topic attention and sentiment time series for topics within the metatopic *Consumer Behavior*. The black line represents the topic attention as a percentage of the total monthly WSJ news production. The red line indicates the topic sentiment, calculated as the average sentiment of articles associated with the topic.

G Additional Exhibits

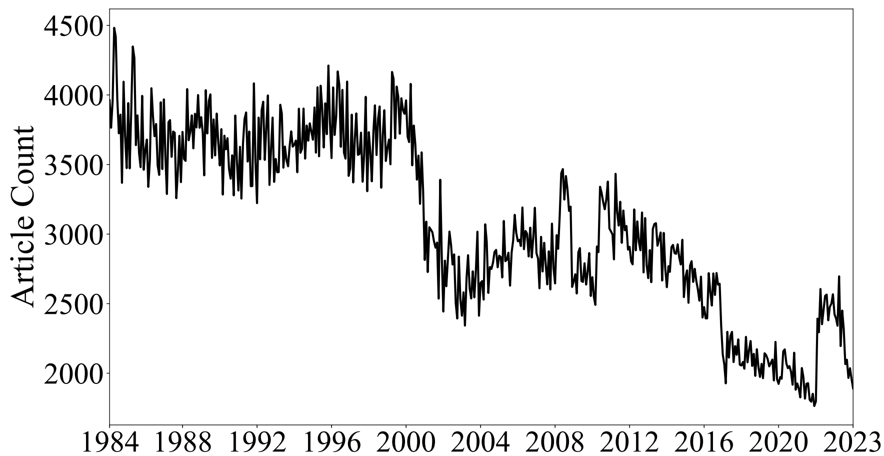

Figure A.15: Monthly Article Counts

Note: Post-processing monthly article count from 1984 to 2023.

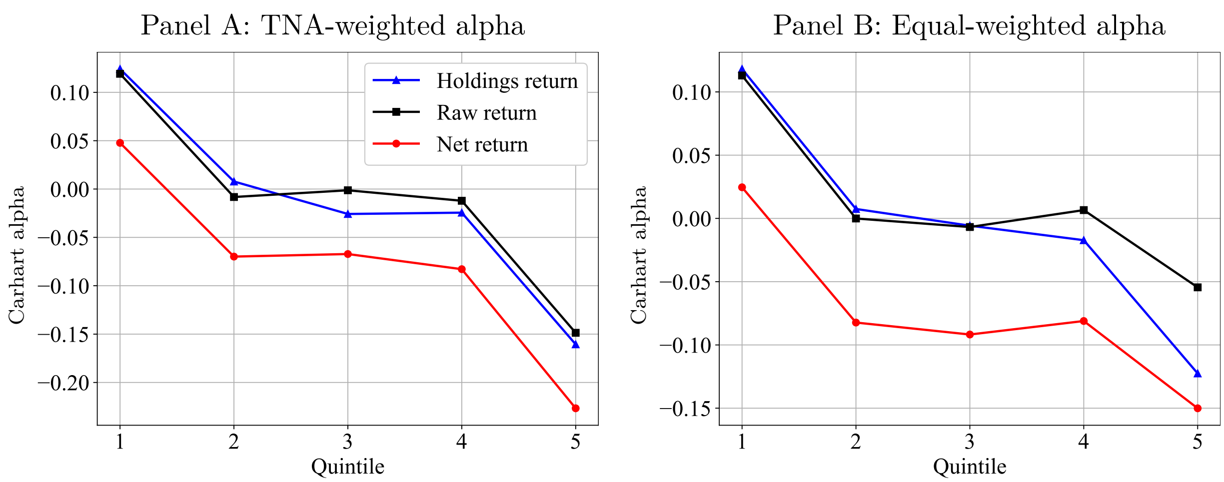

Figure A.16: Carhart alpha of SWE Fund Portfolio Sorts in Quintiles

Note: Carhart alpha for both TNA-weighted and equal-weighted portfolio in one month after portfolio formation. Each month I sort mutual funds into five quintiles based on their SWE, defined in (8), from lowest values (Quintile 1) to highest values (Quintile 5). Holdings return is constructed from TR S12 mutual fund holdings following Kacperczyk et al. (2008). The raw return is the fund total monthly return per share from the CRSP Survivorship Bias Free Mutual Fund Database. The net return is the raw return minus expense ratio. The portfolio period is from 1988 to 2023. All alpha numbers represent monthly alpha in %.

Table A.2: Stock Characteristics Information

Note: The table shows the stock characteristics we use as instruments for the instrumental regression. The characteristics are from Jensen et al. (2023).

Index	Characteristic	Theme	Index	Characteristic	Theme
1	cowc_gr1a	accruals	59	seas_1_1an	profit_growth
2	oaccruals_at	accruals	60	tax_gr1a	profit_growth
3	oaccruals_ni	accruals	61	dolvol_var_126d	profitability
4	taccruals_at	accruals	62	ebit_bev	profitability
5	taccruals_ni	accruals	63	ebit_sale	profitability
6	fnl_gr1a	debt_issuance	64	intrinsic_value	profitability
7	ncol_gr1a	debt_issuance	65	ni_be	profitability
8	nfna_gr1a	debt_issuance	66	o_score	profitability
9	noa_at	debt_issuance	67	ocf_at	profitability
10	aliq_at	investment	68	ope_be	profitability
11	at_gr1	investment	69	ope_bel1	profitability
12	be_gr1a	investment	70	turnover_var_126d	profitability
13	capx_gr1	investment	71	at_turnover	profitability
14	coa_gr1a	investment	72	cop_at	quality
15	col_gr1a	investment	73	cop_atl1	quality
16	emp_gr1	investment	74	gp_at	quality
17	inv_gr1	investment	75	gp_atl1	quality
18	inv_gr1a	investment	76	mispricing_perf	quality
19	lnoa_gr1a	investment	77	op_at	quality
20	mispricing_mgmt	investment	78	op_atl1	quality
21	ncoa_gr1a	investment	79	opex_at	quality
22	nncoa_gr1a	investment	80	qmj_prof	quality
23	noa_gr1a	investment	81	qmj_safety	quality
24	ppeinv_gr1a	investment	82	sale_bev	seasonality
25	ret_60_12	investment	83	corr_1260d	seasonality
26	sale_gr1	investment	84	coskew_21d	seasonality
27	seas_2_5na	investment	85	dbnetis_at	seasonality
28	age	leverage	86	kz_index	seasonality
29	aliq_mat	leverage	87	lti_gr1a	seasonality
30	at_be	leverage	88	pi_nix	seasonality
31	bidaskhl_21d	leverage	89	seas_11_15an	seasonality
32	cash_at	leverage	90	seas_11_15na	seasonality
33	netdebt_me	leverage	91	seas_2_5an	seasonality
34	tangibility	leverage	92	seas_6_10an	size
35	beta_60m	low_risk	93	ami_126d	size
36	beta_dimson_21d	low_risk	94	dolvol_126d	size
37	betabab_1260d	low_risk	95	market_equity	size
38	betadown_252d	low_risk	96	prc	short_term_reversal
39	ivol_capm_21d	low_risk	97	iskew_capm_21d	short_term_reversal
40	ivol_capm_252d	low_risk	98	iskew_ff3_21d	short_term_reversal
41	ivol_ff3_21d	low_risk	99	ret_1_0	short_term_reversal
42	rmax1_21d	low_risk	100	rmax5_rvol_21d	short_term_reversal
43	rmax5_21d	low_risk	101	rskew_21d	short_term_reversal
44	rvol_21d	low_risk	102	at_me	value
45	turnover_126d	low_risk	103	be_me	value
46	zero_trades_126d	low_risk	104	bev_mev	value
47	zero_trades_21d	low_risk	105	chcsho_12m	value
48	zero_trades_252d	low_risk	106	debt_me	value
49	rvol_252d	low_risk	107	div12m_me	value
50	prc_highprc_252d	momentum	108	ebitda_mev	value
51	ret_12_1	momentum	109	eq_dur	value
52	ret_3_1	momentum	110	eqnpo_12m	value
53	ret_6_1	momentum	111	fcf_me	value
54	ret_9_1	momentum	112	ni_me	value
55	seas_1_1na	profit_growth	113	ocf_me	value
56	ocf_at_chg1	profit_growth	114	sale_me	value
57	ret_12_7	profit_growth	115	seas_6_10na	value
58	sale_emp_gr1	profit_growth			

Table A.3: Fund Exposure to Topics

Note: Each month I sort mutual funds into ten deciles based on their SWE, defined in (8), from lowest values (Decile 1 or Quintile 1) to highest values (Decile 10 or Quintile 1). This table reports the average flows and its t-statistics (in parentheses) for both TNA-weighted and equal-weighted portfolio in one month after portfolio formation. The flow is constructed by (5). The portfolio period is from 1988 to 2023. All flow numbers represent monthly flow in %. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

10 Deciles			5 Quintiles		
Decile	TNA-weighted	Equal-weighted	Quintile	TNA-weighted	Equal-weighted
1 (Lowest SWE)	-0.06	0.24***	1 (Lowest SWE)	-0.07	0.19**
	(-0.62)	(2.63)		(-0.87)	(2.38)
2	-0.05	0.19**	2	0.12*	0.24***
	(-0.61)	(2.35)		(1.79)	(2.82)
3	0.07	0.23***	3	0.12	0.28***
	(0.93)	(2.59)		(1.43)	(2.96)
4	0.19***	0.28***	4	0.17**	0.38***
	(2.69)	(3.21)		(2.16)	(4.18)
5	0.07	0.24***	5 (Highest SWE)	0.19*	0.49***
	(0.83)	(2.65)		(1.71)	(3.92)
6	0.16**	0.36***			
	(2.05)	(3.77)			
7	0.17**	0.37***			
	(2.08)	(3.95)			
8	0.14	0.39***			
	(1.64)	(4.10)			
9	0.19*	0.48***			
	(1.82)	(4.40)			
10 (Highest SWE)	0.25**	0.55***			
	(2.04)	(3.84)			
Decile 10 - Decile 1	0.31***	0.31***	Quintile 10 - Quintile 1	0.25***	0.30***
	(3.14)	(2.72)		(3.52)	(3.72)