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ABSTRACT

Beyond the Fundamentals: How Media-Driven Narratives Influence Cross-Border Capital Flows*

We provide the first empirical evidence on how media-driven narratives influence cross-border institutional investment flows. Applying natural language processing techniques to one-and-a-half million newspaper articles, we document substantial cross-country variation in sentiment and risk indices constructed from domestic media narratives about China in 15 countries. These narratives significantly affect portfolio flows, even after controlling for macroeconomic and financial fundamentals. This impact is smaller for investors with greater familiarity or private information about China and larger during periods of heightened uncertainty. Political and environmental narratives are as influential as economic narratives. Investors react more sharply to negative narratives than positive ones.

JEL Classification: F30, G11, G15

Keywords: media narratives, cross-border flows, institutional investors, portfolio investment in China, textual analysis, natural language processing

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1 Introduction

The concept of "Narrative Economics" emphasizes the significant impact that narratives can have on economic decision-making (Shiller, 2017, 2020). Narratives are stories that offer interpretations of economic events. News media play a crucial role in shaping narratives as they make "gatekeeping" editorial decisions (Chahrour et al., 2021; Nimark and Pitschner, 2019; Shoemaker and Vos, 2009). These decisions, which involve choosing the most newsworthy events and determining their positive or negative tone, not only influence public perception but also affect firm and sector-level investment decisions, business cycles, and stock returns (Chahrour et al., 2021; Engle et al., 2020; Bui et al., 2022).[1]

In this paper, we provide the first empirical examination of whether domestic news media based narratives about the destination country affect cross-border investment flows. Specifically, we study whether domestic media narratives influence institutional investors' portfolio flows to China. This case is of particular interest because, in recent decades, China has emerged as one of the most important destinations for global institutional investors' cross-border investments. Moreover, narratives can be particularly important in driving cross-border flows to emerging market economies such as China because of the high cost of acquiring and interpreting market data. This could be because of three reasons. First, global investors face considerable challenges in accessing reliable, timely, and consistent market data for emerging markets. These challenges are exacerbated in an economy like China, where policymaking is opaque and sudden interruptions in data availability are not uncommon.[2] Second, even if data availability is not a constraint, the cost of using this data could be high because many public data sources in China, such as central bank or government websites, may not make information available in English.

[1] For example, Goetzmann et al. (2016) shows that people have an exaggerated assessment of the risk of a stock market crash and this assessment is influenced by the front page news stories they read.

[2] For example, *Bloomberg* reports that China stopped publishing daily global stock flows data in the middle of August 2024.

Third, the complexities of the regulatory environment and rapid economic transformation in China may make it hard for investors to interpret the available information. Therefore, international investors might be influenced by narratives to make sense of this intricate landscape, using them as a lens through which to evaluate the returns and risks associated with investing in China.

Media-driven narratives can influence investors' decisions either by shaping their sentiment towards a country or altering their perceived risk of investing in it. To capture these two dimensions, we construct country-level measures of narratives based sentiment and risk perception about China using natural language processing methods and full text from 1,454,645 news articles published in 38 English newspapers across 15 economies over the period 2007-2022. We believe this is the first paper to leverage such a vast and diverse collection of global newspaper data to construct media-based narrative indices. The sentiment index reflects the intensity of positive and negative sentiments in local newspapers about China, while the risk index captures variations in risk perception regarding investing in China.

These news media-based narrative indices show weak correlations with current economic and financial market conditions in China. Likewise, results from our local projections estimation suggest that these narrative indices do not reliably predict future economic activity. This indicates that the indices are not simply reflections of present or future market fundamentals. Instead, they capture additional layers of information, potentially reflecting broader narratives about China that could diverge from China's underlying economic and financial conditions.

Furthermore, these measures exhibit significant heterogeneity in the cross section. These variations can be attributed to differential coverage of concurrent events related to China as well as differences in country-level heterogeneity in the description of the same event in the local news media. For example, various media outlets created different narratives about the 2016 stock market crash in China. The *Wall Street Journal* was pessimistic about the potential impact, using words like "panic" in article titles, while Singapore's *The Business Times* was much less pessimistic and took a more benign view of the broader impacts of the stock market crash.[3]

To examine whether variations in narrative-based sentiment and risk indices affect cross-border investments in China, we utilize portfolio holdings data for open-ended mutual funds from Morningstar. Using fund-year-quarter level data for roughly 20,000 funds domiciled in 15 economies, we show that changes in sentiment and risk perception stemming from narratives in the local media significantly influence portfolio allocation decisions of institutional investors even after controlling for macroeconomic and financial fundamentals. A one standard deviation increase in the sentiment index is linked to a 2.3% rise in quarterly fund investment flows into China. Similarly, a one standard deviation increase in the risk index is associated with a 2.1% decline in quarterly fund investments. These effects are substantial as they account for about one-fourth of the quarterly average flows into Chinese assets and underscore the importance of narrative-driven sentiment and risk perceptions in influencing cross-border capital flows.

To better understand the mechanisms driving our results, we explore how news media narratives affect the information set of investors either by alleviating frictions in accessing information or by making it easier to interpret available information. Specifically, we examine the heterogeneity in how different investors respond to media-based narratives by leveraging variations in their ability to access and interpret market information about China. Our analysis shows that investors with a longer history of investments in China are less affected by sentiment and risk indices derived from local media. Intuitively, early investors are likely more familiar with the Chinese market and therefore rely less on local media to interpret economic events. Similarly, investors with a greater stock of information about China—measured by larger Chinese asset holdings and earlier entry into the Chinese market—exhibit lower sensitivity to media narratives, as they are likely

[3] See "China's Stocks Are Hit by 'Panic Selling," *Wall Street Journal*, January 5, 2016, and "Stock Market Impact on China's Economy Limited," *The Business Times*, January 25, 2016.

to possess more private or direct knowledge about China. Additionally, investors from countries geographically closer to China show a reduced reliance on these narrative indices, which may reflect greater familiarity with China due to geographical proximity, cultural similarities, or being in similar time zones. We also find that reliance on news media narratives increases in periods of high uncertainty as it is precisely in those periods that interpretation of available market data is more difficult. These results point to an information channel of news media narratives in driving our results.

Next, we develop sentiment and risk indices for several key topics relevant to investors and explore whether narratives about certain topics are more influential in global investment decisions. Specifically, we analyze whether sentiment and risk perceptions related to economic, political, and environmental factors differentially affect investment behavior. On one hand, investors might be more affected by economic narratives due to their direct relevance for economic performance of investors' portfolios. On the other hand, market data on political and environmental issues is harder to interpret, making narratives on these topics more valuable for investors. We find that political and environmental narratives influence investment flows as much as, or more than, economic narratives. This suggests that the absence of standardized data or the high cost of accessing political and environmental information prompts investors to rely more heavily on media-based narratives, elevating the importance of these narratives alongside economic ones. These findings reinforce the idea that narratives have a greater impact on investment decisions when investors face challenges in accessing or interpreting traditional data sources.

Using fund-sector-level data, we then show that these results hold at a more granular level. Media narratives for a specific category influence cross-border investment into sectors affected by sentiment about that category. For example, we find that investment flows to sectors that are affected by environmental factors, either directly or through the impact of these factors on their production networks, indeed respond to changes in the environmental sentiment and risk indices. Similarly, sectors more closely connected to political factors are more sensitive to changes in political sentiment and risk indices.

Finally, we develop positive and negative narrative indices to examine the asymmetric effects of media narratives on cross-border investment flows. Consistent with prior literature (Holbrook et al., 2001; Soroka, 2006), our findings reveal that institutional investors' flows into China are more sensitive to negative than positive narratives. This suggests that investors tend to rely more heavily on media coverage when interpreting adverse events. Moreover, the inherent negative bias in local media coverage may heighten the likelihood of investor overreaction, as suggested by prior research (Goidel and Langley, 1995; Damstra and Boukes, 2021; van Binsbergen et al., 2024).

Related Literature. Our paper contributes to three strands of literature. The first is the literature on the determinants of cross-border capital flows.[4] Our contribution is in identifying a previously overlooked determinant: local media narratives in investors' domicile countries. While existing studies have identified information frictions as an important factor driving cross-border flows (Van Nieuwerburgh and Veldkamp, 2009; Andrade and Chhaochharia, 2010; Karolyi et al., 2020), ours is the first to document that local media narratives can affect the information set of investors by not only offering an additional source of information in an environment with limited access to data but also by offering interpretations of available data that are often noisy. By highlighting the critical role of media narratives in shaping capital flows to an emerging market like China, our research extends the literature on risk factors influencing flows to emerging markets.[5] It reveals that, beyond fundamental economic forces, local media narratives can act as a catalyst for capital flows, adding a new dimension to our understanding of cross-border

[4]An extensive literature has studied the determinants of cross-border flows. Previous studies have highlighted various factors affecting these flows, including quality of governance (Leuz et al., 2009), currency returns (Froot and Ramadorai, 2005), proximity and cultural similarities-induced home bias (Chan et al., 2005), currency denomination (Maggiori et al., 2020), diversification and learning motives (Agarwal et al., 2020), information and transaction technology (Portes and Rey, 2005), tax haven status (Coppola et al., 2021), and economic uncertainty (Alok et al., 2022).

[5]The literature on capital flows to emerging markets has documented several factors affecting investment flows including interest rate differentials, U.S. monetary policy, and investor risk aversion (Lee and Engel, 2024; Ahmed and Zlate, 2014; Ghosh et al., 2014; Forbes and Warnock, 2012; Hutchison and Noy, 2006).

investment behavior.

Second, our paper advances the discussion on the role of narratives in shaping macroeconomic and financial outcomes by extending it to the realm of cross-border investment flows. Prior research has demonstrated the impact of news media on investment dynamics and business cycles within closed economies (Gulen and Ion, 2016; Hassan et al., 2019; Chahrour et al., 2021; Flynn and Sastry, 2024; Bybee et al., 2023; Hu, 2024).[6] Our paper extends the discussion of news media based narratives to open economies where information frictions are more pronounced, potentially making local news narratives more relevant for investment decisions. Complementing the work of Hassan et al. (2019) and Hassan et al. (2024), who study how a firm's risk perception of a destination country affects its investment in that country, our work studies how media-based narratives in institutional investors' domicile countries affect cross-border portfolio investments.

Finally, we contribute to a growing literature that constructs several types of indices using textual sources.[7] Our contribution lies in extracting large-scale textual information from news media in *multiple* countries and drawing on *full-text* news article data. Most studies in this literature extract textual data from newspapers in one country. Furthermore, they rely on keyword searches or article counts (for example, Baker et al. (2016); Chahrour et al. (2021); Bui et al. (2022); Rogers et al. (2024)) rather than using full-text of the article. Using the full-text of the articles enables us to capture richer, multidimensional insights from the same article.[8]

[6] Recent work in this area has also explored how these textual measures affect asset prices. See Calomiris and Mamaysky (2019) and Baker et al. (2021), for example.

[7] Baker et al. (2016) develop economic uncertainty indices using counts of newspaper articles. Handley and Li (2020) create firm-level risk indices for U.S. firms using SEC filings. Ahir et al. (2022) generate country-level uncertainty indices from quarterly country reports by the Economist Intelligence Unit. Hassan et al. (2019) and Hassan et al. (2024) use U.S. firms' earnings call transcripts and 10K filings to develop firm-level political risk indices and perceived risk of several countries. Arteaga-Garavito et al. (2024) compile climate attention indices from tweets posted by leading national newspapers. Caldara and Iacoviello (2022) constructs geopolitical risk index using news articles from several U.S. newspapers.

[8] For example, an article in *The Australian* discusses China's sweeping program to shut down its most polluting factories as part of a green initiative, likely impacting economic growth negatively while reducing environmental damage. Our indices can capture both the positive environmental and negative economic sentiments expressed in the article. See "China Pollution Cut to Slash Growth," *The Australian*, March 6, 2007.

2 Measuring Media Narratives at the Micro Level

In this section, we document our methodology employing natural language processing (NLP) methods to quantify changes in media narratives about China. We first outline the data collection process and then delve into the details about the methodology used. For each country in the sample, we develop time series of media narrative-based indices capturing media sentiments and perceived risks about China. According to Hassan et al. (2019), changes in sentiment primarily affect the expected average outcomes (the first moment), whereas alterations in risk pertain to the variability or uncertainty surrounding those outcomes (the second moment). These two indices will serve as the key narratives-based measures for our subsequent analysis of how cross-country narrative variations about China drive institutional investors' cross-border investment flows.

2.1 Data Collection

We include media outlets, typically newspapers, in countries where institutional investors maintain significant holdings of Chinese assets. For English-speaking countries, our focus is on newspapers that are most widely circulated. In non-English-speaking countries, we prioritize the leading English-language newspapers. Our news article data are sourced from ProQuest TDM Studio, which also guided our final selection of media outlets based on the available sources within the platform (see Table A1 in Appendix A for a full list). To identify news articles related to China, we conducted searches using the keyword "China" for each media outlet. For the Taiwan-based *China Post*, and the Hong Kong-based *China Daily (Hong Kong ed.)*, both of which include "China" in their names, we used the keyword "mainland China" for our searches.

For each media outlet, we conduct a textual analysis to compile the raw data, including: (1) The total number of China-related news articles each month t in each newspaper m ($num_{m,t}$); (2) The total number of news articles in each newspaper each month ($all_{m,t}$); (3)

The total number of words in each China-related article i for each newspaper m on date d ($totalwords_{im,d}$); (4) The total negative word count in each article ($negsum_{im,d}$), using the negative word list developed by Loughran and McDonald (2011) from firm 10-K filings, which contains 2,337 words; (5) The total positive word count in each article ($possum_{im,d}$), using the positive word list in Loughran and McDonald (2011), which includes 353 words.[9] (6) The total count of risk-related words in each article ($risksum_{im,d}$) using the risk word list in Hassan et al. (2019), which includes all single-word synonyms of "risk", "risky", and "uncertainty" as listed in the Oxford Dictionary (excluding "question", "questions", and "venture"). This risk word list comprises 123 words.[10]

If TDM Studio fails to collect content for a newspaper for more than five days within a single month, we exclude the data for that entire month from our analysis. Additionally, if there is a significant deviation in the volume of news articles for a given month relative to adjacent months, indicating a significantly lower count, the data for such a month are omitted. These adjustments help maintain the integrity and consistency of the dataset by eliminating periods of data scarcity or potential reporting anomalies. Detailed information on the sample period for each media outlet can be found in Table A1 in Appendix A. The final dataset includes 1,454,645 China-related news articles from 38 newspapers across 15 economies, covering the period from January 1, 2007 to May 31, 2022.

2.2 Index Construction

We construct two key narrative indices—the sentiment index and the risk index—to capture fluctuations in media narratives about China as portrayed by news outlets in each country. The sentiment index, derived from counts of positive and negative words, reflects the overall tone of media coverage of China—whether it is positive or negative. The risk index, based on the aggregation of risk-related words in news articles, measures

[9] An example of the most frequently used positive and negative words in the *Wall Street Journal (WSJ)* from January 1, 2007, to May 31, 2022, is provided in Table A2 in the Appendix B.

[10] An example of the most frequently used risk words for the *Wall Street Journal (WSJ)* spanning the period January 1, 2007 to May 31, 2022, can be found in Table A3 in the Appendix B.

the perceived risk associated with China in the media narrative.[11]

Sentiment Index. We follow the methodology in Flynn and Sastry (2024) and Hassan et al. (2019) to construct the sentiment index ($sen_{c,t}$) for investors domiciled in country c at quarter t as one of our key variables to measure media narratives. We first sum the positive and negative word counts, scaled by article length, for all China-related articles in each newspaper each month. We standardize each newspaper-level positive and negative monthly word count series to have a unit standard deviation.[12] The sentiment index for each newspaper is constructed using the standardized difference between positive and negative word counts from monthly data. We then average these indices across all newspapers within each country and normalize the series to have a mean of 100 over the period 2007 to 2019. The detailed methodology is documented in Appendix D.2.

Risk Index. We follow the methods in Hassan et al. (2019) to construct the risk index ($risk_{c,t}$) for investors domiciled in country c at quarter t. We sum the risk word counts, scaled by article length, for all articles in each newspaper each month. We standardize these monthly series to have a unit standard deviation, averaged across newspapers in each country, and then normalize the measure to have a mean of 100 over the period 2007-2019. The step-by-step construction of the measure is detailed in Appendix D.3.

2.3 Index Validation

Figure 1 presents the sentiment index (A) and risk index (B), grouped by Major Advanced Economies (G7), Other Advanced Economies (Advanced Economies excluding G7 and Euro Area), and Emerging and Developing Economies (EM), following the IMF World Economic Outlook groups and aggregation information as of April 2023. The figure shows

[11] Furthermore, following existing studies such as Baker et al. (2016), we also develop a news volume index to quantify the extent of China-related news coverage. This index offers insights into the level of attention allocated to China across various countries. Detailed information on the news volume index can be found in Appendix C. Even though we do not use this index in the empirical analysis, the index is useful to understand changes in the risk and sentiment index around certain events such as the Beijing Olympics.

[12] We standardize the media index series using data from 2008 to 2019. Baker et al. (2016) employed data from 1985 to 2009 for standardization and normalization, extending their analysis to 2014. Our approach similarly uses five-sixths of the entire time horizon for standardization.

how the sentiment and risk indices change following major China-related events.

The sentiment indices tend to be more negative during China-related events which could adversely affect the global economy such as the 2016 China stock market collapse, the U.S.-China trade war, and COVID-19, as well as during social and political events like the Zibo train collision, Kunming attack, and Hong Kong protests. Conversely, the indices are more positive during events like the 2008 Beijing Olympics, despite the concurrent global financial crisis. Significant spikes in the risk index are observed during major events such as the Beijing Olympics, Chinese stock market collapse, U.S.-China trade war, Hong Kong protest, and COVID-19. These patterns exhibit variations across different country groups. For instance, during the 70th anniversary of the People's Republic of China, emerging and developing economies displayed more positive sentiment than G7 and other advanced economies. In addition, the G7 economies showed a much higher risk perception during events such as the Hong Kong protests compared to emerging and developing economies.

Table 1 presents summary statistics for both indices while Table 2 shows the Pearson correlation between risk and sentiment indices. There is an inverse relationship between these indices, which serves as a cross-validation of their accuracy. Intuitively, increased risk perception (representing the second moment) correlates with more negative sentiments (representing the first moment), a finding consistent with Hassan et al. (2019), who observed similar relationships using political risk and sentiment indices at the firm level.

3 Understanding Media Narratives Indices

What do the local media narratives measure? Do they merely reflect current or future economic fundamentals of China or do they also contain information beyond the current and future fundamentals? In this section, we attempt to better understand the information content of media narratives. First, we compare the narrative indices with common measures of Chinese market conditions to establish their distinctiveness. Next, we use local projection analysis to assess whether our narrative indices offer insight into future macroeconomic and financial trends in China.

3.1 Media Narrative Indices and Current Market Conditions

Table 3 presents, for each country in the sample, the correlations between our sentiment (Panel A) and risk indices (Panel B) and several common Chinese market and macroeconomic performance measures. For financial market variables, our sentiment indices show a low correlation with the Shanghai Shenzhen CSI 300 index—a stock market index that tracks the performance of the 300 largest and most liquid stocks traded on the Shanghai and Shenzhen Stock Exchanges—with this correlation even turning negative for G7 economies.[13] Similarly, the risk indices exhibit relatively low correlations with stock market volatility, which we measure using the volatility of the Shanghai Shenzhen CSI 300 index.[14]

Turning to macroeconomic variables, increases in the sentiment index are typically associated with Chinese currency depreciation (a decrease in EX), a decline in the industrial production index (IP), and an increase in the CPI index (CPI), though these correlations remain low. Similarly, increases in the media risk perception index are linked to exchange rate appreciation, industrial production growth, and inflation rises, but these correlations are also very low.

The consistently low correlations suggest that our narrative indices capture information beyond the current state of China's economic activity, as reflected in existing market indicators. This implies that the narrative indices incorporate additional dimensions of information that are not fully reflected in traditional market measures.

[13]To facilitate comparison with the media-based sentiment and risk indices, we calculate the monthly average of the Shanghai Shenzhen CSI 300 index and normalize it to have a mean of 100 over the period 2007 to 2019.

[14]Since there is no official monthly stock market volatility index for the Chinese stock market, we calculate the monthly volatility using daily Shanghai Shenzhen CSI 300 index data. We also normalize the volatility index to have a mean of 100 over the period 2007 to 2019.

3.2 Media Narrative Indices and Future Market Conditions

The previous section shows a weak correlation between the narrative media indices and current economic and financial conditions. This observation suggests a plausible hypothesis that these indices may, instead, capture anticipations of future macroeconomic and financial fundamentals, even if they deviate from present conditions—similar to the "news" hypothesis discussed in Flynn and Sastry (2024). Hence, we explore whether the narrative indices predominantly capture forward-looking market information or do they instead capture positive or negative media perception about future economic activity in China that may deviate from the actual market conditions in the future, which would be consistent with a "narrative" hypothesis.

We do so by estimating the following local projection panel regressions.

$$Z_{t+h} = \mu_c^h + \sum_{k=0}^{2} \beta_k^h index_{c,t-k} + \sum_{j=0}^{2} \gamma_j^h X_{t-j} + \epsilon_{c,t}^h \tag{1}$$

where Z_{t+h} is the h-month-ahead macroeconomic or financial market indicator for China, including the log of the SSE Composite return index, the log of the SSE 380 volatility-weighted index, and the log of the seasonally-adjusted industrial production index. $index_{c,t-k}$ is the narrative sentiment or risk index constructed using the local media narratives of investor domicile country c about China at time $t-k$, where k can range between 0 and 2. We also control for other macroeconomic and financial variables that could predict future economic activity in China, including the log exchange rate index, the policy rate, and the log CPI index. μ_c^h is the investor domicile country fixed effect. Standard errors are clustered at country levels to correct for potential cross-sectional and serial correlation in the error term $\varepsilon_{c,t}^h$.

β_0^h is our key variable of interest and measures how changes in the current local media-based sentiment and risk indices predict future economic and financial activity in China. If the "news" hypothesis is true, we would expect β_0^h to be positive for stock return index and industrial production and negative for stock volatility index since the positive sentiment today indicates better performance in the future as the positive news about future fundamentals are incorporated into the news today. If the "narrative" hypothesis is true, we would expect $\beta_0^h \leq 0$ since the local media coverage of China in investors' domicile country either fails to predict future economic and financial fundamentals of China or predicts its future market condition in the wrong direction.

Our findings, presented in Figure 2, challenge the "news" hypothesis and lend support to the "narrative" hypothesis. Specifically, we find that β_0^h is not statistically significant for both sentiment and risk indices across advanced economies. In G7 economies and emerging market economies, an increase in the current sentiment index is correlated with a decline in the future industrial production index, while an increase in the risk index is associated with an increase in industrial production. These trends suggest that media narratives about China in G7 and emerging market economies are generally predicting China's economic prospects in the wrong direction — higher sentiment today associated with lower future economic activity and lower sentiment today associated with higher future economic activity.

4 Media Narrative Variations Across Countries

Having shown that the media narrative indices deviate from both current and anticipated macroeconomic and financial conditions in China, we turn next to an evaluation of the cross-country consistency of these narratives. We show that there is in fact considerable heterogeneity in media narratives about China across different investor domicile countries. We document that the variation in narrative-based indices can be attributed to differences in topic coverage across countries as well as disparities in the narratives within the same topic. We then show the extent of variation more formally using a cross-sectional analysis.

4.1 Media Topic Variations and Narrative Variations

Media narratives related to China exhibit considerable variation across countries. We decompose these variations into two key components. The first component is related to the differential topic coverage in the news media within the same period, highlighting the differences in the subjects covered by local media in the investors' domicile countries. To document how media in different countries covers different topics in news articles related to China, Figure 3 shows word clouds of bigrams from all China-related news coverage in January 2016 for newspapers in the U.S., the U.K., Korea, and Singapore.[15]

During January 2016, many events with potential impact on China occurred, such as the China stock market collapse, the plunge in oil prices, the North Korean nuclear test, and the Taiwan election. The bigram word cloud plots show that the U.S. and U.K. media focus more on the oil price plunge and domestic monetary policy changes, even when reporting China-related news, although they also pay attention to China stock market crash and its consequential impact. In contrast, Korean media focus more on the North Korean nuclear test when covering news related to China. Singaporean media concentrate more on the Taiwan election and its consequential political impact, although they also focus on stock market changes. Such variations in the topics covered by domestic news media can generate cross-country heterogeneity in the narrative sentiment and risk indexes for China.

The second component of heterogeneity in media narratives arises from differences in sentiment, even when reporting on the same event. Media outlets in various countries often express divergent sentiments in their coverage of identical events. Figure 4 displays sentiment word clouds for the China stock market collapse in January 2016, as reported by media outlets in the U.S., the U.K., Korea, and Singapore.[16] U.S. and U.K. media expressed

[15]These bigrams in all China-related news from newspapers in a given country are ranked by weight, calculated as the term frequency times the inverse document frequency when pooling all the news with the keyword "China". The inverse document frequency is calculated using an additional library from January 2017, which includes all news with the keyword China from the same group of newspapers in each country.

[16]News related to the China stock market collapse was identified using the keywords "China" and "stock"

relatively more negative sentiments toward the China stock market collapse compared to media in Singapore. Furthermore, U.S. coverage emphasized concerns about a broader economic slowdown and potential recession, while U.K. media focused more heavily on market-wide fears, employing strongly negative terms such as "worst." Although Singaporean media also adopted a negative tone, they used more moderate language.

Next, we formally investigate the heterogeneity in media narratives about China across countries, considering both event-coverage variations and sentiment variations within each event.

4.2 Cross-Sectional Analysis: Media Narrative Variations Across Countries

To study the the cross-sectional variation in media narratives across countries, we estimate the following regression for each country c.

$$ln(sen_{c,t}) = \beta_c^{sen} ln(Comp_t) + \epsilon_{c,t} \tag{2}$$

$$ln(risk_{c,t}) = \beta_c^{risk} ln(Vol_t) + \epsilon_{c,t} \tag{3}$$

where $ln(sen_{c,t})$ is the natural logarithm of the sentiment index and $ln(risk_{c,t})$ is the natural logarithm of the risk index. $ln(Comp_t)$ is the natural logarithm of the monthly average Shanghai Shenzhen CSI 300 index, capturing the overall performance of the Chinese stock market, and representing the first moment effect. $ln(Vol_t)$ is the natural logarithm of the monthly volatility of the Shanghai Shenzhen CSI 300 index, capturing the second moment effect (market volatility).

The coefficient β_c^{sen} captures the average sentiment perception of China's financial market performance as reflected in the local media of country c. We expect β_c^{sen} to be positive, as stronger stock market performance should be associated with more favorable media sentiment. A higher value of β_c^{sen} indicates that the media in that country is

in January 2016. The positive and negative sentiment word lists are from Loughran and McDonald (2011).

more sensitive to changes in market conditions. Similarly, β_c^{risk} measures the average risk perception of China by the local media in country c, and is likewise expected to be positive. Intuitively, greater stock market volatility in China corresponds to increased risk perception, with a more positive β_c^{risk} indicating that the local media in that country is more responsive to fluctuations in market risk.

Figure 5 displays the sentiment beta (top panel) and risk beta (bottom panel) by country. In Asian economies such as Hong Kong and Korea, stronger financial market performance in China tends to generate more positive sentiment about China, as reflected in their higher sentiment betas. In contrast, advanced economies like Canada, Ireland, and the U.K. adopt a more cautious stance in reporting positive financial market outcomes, reflecting a broader and more conservative interpretation of China's economic and financial fundamentals. Additionally, the fact that many sentiment betas are statistically insignificant or even negative suggests that sentiment often diverges from underlying market fundamentals of China. This indicates that local media narratives may incorporate additional layers of information beyond what is captured by conventional market indicators.

Many economies show significant negative correlations between their risk indices and stock market volatility, as well as negative correlations between their sentiment indices and market returns. This pattern suggests that these economies often report financial market conditions in a manner that contrasts with the actual stock market performance. Narratives from G7 economies such as the U.S. and Canada, along with those from other advanced economies like Ireland and Australia, typically exhibit this negative correlation between media narratives and financial market conditions of China. In contrast, geographically close economies such as Hong Kong, Singapore, Thailand, and the Philippines have media risk perceptions that are more closely aligned with actual market volatility in China. This alignment may result from these countries having access to more accurate risk information, possibly due to their proximity to China.

5 Local Media Narratives and Cross-Border Flows to China

Having established that there is substantial cross-country variation in media narratives, we now turn our attention to the impact of local media narratives in investors' domicile countries on cross-border investments in China. We formally investigate the extent to which media narratives shape portfolio flows to China, utilizing quarterly global institutional investor portfolio holdings data from Morningstar. The majority of foreign holdings of Chinese assets are accounted for by open-ended funds, which also tend to be more active investors relative to ETFs and money market funds in response to market and other developments. Hence, our empirical analysis focuses on open-ended funds.[17]

We estimate the impact of local media narratives on cross-border flows of institutional investors using the following regression specification:

$$Flow_{ic,t} = \beta_0 + \beta_1 Index_{c,t-1} + \beta_2 X_{c,t-1} + \delta QRT_t + \alpha_i + \varepsilon_{ic,t} \tag{4}$$

where i indexes funds, c indexes fund domicile country, and t indexes calendar quarter. $Flow_{ic,t}$ measures fund i's capital flow to Chinese assets in quarter t. Specifically, we define flow as follows:

$$Flow_{ic,t} = \frac{\sum_{a \in C_{ic,t}} P^a_{t-1}(N^a_{ic,t} - N^a_{ic,t-1})}{\sum_{a \in C_{ic,t-1}} P^a_{t-1} N^a_{ic,t-1}}$$

where $C_{ic,t}$ is the collection of all unique Chinese assets held by fund i at quarter t domiciled in the country c. P^a_{t-1} denotes the dollar value of the asset a at the end of quarter $t-1$. $N^a_{ic,t}$ is the number of units of asset a held by fund i domiciled in c at quarter t. Therefore, the numerator represents the total value of changes in Chinese asset holdings, calculated using the unit price of the asset from the previous quarter, which excludes the impact of market price fluctuations.[18]

[17] Details about the Morningstar dataset, as well as the country and asset composition of institutional investor positions in China, are provided in Online Appendix L.

[18] Since it is hard to interpret valuation changes for derivative assets, we exclude all derivative holdings from our analysis. This ensures that our data reflects more accurately the actual market positions without

$Index_{c,t-1}$ is the media-narrative based sentiment or risk index for investors in domicile country c at time $t-1$ and is our main variable of interest.[19] $X_{c,t-1}$ is the set of one-quarter-lagged macroeconomic controls that could potentially affect flows to China, including quarterly GDP growth difference between China and the domicile country ($Growthdiff_{c,t-1}$), exchange rate appreciation of China (EX_{t-1}), interest rates in China relative to the fund domicile area ($Intdiff_{c,t-1}$), and China's equity performance, including the stock return (Ret_{t-1}) and volatility (Vol_{t-1}).[20] To enhance clarity and facilitate comparisons, we standardize the risk index and sentiment index for each country, as well as China's stock return and volatility. The α_i's are fund fixed effects, and QRT_t is a year-end dummy variable equal to 1 for the fourth quarter, used to control for potential seasonality in fund investments, such as tax considerations and end-of-year portfolio adjustments by managers. Standard errors are clustered at the fund level to correct for potential serial correlation in the error term $\varepsilon_{ic,t}$.

Table 4 shows the baseline results from various specifications of Equation (4), using different combinations of indices and controls. Columns (1) through (4) show results for the sentiment index and columns (5) through (8) show results for the risk index. Columns (1) through (4) show that a more positive domestic media sentiment about China correlates with an increase in fund flows to China. Conversely, columns (5) through (8) reveal that heightened domestic media risk perception about China correlates with an increase in fund outflows from China. Specifically, as illustrated in column (4), after controlling for macroeconomic and financial variables, a one standard deviation increase in the domestic media sentiment index about China corresponds to a 2.3% increase in quarterly investment flows to China, which annualizes to a 9.2% increase. Additionally, column (8) shows that a one standard deviation increase in the domestic media risk index about China leads to a

the distortions that derivatives might introduce due to their complex accounting treatments. Additionally, to reduce the impact of extreme outliers, $Flow_{ic,t}$ has been winsorized at the 0.5% level in each tail.

[19] Since we construct media indices at a monthly frequency, we use the arithmetic average of those indices in three months of the quarter ending in $t-1$ in equation 4.

[20] See Table A4 in Appendix G for the definition of all control variables and their data sources.

2.1% quarterly and a 8.4% annual withdrawal of investments from China. These results suggest that media narratives have a substantial effect on investment flows given that the average quarterly fund flows into China is 7.4%.

Collectively, these results underscore the profound influence of domestic media narratives about China in shaping investment decisions. Optimistic sentiment about China in domestic media, reflected by higher sentiment indices, directly fosters higher investment flows to China. Conversely, elevated risk perceptions of China portrayed by domestic media lead open-ended funds to reduce their investments in China.

6 Exploring the Mechanism: The Information Channel

To deepen our understanding of how domestic media narratives influence investment flows to China, we explore the channels through which news media narratives might affect investors' information sets. This exploration considers whether media narratives alleviate frictions to information access or simplify the interpretation of available data. We leverage the rich heterogeneity among open-ended funds investing in China to examine variations in their information sets and how this variation in information sets influences their investment response to changes in local media narratives about China. Additionally, we analyze how the impact of local media narratives differs across periods of high and low market volatility, given that interpreting market data could be more challenging during times of high volatility.

6.1 Heterogeneous Effects of Media Narratives in the Cross-section

We first explore how the heterogeneity in the information sets of different institutional investors shapes their investment response to local media narratives about China. We characterize the information sets of institutional investors using four measures: date of initial investment in China, the share of Chinese asset holdings as a percentage of total assets under management, the accumulated stock of information about China, and the geographical locations of their domiciles.

Initial Investment Dates. Institutional investors initiated their investments in China at different times. Figure 6 plots these initial investment dates for all open-ended funds in our sample, alongside a timeline of major capital account liberalization events in the Chinese stock and bond markets. We infer the first investment date from the earliest recorded purchase of Chinese assets in each fund. When direct records are unavailable, we rely on the earliest date the fund held Chinese assets in its portfolio, as documented by Morningstar. Several stock market liberalization policies, such as the Qualified Foreign Institutional Investor Program (QFII) and the Stock Connect, have significantly encouraged institutional investors to begin their investments in China. Additionally, events like the inclusion of China's A-shares in the MSCI Emerging Market Index spurred further investment. We hypothesize that institutional investors who began investing in China earlier exhibit different sensitivities to media narratives compared to those who entered more recently. A longer investment tenure presumably correlates with a better understanding of Chinese market dynamics, potentially reducing reliance on media narratives when making investment decisions. Conversely, newer investors are more likely to be influenced by changes in media narratives during their information-gathering phase. To analyze this, we construct a dummy variable, $EarlyStart_i$, which equals one if a fund's initial investment date in China precedes the median initial investment date of all open-ended funds holding Chinese assets in our dataset, and zero otherwise.

Chinese Asset Share. The share of a fund's total assets invested in China might affect its reliance on local media narratives about China. On one hand, institutional investors with significant holdings in Chinese assets could be less influenced by media narratives about China due to the private information they access through their substantial investments. On the other hand, these investors may also have a higher demand for information about China, resulting in increased sensitivity to local media narratives about changes within the country. To examine this, we construct a dummy variable, $HighShare_{i,t}$, which equals one if the Chinese asset holdings of fund i at quarter t exceed the median holdings of all open-ended funds with Chinese asset holdings in our dataset, and zero otherwise.

Stock of Information. We further explore the historical stock of information about China held by institutional investors by combining data on their initial investment start dates with their share of Chinese asset holdings. Intuitively, investors with earlier start dates and high shares of Chinese assets are likely to have accumulated extensive private information about these assets, reflecting a high information stock. Consequently, when making investment decisions, these investors are more inclined to rely on the private information they have accumulated rather than on local media narratives. To quantify this, we construct the dummy variable $HighInfoStock_{i,t}$, which is set to one if fund i's initial investment date in China predates the median among all open-ended funds holding Chinese assets, and if at quarter t, this fund's holdings of Chinese assets exceed the median holdings of all open-ended funds with Chinese assets in our dataset. The variable is set to zero otherwise.

Geographical Proximity. Finally, we investigate whether investors from economies geographically closer to China exhibit distinct sensitivity to local media narratives about China. Intuitively, these investors are likely to have greater familiarity with China, attributable to geographical proximity, cultural similarities, or alignment in time zones. To assess this, we construct a dummy variable $GeoClose_{i,t}$, which is set to one for funds domiciled in countries closer to China including Hong Kong, India, Malaysia, the Philippines, Singapore, South Korea, Taiwan, and Thailand.

To study how the different information sets of institutional investors affect their investment response to local media narratives about China, we estimate the following equation:

$$Flow_{ic,t} = \beta_0 + \beta_1 Index_{c,t-1} + \beta_2 Het_{i,t-1} + \beta_3 Index_{c,t-1} \times Het_{i,t-1} + \beta_4 X_{c,t-1} + \delta QRT_t + \alpha_i + \varepsilon_{ic,t} \quad (5)$$

where $Het_{i,t-1}$ is a dummy variable capturing fund-level heterogeneity along the four dimensions discussed above: $EarlyStart_i$, $HighShare_{i,t}$, $HighInfoStock_{i,t}$, or $GeoClose_{i,t}$. β_3 is our key coefficient of interest and measures the extent to which having better or private information about China alleviates the impact of media narratives on investment flows to China.

Table 5 reports the estimated results. We find that the initial investment date appears to play a significant role in determining sensitivity of investor flows to local media narratives. As shown in columns (1) and (6), investors who began investing in China earlier reveal a 1.6% lower quarterly increase in investment for every one standard deviation increase in the local media sentiment index. They also show a 0.2% lower quarterly decline in investment for each one standard deviation increase in the local media risk index, although these results are not highly significant. This suggests that having an earlier start date in Chinese markets either increases the stock of private information that these investors have about China or enables them to better interpret market data, making them less reliant on local media narratives.

The results in Columns (2) and (7) indicate that institutional investors with a high share invested in Chinese assets see a 0.3% smaller increase and a 0.2% smaller decrease in their investments for each one standard deviation increase in local media sentiment and risk indices about China, respectively. However, these effects are not significant. This could be because of two offsetting forces: investors with substantial Chinese asset holdings may rely less on local media due to more private information, or they may depend more on local narratives for additional information due to their significant information needs.

Columns (3) and (8) show that investors with substantial stock of information about China experience a 1.5% smaller quarterly increase and a 0.5% smaller quarterly decline in their investments for each one standard deviation increase in local media sentiment and risk indices, respectively.

Finally, as observed in columns (4) and (9), investors geographically close to China experience a 2.1% smaller quarterly increase and a 3.8% smaller quarterly decrease in their investments for each one standard deviation increase in local media sentiment and risk indices, respectively. These investors likely possess more information about China due to their proximity, cultural ties, or shared time zones and therefore, do not rely as much on local media.

These results from the heterogeneity analysis suggest that local media narratives significantly impact cross-border investment flows into China via the information channel. Institutional investors who entered the Chinese market earlier, who hold substantial stocks of information about China, and who are from economies geographically close to China are likely to have access to alternative sources of private information about Chinese assets or can interpret Chinese market data better. This reduces their reliance on local media for news about China.

6.2 Heterogeneous Effects of Media Narratives in the Time Series

We further explore whether investors' investment sensitivity to local media narratives exhibits different patterns through the information channel during high volatility periods. Specifically, we create a dummy variable $HighVol_t$ that is set to one if stock market volatility in that quarter exceeds the 75th percentile of all observed periods in our analysis, and zero otherwise. Columns (5) and (10) in Table 5 present results with an interaction term between the narrative index and the dummy variable. After controlling for macroeconomic fundamentals, a one standard deviation increase in the sentiment index is associated with an additional 2.0% increase in quarterly investment flow into Chinese assets during high volatility periods, compared to other times. Moreover, during such periods, a one standard deviation increase in the risk index results in a 4.4% decrease in quarterly investment flow. Intuitively, during high volatility periods, interpreting market data becomes harder so investors increasingly rely on local media narratives for better understanding the data during such periods.

7 Decomposing Media Narratives into Categories

We demonstrated in Section 4 that variations in media narratives across countries can be broken down into differences in topic coverage and variations in narratives within the same topic. To investigate whether narratives about specific topics significantly influence global investors' investment decisions, we concentrate on three principal narrative topics: economic, political, and environmental. In this section, we introduce our methodology for developing categorical narrative sentiment and risk indices for these three categories.

7.1 Category Word Libraries

To construct categorical sentiment and risk indices from news articles, we first develop word lists corresponding to political, economic, and environmental topics related to China through the following steps:

Generate word libraries. We develop word libraries for economic, political, environmental, and entertainment topics using news articles from January 1, 2007, to May 31, 2022. Following the methodology outlined by Hassan et al. (2019), we source articles from four major newspapers: *the New York Times*, *U.S.A. Today*, *the Wall Street Journal*, and *the Washington Post*. For the library of economic words, we select news articles containing the keyword "China" and with the subject "economic" or "economics". For the library of political words, we select news articles with the keyword "China" and with the subject "political" or "politics". For the library of environmental words, we select news articles with the keyword "China" and with the subject "environment", "environmental","energy" or "emission", or "climate". We also construct a library of entertainment words to address the zero weight problem for certain words related to China, selecting articles with the keyword "China" and with the subject "sport", "entertainment","movie" or "art". Additionally, following Hassan et al. (2019), we use the Santa Barbara Corpus of Spoken American English to build a library of common words.

Count the term frequency for each library. Overall, we have developed four libraries: economic, political, environmental, and entertainment. For each library, we rank the bigrams and count the total number of bigrams in each library. We remove the bigrams that coincide with the top 500 bigrams found in the common words library following Hassan et al. (2019). We then calculate the term frequency (tf) of each bigram (b) within its respective categorical library. This is done by dividing the frequency of each bigram in its category ($f_{b,Category}$) by the total number of bigrams in that library ($B_{Category}$):

$$tf_{b,Category} = \frac{f_{b,Category}}{B_{Category}}.$$

Count the inverse document frequency. We further count in how many libraries the bigram ranks among the top 2000 bigrams for each of the four libraries. We calculate the inverse document frequency (idf) of each bigram b as the logarithm of the ratio of four categorical libraries divided by the number of libraries the bigram appears in ($f_{b,4}$):

$$idf_b = log(\frac{4}{f_{b,4}}).$$

The inclusion of an entertainment word list serves to prevent the zero weight issue for certain bigrams. For example, bigrams like "President Obama" might rank highly in economic, political, and environmental lists but not in the entertainment list. Including an entertainment list ensures that such bigrams are retained in our analysis. However, we will not be building a separate list of entertainment words.

Generate the weight of each bigram in each library. We calculate the weight of each bigram b in each categorical library as the product of term frequency and inverse document frequency:

$$Weight_{b,Category} = tf_{b,Category} \times idf_b.$$

The weight of a bigram intuitively reflects the strength of its association with a specific topic within the library. After calculating the weights, we rank the bigrams in each library and list the top 500 for each category. Table 6 presents the top 30 bigrams related to economic, political, and environmental topics. A full list of these bigrams is provided in Appendix H. The bigrams identified by the algorithm effectively capture the relevant content, demonstrating the accuracy of the method.

7.2 Category-Specific Narrative Index Construction

Category-Specific Sentiment Index. We define the categorical sentiment indices using article i in newspaper m on date d as follows:

$$Categorypos_{im,d} = \frac{\sum_b^{B_{im,d}} \left(\mathbb{1}[b \in Category] \times \mathbb{1}[|b - pos| < 10] \times Weight_{b,Category} \right)}{B_{im,d}}$$

$$Categoryneg_{im,d} = \frac{\sum_b^{B_{im,d}} \left(\mathbb{1}[b \in Category] \times \mathbb{1}[|b - neg| < 10] \times Weight_{b,Category} \right)}{B_{im,d}}$$

where $Categorypos_{im,d}$ and $Categoryneg_{im,d}$ represent the categorical positive and negative sentiment measures, respectively. And $Category$ denotes the corresponding economic, political, and environmental bigram lists constructed in the previous section. pos and neg refer to the positive and negative sentiment word lists, respectively. $B_{im,d}$ is the total number of bigrams in article i from newspaper m on date d. In each formula, the first two terms in the numerator count the number of bigrams associated with economic, political, or environmental content that occur in proximity to a sentiment-related synonym. Each bigram is then weighted using the weight calculated in the previous step (the third term), which reflects how strongly the bigram is associated with the relevant topic.

Finally, we follow the methodology of Hassan et al. (2019) to construct sentiment indices by category. For each category, we first calculate the sum of positive and negative raw indices from all articles in each newspaper for each month. Using data from 2007 to 2019 for standardization and normalization, we standardize these series to have a unit standard deviation, average the indices across newspapers within each country, and normalize them to a mean of 100. The resulting categorical sentiment index, $Categorysen_{c,t}$ (where $Category$ denotes pol, $econ$, or env), are described in detail in Appendix I.1.

Figure 7 displays the economic, political, and environmental sentiment indices, averaged by country groups. Additional country-level categorical sentiment indices are provided in Appendix J. Several notable trends emerge from these figures, particularly in response to major global events such as the COVID-19 pandemic and the U.S.-China trade conflicts, both of which have significantly impacted sentiment across all categories. These observations align with the intuition that global events have far-reaching effects on economic, political, and environmental dimensions. For example, the economic downturn caused by COVID-19, coupled with quarantine policies, has heightened environmental concerns and prompted diverse political perspectives on policy responses.

Furthermore, these indices effectively capture variations in sentiment following significant events within each category. For instance, the China stock market collapse from late 2015 to early 2016 significantly depressed economic sentiment, while the impact was less pronounced in the political and environmental indices. The indices also reveal variations across country groups. For example, during the Evergrande Group crisis in October 2021, when the company missed interest payments on two foreign bonds, the economic sentiment in G7 and other advanced economies declined significantly, whereas there were no major changes in economic sentiment for emerging and developing economies.

Category-Specific Risk Index. We define the categorical risk indices using article i in newspaper m on date d as follows:

$$Categoryrisk_{im,d} = \frac{\sum_b^{B_{im,d}} \left(\mathbb{1}[b \in Category] \times \mathbb{1}[|b-r| < 10] \times Weight_{b,Category} \right)}{B_{im,d}}$$

where $Categoryrisk_{im,d}$ represents the categorical risk measure. $Category$ denotes the corresponding economic, political, and environmental bigram list. $B_{im,t}$ is the total number of bigrams in article i from newspaper m. The first two terms in the numerator count the number of bigrams related to categorical content that appear in proximity to a synonym for risk or uncertainty (within 10 words). In the third term, each bigram is weighted by a score reflecting how strongly it is associated with the relevant topic, using the weight calculated in the previous step.

We construct category-specific risk indices by first summing the raw risk indices for all articles in each newspaper each month. Using data from 2007 to 2019, we standardize these monthly series to have a unit standard deviation and then average them across newspapers within each country. Finally, we normalize the series to a mean of 100. The resulting normalized time-series categorical risk index, $Categoryrisk_{c,t}$ (where $Category$ refers to pol, $econ$, or env), is described in detail in Appendix I.2.

Figure 8 presents the economic, political, and environmental risk indices, averaged by country groups. Country-level categorical risk indices are available in Appendix J. Similar to the sentiment indices, risk indices across all categories exhibit spikes during global events such as COVID-19, highlighting a shared vulnerability to such disruptions. Each categorical risk index also shows heightened sensitivity to major events within its specific domain. For example, economic risk indices react strongly to macroeconomic and financial market events, such as China's growth slowdown and the stock market collapse. Political risk indices are more responsive to political events, including Trump's inauguration, the Xi-Trump meeting at Mar-a-Lago, and the Hong Kong protests. In contrast, environmental risk indices are particularly sensitive to major environmental agreements, such as China's 12th Five-Year Plan on Environmental Protection, the Paris Agreement, and China's national climate commitments. Additionally, the sensitivity of these indices to the same event varies across country groups. For instance, China's national climate commitment under the Paris Agreement in October 2021 generated significant environmental risk perceptions in G7 and other advanced economies, but received limited attention from emerging and developing economies.

8 Categorical Narratives and Cross-border Investment Flows

After constructing the time series for different categorical narrative indices, we examine their impact on investment flows into China by addressing two aspects: first, we assess whether any particular narrative category has a more significant influence on investment flows; second, we explore how investors adjust their investment flows to different sectors in China in response to variations in these categorical indices.

8.1 Which Categorical Narratives Matter Most for Investment Flows?

We first investigate whether changes in specific categorical media indices have a greater influence on investment flows into China than others. Table 7 shows how the fund-level and fund-sector-level flows respond to variations in the media sentiment and risk indices across the economic, political, and environmental categories.

Institutional investors' investments in China, at both the fund and fund-sector levels, fluctuate with changes in local media-based economic, political, and environmental sentiment and risk indices, after controlling for macroeconomic and financial variables. When categorical sentiment is more positive and the categorical risk index declines, institutional investors allocate more funds to Chinese assets. Notably, fund-level and fund-sector level flows to China are more sensitive to changes in the economic sentiment index, followed by environmental sentiment, and then political sentiment. However, there do not appear to be significant differences in the magnitude of impact across sentiment indices in different categories. For example, a one standard deviation increase in the domestic media-based economic sentiment index about China is associated with a 2.5% quarterly increase in fund flows into a specific sector. Similarly, a one standard deviation increase in the environmental sentiment index leads to a 2.4% quarterly increase, while a one standard deviation increase in the political sentiment index results in a 2.2% quarterly increase at the fund-sector level.

Conversely, investment flows decline more in response to changes in the environmental risk index, followed by the economic risk index, and then the political risk index. A one standard deviation increase in the environmental risk index leads to a 2.3% quarterly decline in fund-sector level investment flows, followed by a 2.3% decline for the economic risk index, and a 2.0% decline for the political risk index.

Investors might be expected to prioritize economic narratives, given their direct impact on financial performance. However, our results indicate that investors equally consider political and environmental narratives when making investment decisions. Building on the information channel discussed in Section 6, this is likely because the absence of standardized data or the high cost of accessing political and environmental information, particularly information related to risk, drives investors to rely more heavily on media-based sentiment, thus raising the importance of these narratives alongside economic ones.

8.2 Categorical Narratives and Investment Flows: Fund-Sector-level Analysis

Tables 8 and 9 show how sector-level fund flows respond to variations in the sentiment and risk index for each sector, respectively.[21] The results reveal several notable patterns. Political and environmental narratives have a stronger impact on sectoral investment flows compared to economic narratives for some sectors. For instance, a one standard deviation increase in political sentiment leads to approximately 5.4% quarterly increase in flows to the consumer defensive sector, while a similar rise in the environmental sentiment results in a 5.2% increase. These effects are more than one and a half times as large as those of a one standard deviation increase in economic sentiment, which leads to a 3.8% increase in quarterly flows. These findings reveal the growing reliance of institutional investors on local media for understanding political and environmental issues in China that might be relevant for their investment decisions.

[21] See Table A8 in Appendix K for sector definitions along with example firms in each sector.

Several interesting cross-sector trends emerge as well. The consumer defensive sector—encompassing industries such as food and beverage manufacturing, household and personal products, packaging, tobacco, and services like education and training—displays significant sensitivity to changes in both sentiment and risk indices across almost all categories. For instance, a one standard deviation increase in political sentiment leads to an approximate 5.4% quarterly rise in investment flows into this sector, the largest increase observed across all sectors. This heightened sensitivity is likely due to the close connection of companies in these industries (e.g., New Oriental Education & Technology Group Inc., China Mengniu Dairy Co. Ltd.) with daily activities, which subjects them to greater media coverage. This finding aligns with previous literature, which indicates that sectors receiving more media attention tend to attract higher levels of investment Chahrour et al. (2021).

Finally, shifts in media narratives for specific categories significantly influence cross-border investments into sectors affected by sentiment in those categories. Economic sentiment indices tend to have a uniform impact across various sectors, indicating that when economic sentiment changes, investors adjust their Chinese asset allocations across these sectors by similar percentages. However, when economic risk increases, investors typically reduce their flows into the consumer defensive, and financial services and real estate sectors.

In contrast, political sentiment indices exhibit varying impacts across sectors. The consumer defensive sector is particularly sensitive to changes in political sentiment. Similarly, institutional investors' holdings in the consumer cyclical sector—which includes retail, auto manufacturing, residential construction, lodging, restaurants, and entertainment—as well as in the energy and utility sectors, are highly responsive to shifts in political sentiment. Furthermore, an increase in political risk leads investors to reduce their holdings in the consumer cyclical and consumer defensive sectors. This heightened sensitivity likely reflects the significant presence of state-owned enterprises in these industries, which are more vulnerable to political shifts due to the nature of their operations.

The relative impact of environmental sentiment indices is largest for investment flows into the consumer defensive, consumer cyclical, and basic materials sectors—which include manufacturers of chemicals, building materials, and paper products—along with the financial services and real estate sectors. A one standard deviation increase in the environmental sentiment index results in a 2.6% quarterly increase in flows into the basic materials sector and a 2.5% increase into the financial services and real estate sectors. Conversely, when environmental risk rises, investors tend to reduce their portfolios in sectors such as consumer defensive, financial services and real estate, technology, and consumer cyclical sectors. These industries are either directly connected to environmental issues or significantly influenced by environmental factors within their production networks. For instance, financial services are linked to environmental risks through financing options, while the real estate sector relies on raw materials that are environmentally sensitive. These trends highlight how institutional investors actively adjust their portfolios in response to shifts in local media narratives specific to environmental concerns.

9 The Asymmetric Effects of Positive and Negative Narratives

The existing literature has documented that news media disproportionately focus on negative events, often exhibiting a bias towards negative news (Goidel and Langley, 1995; Damstra and Boukes, 2021; van Binsbergen et al., 2024). Moreover, some studies suggest that people tend to respond more strongly to negative information (Holbrook et al., 2001; Soroka, 2006). Motivated by these findings, we further explore the asymmetric effects of positive and negative narratives in local media on cross-border flows. Specifically, we examine whether institutional investors adjust their portfolios more aggressively in response to negative narratives compared to positive ones. If so, this would confirm that investors respond to shifts in local media narratives and may be particularly influenced by the media's bias towards negative news, even after controlling for real economic activity.

To distinguish between the two types of news, we derive separate positive and negative indices about China based on the frequency of positive and negative word mentions, respectively. The detailed methodologies are described in Appendixes D.4 and D.5.[22] Table 10 presents the results from equation (4), where the media narrative index is replaced with both positive and negative indices simultaneously. As shown in column (4), a one standard deviation increase in the positive index is associated with a 0.6% quarterly increase in fund flows into Chinese assets, whereas a one standard deviation increase in the negative index is linked to a 2.8% quarterly decline in fund flows out of Chinese assets.[23] Intuitively, negative news tends to be more prominent and garners greater attention from investors as they gather market information about China from local newspapers. Consequently, investors are likely to react more strongly to decreases in sentiment than to increases.

These results confirm the significant and asymmetric effects of local media narratives on cross-border institutional investments. Furthermore, the potential negative bias in local media may increase the likelihood of investor overreaction to negative narratives. It seems that investors are generally more conservative in their cross-border investments, prioritizing the identification of negative narratives and withdrawing funds over increasing investments following positive news.

10 Conclusion

We provide novel empirical evidence on the role of narratives in driving cross-border flows. Our findings reveal substantial cross-country variation in narratives about China, driven by differences in both the topics and sentiments published in local media. Using fund-level data from Morningstar, we show that these narratives significantly impact cross-border

[22] Similarly, Rey, Stavrakeva and Tang (2024) define two risk news indices—'risk on' (U.S. news that appreciates the USD) and 'risk off' (U.S. news that depreciates the USD)—to explore the relationship between exchange rates and the global network of equity holdings.

[23] In column (1) and (3) of Table 10, the coefficient for the positive index is unexpectedly negative, possibly due to a high correlation between the negative and positive indices. This correlation may arise from heightened Chinese news coverage during major events such as the COVID-19 pandemic and the Beijing Olympics. In columns (2) and (4), this effect is mitigated by the inclusion of macroeconomic controls.

flows of institutional investors, even after controlling for macroeconomic fundamentals. We attribute this to the information channel and demonstrate that narratives have a stronger effect on cross-border flows when investors are less familiar with China or have less access to private information. Political and environmental narratives affect flows as much as, or more than, economic narratives, suggesting that the marginal value of narratives increases when reliable market-based information is scarce. Finally, we find asymmetric effects of narratives, with investors reacting more strongly to negative narratives than to positive ones, underscoring the heightened risk of investor overreaction to negative news driven by the negative bias in media coverage.

The results of our study offer critical insights for both policymakers and investors. Understanding the significant role of media narratives can improve investment strategies and help mitigate the risks associated with over-reliance on local media for information about investment destination countries. For investors, recognizing the influence of local media on perceptions can lead to more informed decisions and better investment outcomes. Policymakers in emerging markets can enhance the quality of investment by increasing the availability of market information. This includes translating local policies and market data into multiple languages to lessen reliance on potentially biased local media in investors' home countries. Furthermore, increasing the frequency of local data publication can attract cross-border investments by providing more reliable information, fostering a more transparent and appealing investment environment.

Future research could explore in greater detail how media narratives affect different types of investments and cross-border flows at a more granular level. For example, investigating how local media coverage of specific industries or firms influences foreign direct investment in those sectors could yield valuable insights. Additionally, expanding this analysis to other emerging markets would help assess the generalizability of these findings and provide a broader understanding of how media narratives shape global investment patterns.

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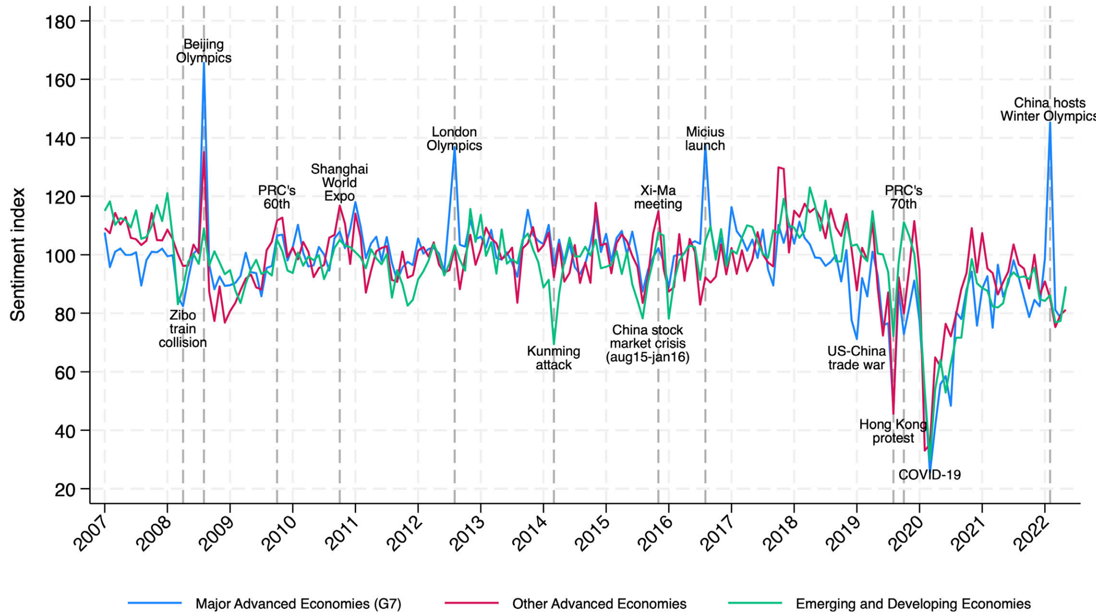
(A) Sentiment Index



(B) Risk Index

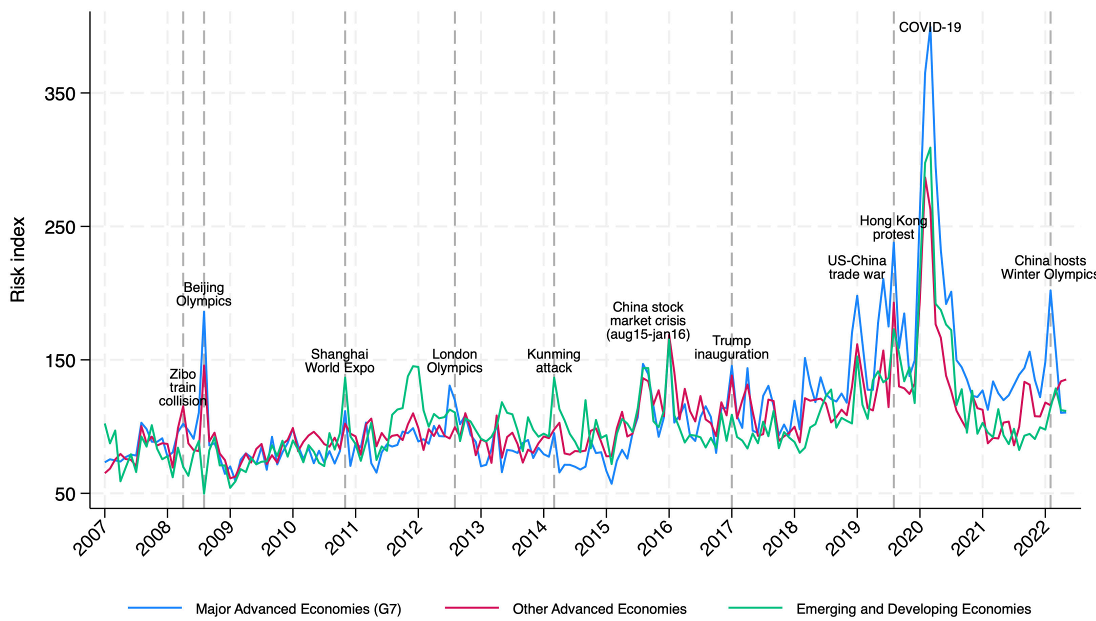


Figure 1: Sentiment index and risk index

Notes: This figure plots the average time series of the (A) sentiment index ($sen_{c,t}$) and (B) risk index ($risk_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The detailed methodologies for constructing those indices are provided in Section 2.2. Time series of country-level sentiment and risk indices for each country in the sample can be found in Appendix E.

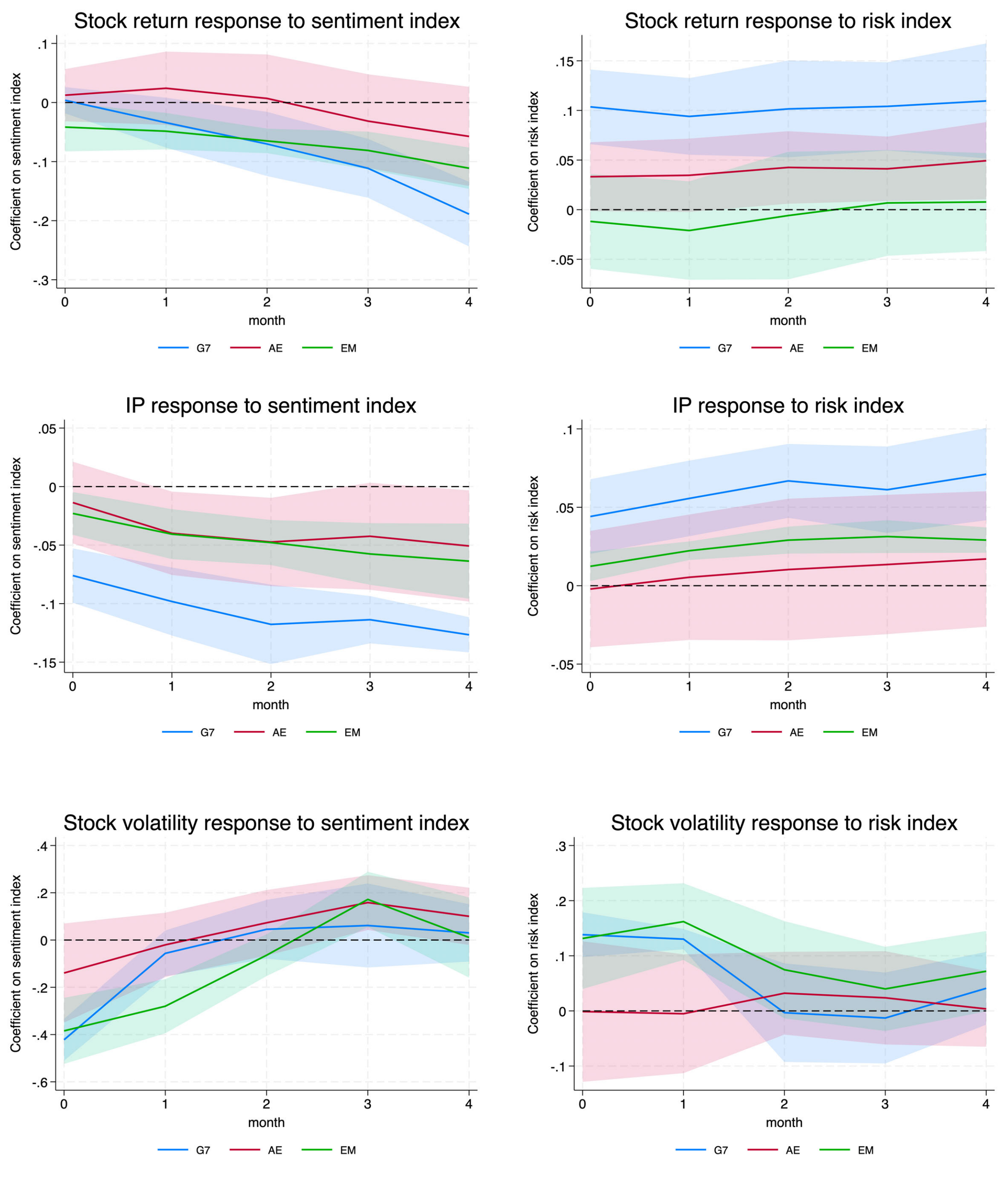


Figure 2: Dynamic relationship between media indices and economic performance

Notes: This figure shows the estimated β_0^h from equation (1). The shaded area represents the 95% confidence interval. The blue, red, and green lines correspond to country groups Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies, respectively.

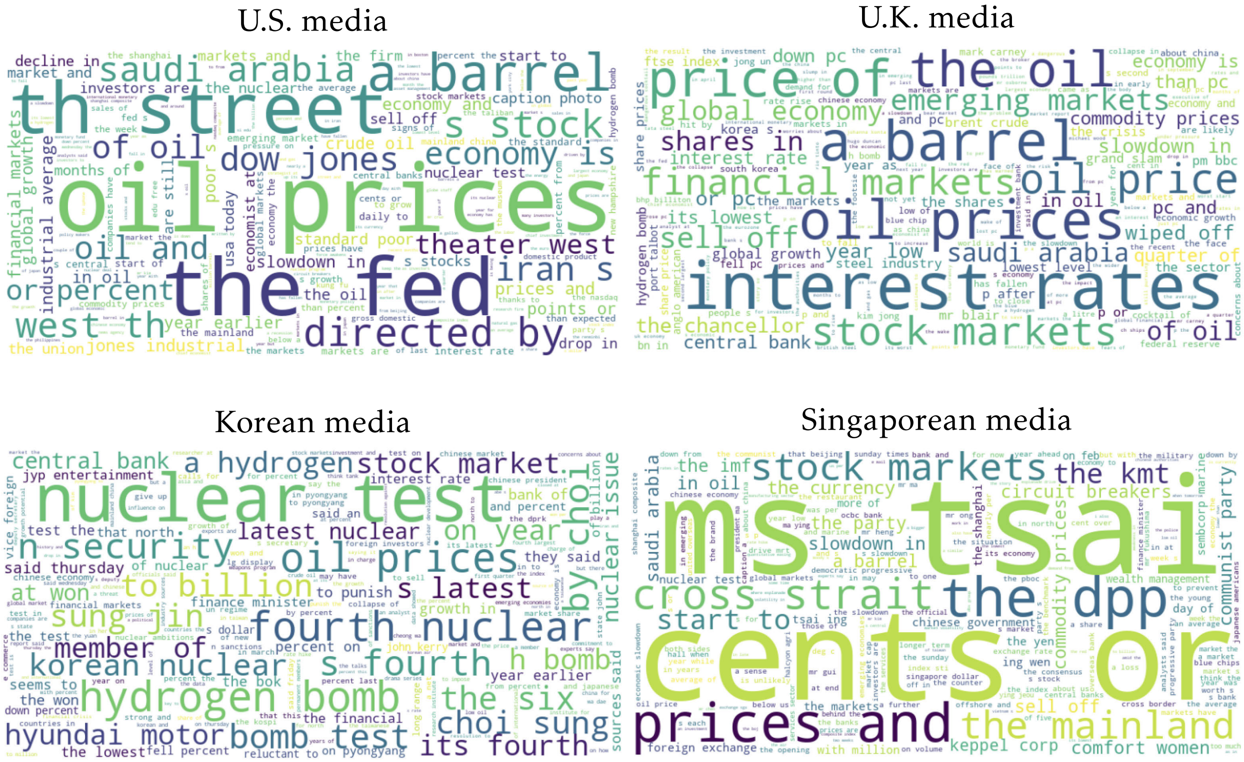


Figure 3: Topic bigram word cloud of China-related news: January 2016

Notes: This graph plots the word cloud of topic bigrams in the news media of the U.S., U.K., Korea, and Singapore, constructed using all the news articles with the keyword "China" in January 2016. The U.S. media include the *Wall Street Journal*, *New York Times*, *The Washington Post*, *U.S.A Today*, *Boston Globe*, and *The Los Angeles Times*. The U.K. media include the *Daily Mail*, *The Daily Telegraph*, *The Daily Mirror*, and *Evening Standard*. The Korean media include *The Korea Times*, and the Singaporean media include *The Straits Times and The Business Times*. See Section 4.1 for details on construction of topic bigrams.

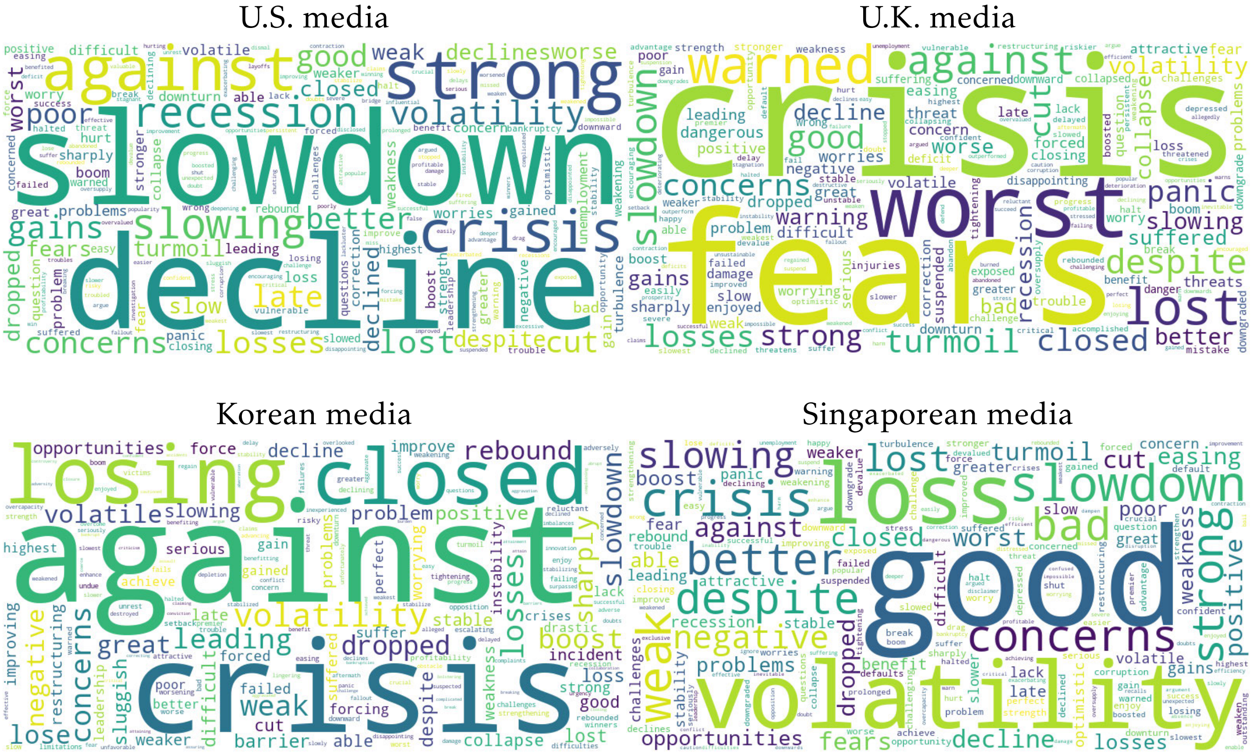


Figure 4: Sentiment word cloud: China stock market collapse (Jan 2016)

Notes: This graph plots the word cloud of the sentiment words in the news media of the U.S., U.K., Korea, and Singapore, constructed using all the news articles with the keyword "China" and "stock" in January 2016. The U.S. media include the *Wall Street Journal*, *New York Times*, *The Washington Post*, *U.S.A Today*, *Boston Globe*, and *The Los Angeles Times*. The U.K. media include the *Daily Mail*, *The Daily Telegraph*, *The Daily Mirror*, and *Evening Standard*. The Korean media include *The Korea Times*, and the Singaporean media include *The Straits Times and The Business Times*. The sentiment words are from Loughran and McDonald (2011). We rank the bigrams by frequency to construct the word cloud.

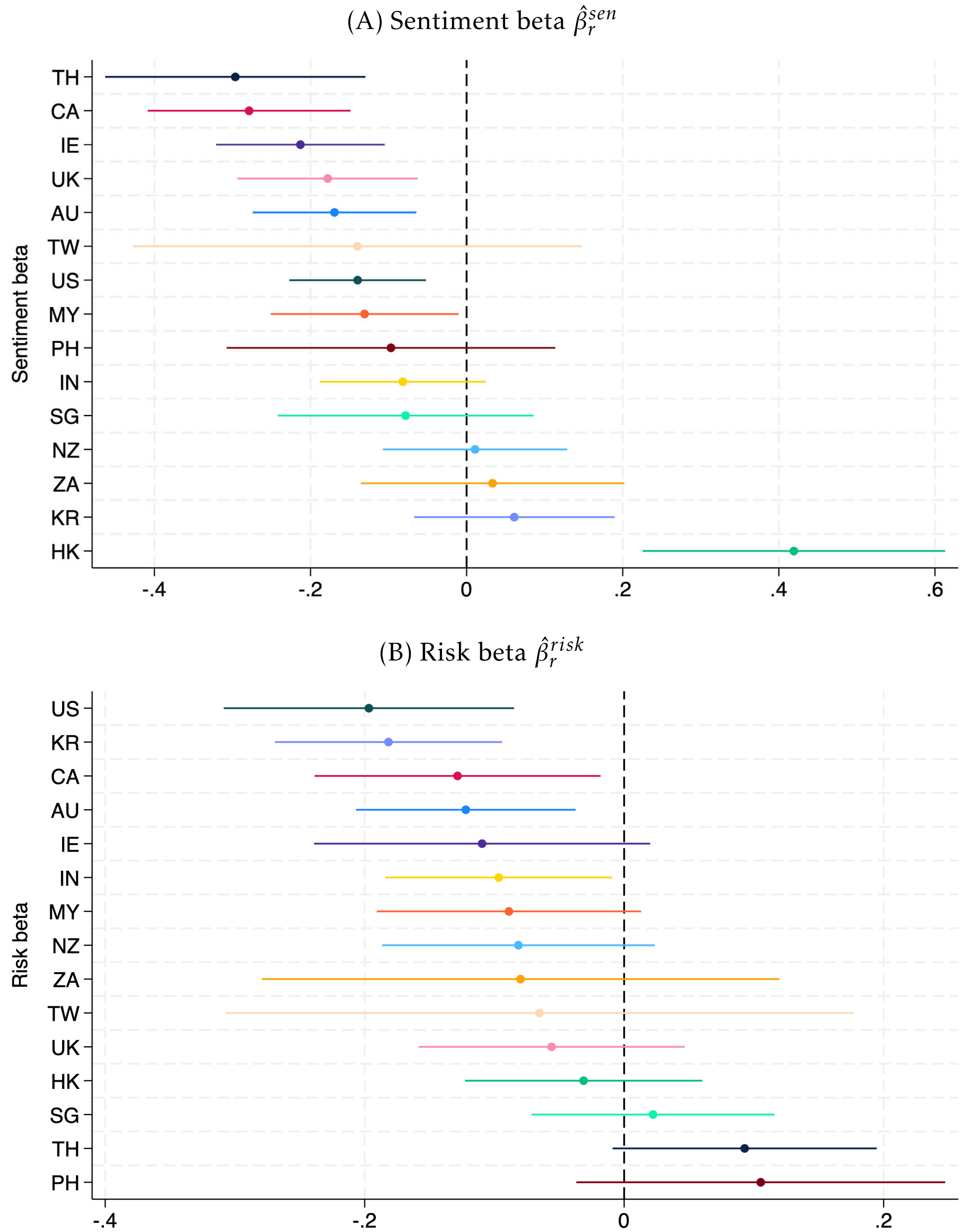


Figure 5: Sentiment beta and risk beta

Notes: Panel (A) shows the sentiment beta ($\hat{\beta}_r^{sen}$), estimated from the regression in equation (2). Panel (B) shows the risk beta ($\hat{\beta}_r^{risk}$), estimated from the regression in equation (3). A positive β_r^{sen} indicates that better stock market performance of China is associated with a more positive local media sentiment about China. A positive β_r^{risk} indicates that higher stock market volatility in China is associated with higher local media risk perception of China. The dot represents the point estimate, while the line represents the 95% confidence interval.

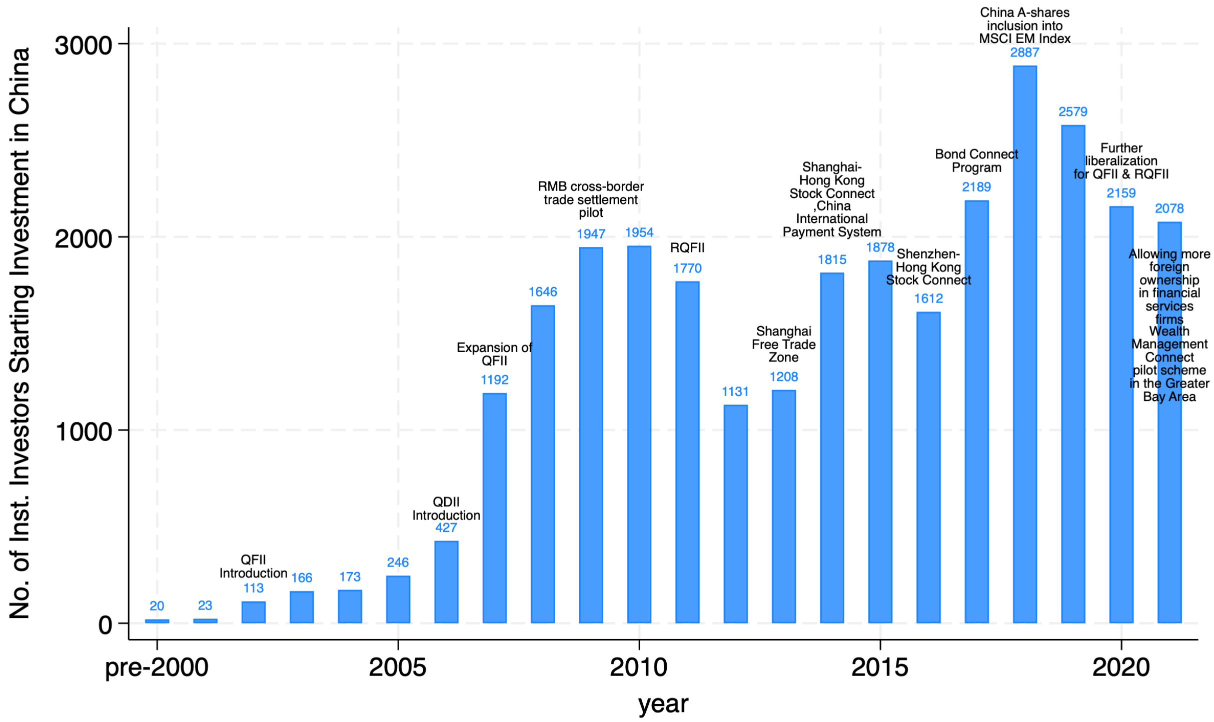
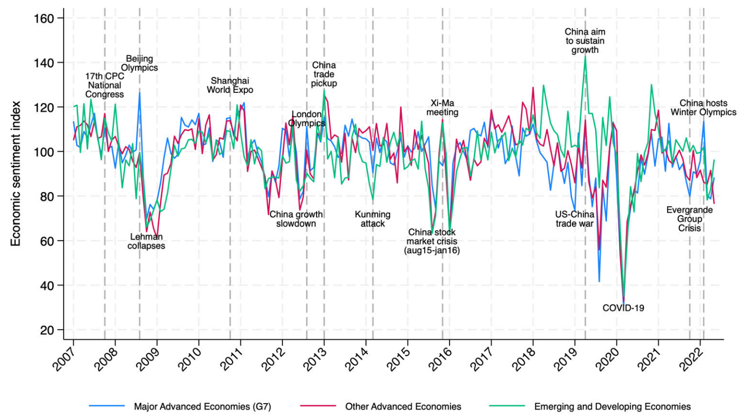


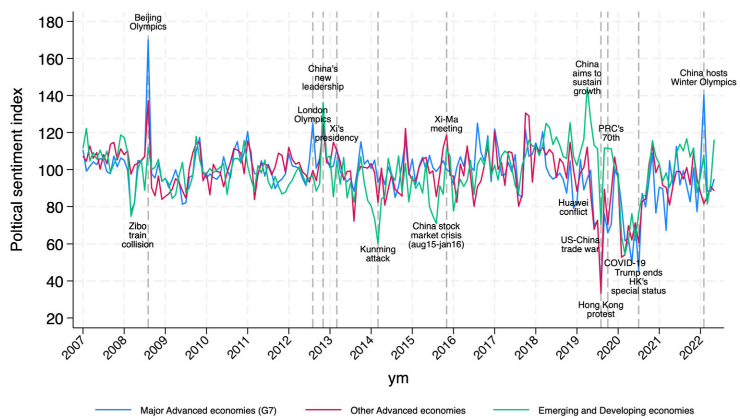
Figure 6: Initial investment dates in China

Notes: This figure plots the initial investment dates in Chinese assets for all open-ended funds from Morningstar, along with the timeline of major events related to China's stock and bond markets.

(A) Economic sentiment index: $econsen_{c,t}$



(B) Political sentiment index: $polsen_{c,t}$



(C) Environmental sentiment index: $envsen_{c,t}$

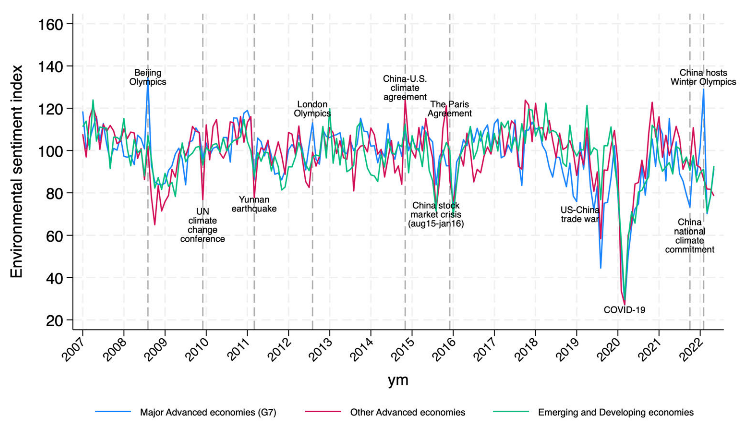
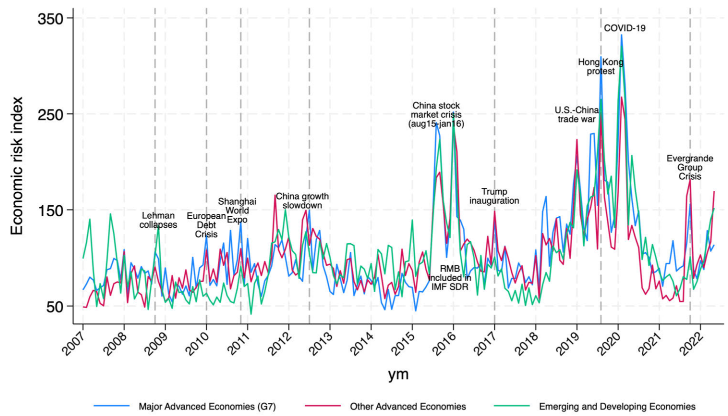


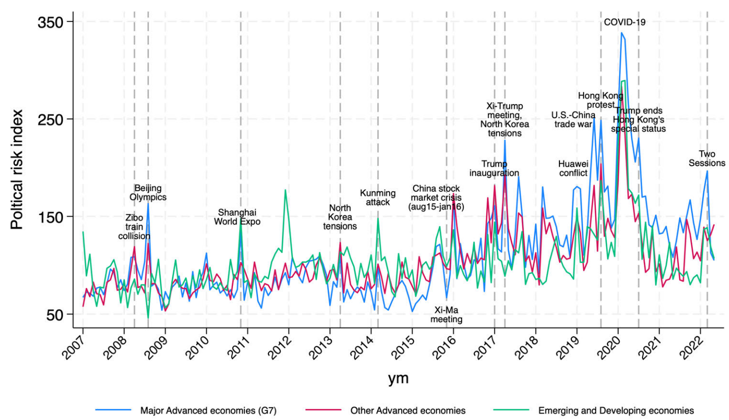
Figure 7: Categorical sentiment index: $Categorysen_{c,t}$

Notes: This figure plots the time series of the economic, political, and environmental sentiment indices, averaged by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The categorical sentiment index reflects the local media-based sentiment about a specific topic or category in China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. Appendix J shows all categorical indices at the country-level.

(A) Economic risk index: $envrisk_{c,t}$



(B) Political risk index: $polrisk_{c,t}$



(C) Environmental risk index: $envrisk_{c,t}$

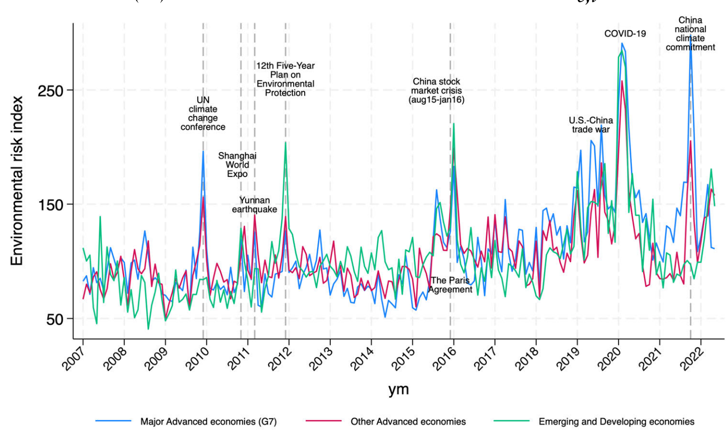


Figure 8: Categorical risk index: $Categoryrisk_{c,t}$

Notes: This figure plots the time series of the categorical risk index ($Categoryrisk_{c,t}$), averaged across Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The categorical risk index reflects the local media-based risk perception of a topic or category in China and is constructed using textual analysis of all China-related news articles in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. Appendix J shows all categorical indices at the country-level.

Table 1: Summary statistics

	mean	**sd**	**p5**	**p25**	**p50**	**p75**	**p95**	**count**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Indices (monthly)								
$sen_{c,t}$	97.09	18.08	65.44	89.13	98.48	106.39	122.31	2397
$risk_{c,t}$	106.28	44.58	57.65	79.35	96.81	122.04	177.97	2397
$econsen_{c,t}$	98.66	19.88	67.44	88.50	98.90	109.71	128.06	2400
$polsen_{c,t}$	98.39	21.50	63.90	87.85	98.39	108.19	133.51	2400
$envsen_{c,t}$	97.99	19.35	66.33	88.31	98.97	108.11	126.87	2400
$econrisk_{c,t}$	102.77	58.73	38.39	65.63	88.63	124.05	208.31	2400
$polrisk_{c,t}$	106.23	49.09	51.40	73.89	94.99	127.02	198.92	2400
$envrisk_{c,t}$	105.75	49.94	47.95	73.20	95.85	126.26	195.56	2400
$Comp_t$	96.92	48.59	40.78	62.54	83.27	121.06	201.16	185
Vol_t	107.22	28.26	68.99	82.50	103.81	123.39	158.00	185
Panel B: Other variables (quarterly)								
$Flow_{ic,t}$	7.36	49.19	-32.56	-4.67	0.00	6.92	58.62	344253
$Flow_{ic,t}(Sector)$	8.50	56.15	-39.08	-5.36	0.00	7.80	70.51	1196494
$Growthdiff_{c,t}$	5.08	4.66	-1.23	2.83	4.75	7.30	12.52	915
EX_t	0.67	2.39	-2.73	-1.29	0.71	2.26	4.28	61
$Intdiff_{c,t}$	0.72	2.88	-5.09	-0.80	0.97	2.74	5.13	903

Notes: This table reports the summary statistics of all variables used in the empirical analysis. All media indices are at a monthly frequency and cover the period from January 2007 to May 2022. $sen_{c,t}$ and $risk_{c,t}$ are the media sentiment and risk perception indices for country c as detailed in Section 2. $Categorysen_{c,t}$ and $Categoryrisk_{c,t}$ are the categorical sentiment and risk indices constructed as characterized in Section 7, where $Category$ represents economic ($econ$), political (pol), or environmental (env) categories. Stock Composite ($Comp_t$) is the stock performance measure, calculated as the monthly average of the daily Shanghai Shenzhen CSI 300 index. Stock volatility (Vol_t) is measured by the monthly volatility of the daily Shanghai Shenzhen CSI 300 index. To ensure comparability, both the stock market return and volatility indices are standardized to have a mean of 100 over the period from 2007 to 2019. $Flow_{ic,t}$ represents the quarterly investment flows of fund i in country c into Chinese assets, as described in Section 5, while $Flow_{ic,t}(Sector)$ represents these flows within each sector. $Growrhdiff_{ic,t}$ denotes the growth difference between China and the investor's domicile country. EX_t is China's exchange rate index, and $Indiff_{c,t}$ is the interest rate difference between China and the domicile country. Detailed definitions of all macroeconomic and financial variables are provided in Appendix G.

Table 2: Correlation between sentiment and risk indices

		$sen_{c,t}$ & $risk_{c,t}$	
	Country	**Corr.**	**p**
G7	CA	-0.53	0.00
	UK	-0.51	0.00
	US	-0.53	0.00
AE	AU	-0.47	0.00
	HK	-0.31	0.00
	IE	-0.47	0.00
	NZ	-0.45	0.00
	SG	-0.37	0.00
	KR	-0.34	0.00
	TW	-0.14	0.25
EM	IN	-0.51	0.00
	MY	-0.45	0.00
	PH	-0.25	0.01
	ZA	-0.44	0.00
	TH	-0.63	0.00

Notes: This table reports the correlation between sentiment index ($sen_{c,t}$) and risk index ($risk_{c,t}$) and the corresponding p-values for each country in the sample.

Table 3: Correlation between narrative indices and common market performance measures

		Panel A: $sen_{c,t}$							
		Stock Composite		**EX**		**IP**		**CPI**	
	Country	**Corr.**	**p**	**Corr.**	**p**	**Corr.**	**p**	**Corr.**	**p**
G7	CA	-0.31	0.00	-0.11	0.15	-0.27	0.00	0.00	0.96
	UK	-0.23	0.00	-0.25	0.00	-0.34	0.00	-0.04	0.61
	US	-0.23	0.00	-0.14	0.06	-0.28	0.00	0.00	0.97
AE	AU	-0.24	0.00	-0.16	0.03	-0.29	0.00	0.09	0.23
	HK	0.31	0.00	-0.06	0.44	0.06	0.44	0.03	0.76
	IE	-0.32	0.00	-0.15	0.04	-0.29	0.00	0.03	0.64
	KR	0.14	0.05	-0.23	0.00	-0.22	0.00	0.08	0.29
	NZ	0.03	0.68	-0.09	0.26	-0.11	0.17	0.04	0.59
	SG	-0.04	0.62	-0.02	0.85	-0.02	0.84	-0.23	0.01
	TW	-0.11	0.37	-0.20	0.09	-0.35	0.00	0.21	0.08
EM	IN	-0.08	0.26	-0.27	0.00	-0.35	0.00	0.13	0.07
	MY	-0.18	0.01	-0.21	0.00	-0.24	0.00	-0.01	0.85
	PH	-0.14	0.17	-0.12	0.24	-0.15	0.13	-0.21	0.04
	TH	-0.29	0.00	-0.12	0.13	-0.19	0.02	0.04	0.66
	ZA	0.05	0.58	0.01	0.90	0.04	0.68	-0.10	0.23
		Panel B: $risk_{c,t}$							
		Stock Volatility		**EX**		**IP**		**CPI**	
	Country	**Corr.**	**p**	**Corr.**	**p**	**Corr.**	**p**	**Corr.**	**p**
G7	CA	-0.12	0.10	0.30	0.00	0.51	0.00	0.05	0.52
	UK	-0.01	0.89	0.32	0.00	0.42	0.00	0.05	0.50
	US	-0.14	0.07	0.40	0.00	0.57	0.00	0.01	0.93
AE	AU	-0.12	0.12	0.48	0.00	0.61	0.00	-0.04	0.61
	HK	-0.10	0.22	0.08	0.35	-0.04	0.59	0.01	0.94
	IE	-0.01	0.86	0.32	0.00	0.45	0.00	0.09	0.20
	KR	-0.23	0.00	0.18	0.01	0.22	0.00	0.09	0.24
	NZ	-0.03	0.67	0.40	0.00	0.42	0.00	0.00	0.99
	SG	0.11	0.21	0.31	0.00	0.48	0.00	0.07	0.41
	TW	-0.05	0.69	0.33	0.00	0.27	0.02	-0.15	0.22
EM	IN	-0.07	0.33	0.12	0.09	0.19	0.01	0.14	0.07
	MY	-0.06	0.45	0.37	0.00	0.41	0.00	0.02	0.81
	PH	0.20	0.05	-0.23	0.02	-0.09	0.40	0.50	0.00
	TH	0.09	0.25	0.00	0.96	0.19	0.02	0.37	0.00
	ZA	0.00	1.00	0.37	0.00	0.45	0.00	0.14	0.12

Notes: This table reports the correlation between the sentiment index ($sen_{c,t}$), the risk index ($risk_{c,t}$) and several common economic and financial market performance measures for China. Stock Composite is the stock performance measure, calculated as the monthly average of the daily Shanghai Shenzhen CSI 300 index. Stock volatility is measured by the monthly volatility of the daily Shanghai Shenzhen CSI 300 index. To ensure comparability, both the stock market return and volatility indices are standardized to have a mean of 100 over the period from 2007 to 2019. EX is the BIS Chinese Renminbi effective exchange rate. IP is the seasonally-adjusted industrial production index in China. CPI is the CPI index.

Table 4: Baseline: media narratives and flows

Dep. Var.:	$Flow_{ic,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.$sen_{c,t}$	1.755***	2.399***	1.889***	2.343***				
	(0.105)	(0.112)	(0.105)	(0.113)				
L.$risk_{c,t}$					-2.011***	-1.977***	-2.156***	-2.046***
					-0.091	(0.098)	(0.093)	(0.099)
L.$Growthdiff_{c,t}$		0.328***		0.317***		0.203***		0.193***
		(0.017)		(0.017)		(0.017)		(0.018)
L.EX_t		0.334***		0.245***		0.245***		0.138**
		(0.044)		(0.046)		(0.044)		(0.045)
L.$Intdiff_{c,t}$		-1.218***		-0.936***		-1.109***		-0.779***
		(0.091)		(0.099)		(0.089)		(0.096)
L.Ret_t			3.614***	0.468			0.961	-1.063
			(0.837)	(0.859)			(0.846)	(0.865)
L.Vol_t			0.042***	0.021***			0.043***	0.027***
			(0.003)	(0.003)			(0.003)	(0.003)
$Yearend_t$		-0.349	-0.495*	-0.401*		-0.747***	-0.826***	-0.856***
		(0.199)	(0.197)	(0.201)		(0.199)	(0.196)	(0.201)
$Constant$	7.615***	9.351***	4.031***	6.749***	7.834***	10.012***	4.276***	6.841***
	(0.015)	(0.301)	(0.241)	(0.474)	(0.022)	(0.311)	(0.241)	(0.472)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.044	0.046	0.045	0.046	0.045	0.046	0.046	0.046
N	307588	307526	307588	307526	307588	307526	307588	307526

Notes: This table reports results from equation (4) estimated at the fund-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 15 countries. The dependent variable is the percentage change in the flow of institutional investors' investments in China. The main independent variable is either the sentiment index (columns (1), (2), (3), and (4)) or the risk index (columns (5), (6), (7), and (8)). The sentiment index and risk index are standardized for each country. Columns (2), (4), (6), (8) include a set of macroeconomic controls that can affect cross-border flows: the year-on-year real GDP growth differential between China and the investor's domicile economy, China's effective foreign exchange rate, the interest rate differential between China and the investor's domicile economy. Columns (3), (4), (7), (8) include a set of financial controls: the return of the Chinese stock market measured as the percentage change in the Shanghai Shenzhen CSI 300 index, and the volatility of the Chinese stock market measured as the volatility of the Shanghai Shenzhen CSI 300 index. All independent variables are lagged by one quarter. All columns include fund fixed effects. Standard errors are clustered at the fund level and are reported in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.

Table 5: Information channel and narrative-driven flows

Dep. Var.:	$Flow_{ic,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.$sen_{c,t}$	3.067***	2.098***	2.592***	2.439***	2.013***					
	(0.156)	(0.192)	(0.142)	(0.116)	(0.112)					
L.$sen_{c,t} \times EarlyStart_i$	-1.597***									
	(0.207)									
L.$sen_{c,t} \times L.HighShare_{i,t}$		-0.298								
		(0.222)								
L.$sen_{c,t} \times L.HighInfoStock_{i,t}$			-1.456***							
			(0.193)							
L.$sen_{c,t} \times GeoClose_i$				-2.052***						
				(0.484)						
L.$sen_{c,t} \times HighVol_t$					2.034***					
					(0.454)					
L.$risk_{c,t}$						-2.142***	-1.789***	-1.993***	-2.189***	-1.659***
						(0.137)	(0.167)	(0.124)	(0.100)	(0.103)
L.$risk_{c,t} \times EarlyStart_i$						0.224				
						(0.181)				
L.$risk_{c,t} \times L.HighShare_{i,t}$							0.142			
							(0.193)			
L.$risk_{c,t} \times L.HighInfoStock_{i,t}$								0.450**		
								(0.169)		
L.$risk_{c,t} \times GeoClose_i$									3.749***	
									(0.514)	
L.$risk_{c,t} \times HighVol_t$										-4.365***
										(0.438)
$HighShare_{i,t}$		-11.349***					-11.391***			
		(0.378)					(0.380)			
$HIghInfoStock_{i,t}$			-11.593***					-11.563***		
			(0.499)					(0.499)		
$HighVol_t$					2.295***					2.050***
					(0.320)					(0.320)
Macro & Financial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.046	0.051	0.049	0.046	0.047	0.046	0.051	0.049	0.046	0.047
N	307526	307526	307526	307526	307526	307526	307526	307526	307526	307526

Notes: This table reports results from equation (4) estimated at the fund-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 15 countries, with additional interaction terms. The $EarlyStart_i$ is a dummy that equals one if the investor has an initial investment quarter in Chinese assets earlier than the median of all investors in the dataset and zero if below the median. The $HighShare_{i,t}$ is a dummy that equals one if the investor has a Chinese asset share lower than the median of all investors in the dataset and zero if below the median. The $HighInfoStock_i$ is a dummy that equals one if the investor has historically accumulated substantial information about China, characterized by both higher Chinese asset holdings and an earlier investment start date than the median investors, and zero otherwise. $GeoClose_i$ is a dummy variable that equals one if the investor is domiciled in an economy geographically close to China, and zero otherwise. $HighVol_t$ is a dummy that equals one if the stock market volatility in that quarter is higher than the 75th percentile of all observed periods in our analysis. The main independent variable is either the sentiment index (columns (1)-(5)) or the risk index (columns (6)-(10)). The sentiment index and risk index are standardized for each country. The coefficients of $EarlyStart_i$ and $GeoClose_i$ are omitted due to collinearity with the fund fixed effects. All columns include a set of macroeconomic controls that can affect cross-border flows (the year-on-year real GDP growth differential between China and the investor's domicile economy, China's effective foreign exchange rate, the interest rate differential between China and the investor's domicile economy), and a set of financial controls (the return of the Chinese stock market measured as the percentage change in the Shanghai Shenzhen CSI 300 index, and the volatility of the Chinese stock market measured by the volatility of the Shanghai Shenzhen CSI 300 index). All independent variables are lagged by one quarter. All columns include fund fixed effects. Standard errors are clustered at the fund level and are reported in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.

Table 6: Top 30 economic, political, and environmental bigrams

Economic bigrams:

Bigram	Weight ($\times 10^5$)	Freq	Bigram	Weight ($\times 10^5$)	Freq
the euro	11.31	1207	central banks	10.71	5506
emerging markets	11.28	1203	the fed	10.64	1135
gross domestic	11.23	1198	monetary policy	10.62	1133
domestic product	11.19	1194	s p	10.36	1105
the economy	11.13	1187	financial markets	10.35	1104
economist at	11.13	1187	consumer spending	10.33	1102
growth in	11.12	1186	bank s	10.32	2202
the yuan	11.02	1176	policy makers	10.29	1098
the imf	10.96	1169	global financial	10.28	1097
fed s	10.95	1168	a recession	10.26	1095
international monetary	10.95	1168	chief economist	10.26	1095
euro zone	10.91	1164	global growth	10.21	1089
monetary fund	10.89	5600	the labor	10.18	1086
interest rate	10.84	1156	percent in	10.18	1086
second quarter	10.71	1143	mr trump	10.17	1085

Political bigrams:

Bigram	Weight ($\times 10^5$)	Freq	Bigram	Weight ($\times 10^5$)	Freq
mr trump	10.04	1426	kim jong	9.49	1347
the police	9.99	1419	the taliban	9.45	1342
party s	9.97	1415	ambassador to	9.44	1341
the communist	9.95	1413	s campaign	9.42	1337
pro democracy	9.89	1404	social media	9.42	1337
of hong	9.86	1400	about his	9.39	1333
mrs clinton	9.84	1397	cold war	9.35	1328
mr romney	9.80	1392	the protests	9.35	1328
hillary clinton	9.74	1383	of trump	9.32	2648
chinese communist	9.66	1372	served as	9.23	1310
s political	9.64	1369	chief of	9.22	6308
the presidential	9.62	1366	democratic party	9.13	1296
the authorities	9.58	1360	the soviet	9.11	1294
the hong	9.55	1356	mr xi	9.09	1290
his campaign	9.52	1352	state department	9.08	1289

Environmental bigrams:

Bigram	Weight ($\times 10^5$)	Freq	Bigram	Weight ($\times 10^5$)	Freq
carbon dioxide	13.80	914	greenhouse gases	12.14	804
greenhouse gas	13.80	914	of carbon	12.08	800
on climate	13.71	908	s energy	12.02	1592
climate change	13.60	901	the planet	11.94	791
gas emissions	13.57	1798	the environment	11.78	780
renewable energy	13.45	891	solar panels	11.76	779
fossil fuels	12.98	860	oil prices	11.74	3747
power plants	12.97	859	the environmental	11.68	774
the climate	12.94	857	energy agency	11.61	769
of climate	12.62	836	fossil fuel	11.58	767
carbon emissions	12.55	831	the energy	11.57	1533
global warming	12.53	830	of coal	11.52	763
nuclear power	12.48	827	environmental protection	11.47	1520
of energy	12.39	821	and gas	11.47	760
clean energy	12.27	813	coal fired	11.41	1512

Notes: This table shows the top 30 economic, political and environmental bigrams with the highest weight in the construction of the categorical sentiment and risk indices. The methodology is detailed in Section 7.1. A full list of these bigrams is available in Appendix H. The bigram containing the word "s" typically indicates a possessive case. For example, in the sentence "*...it brings plaudits from Mr. Trump's most ardent political base, nationalists who portray the trade war as a tough but necessary piece...*," the word "Trump's" is broken into the bigram "trump s".

Table 7: Categorical media sentiment and flow

Panel A: Economic index				
	$Flow_{ic,t}$		$Flow_{ic,t}$ (Sector)	
L.$econsen_{c,t}$	2.567***		2.484***	
	(0.136)		(0.139)	
L.$econrisk_{c,t}$		-2.242***		-2.272***
		(0.119)		(0.124)
Macro & Financial Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes
Adj. R^2	0.046	0.046	0.050	0.050
N	307526	307526	1068868	1068868
Panel B: Political index				
	$Flow_{ic,t}$		$Flow_{ic,t}$ (Sector)	
L..$polsen_{c,t}$	1.977***		2.150***	
	(0.117)		(0.124)	
L.$polrisk_{c,t}$		-2.075***		-1.961***
		(0.106)		(0.114)
Macro & Financial Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes
Adj. R^2	0.046	0.046	0.050	0.050
N	307526	307526	1068868	1068868
Panel C: Environmental index				
	$Flow_{ic,t}$		$Flow_{ic,t}$ (Sector)	
L..$envsen_{c,t}$	2.426***		2.373***	
	(0.119)		(0.124)	
L.$envrisk_{c,t}$		-2.399***		-2.292***
		(0.122)		(0.125)
Macro & Financial Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Sector FE	No	No	Yes	Yes
Adj.R^2	0.046	0.046	0.050	0.050
N	307526	307526	1068868	1068868

Notes: This table reports results from equation (4) estimated at the fund-quarter level and fund-sector-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 15 countries. The dependent variable is the percentage change in the flow or sector flow of institutional investors' investments in China. The main independent variable is either the sentiment index or the risk index. The risk index and sentiment index are standardized for each country. The top, middle, and bottom panels show the results using economic, political, and environmental indices, respectively. All columns include a set of macroeconomic controls that can affect cross-border flows: the year-on-year real GDP growth differential between China and the investor's domicile economy, China's effective foreign exchange rate, the interest rate differential between China and the investor's domicile economy, the return of the Chinese stock market measured as the percentage changes in the Shanghai Shenzhen CSI 300 index, and the volatility of the Chinese stock market measured as the volatility of the Shanghai Shenzhen CSI 300 index. All independent variables are lagged by one quarter. All columns include fund-fixed effects. The results using fund-sector flow also include the sector fixed effects. Standard errors are clustered at the fund level and are reported in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.

Table 8: Categorical media sentiment and fund sector-level flow by sector

				Panel A: Economic sentiment index					
$Flow_{isc,t}$:	Basic materials	Communication services	Consumer cyclical	Consumer defensive	Energy & Utilities	Financial Services & Real Estate	Healthcare	Industrials	Technology
L.$econsen_{c,t}$	2.455***	2.424***	2.799***	3.818***	2.268***	2.295***	2.466***	2.273***	3.296***
	(0.295)	(0.293)	(0.226)	(0.326)	(0.289)	(0.212)	(0.386)	(0.241)	(0.261)
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.026	0.042	0.033	0.047	0.034	0.045	0.038	0.045	0.042
N	74633	88310	146458	77259	74590	186000	57748	107168	151588
				Panel B: Political sentiment index					
$Flow_{isc,t}$:	Basic materials	Communication services	Consumer cyclical	Consumer defensive	Energy & Utilities	Financial Services & Real Estate	Healthcare	Industrials	Technology
L.$polsen_{c,t}$	2.301***	1.258***	2.941***	5.367***	2.245***	2.325***	1.705***	2.448***	1.544***
	(0.264)	(0.249)	(0.192)	(0.325)	(0.268)	(0.189)	(0.318)	(0.216)	(0.208)
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.025	0.041	0.032	0.047	0.033	0.043	0.034	0.044	0.037
N	74633	88310	146458	77259	74590	186000	57748	107168	151588
				Panel C: Environmental sentiment index					
$Flow_{isc,t}$:	Basic materials	Communication services	Consumer cyclical	Consumer defensive	Energy & Utilities	Financial Services & Real Estate	Healthcare	Industrials	Technology
L.$envsen_{c,t}$	2.573***	1.854***	2.930***	5.239***	2.442***	2.544***	1.633***	2.483***	2.409***
	(0.270)	(0.237)	(0.198)	(0.301)	(0.286)	(0.188)	(0.318)	(0.216)	(0.222)
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.025	0.041	0.032	0.046	0.033	0.044	0.034	0.044	0.038
N	74633	88310	146458	77259	74590	186000	57748	107168	151588

Notes: This table reports results from equation (4) estimated at the fund-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 15 countries, grouped by sectors of China asset holding. The dependent variable is the percentage change in the sectoral flow of institutional investors' investments in China. The main independent variable is the sentiment index, which is standardized for each country. The top, middle, and bottom panels show the results using economic, political, and environmental indices, respectively. All columns include a set of macroeconomic controls that can affect cross-border flows: the year-on-year real GDP growth differential between China and the investor's domicile economy, China's effective foreign exchange rate, the interest rate differential between China and the investor's domicile economy, the return of the Chinese stock market measured as the percentage changes in the Shanghai Shenzhen CSI 300 index, and the volatility of the Chinese stock market measured as the volatility of the Shanghai Shenzhen CSI 300 index. All independent variables are lagged by one quarter. All columns include fund fixed effects. Standard errors are clustered at the fund level and are reported in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.

Table 9: Categorical media risk perception and fund sector-level flow by sector

Panel A: Economic risk index

$Flow_{isc,t}$:	Basic materials	Communication services	Consumer cyclical	Consumer defensive	Energy & Utilities	Financial Services & Real Estate	Healthcare	Industrials	Technology
L.$econrisk_{c,t}$	-1.957***	-1.826***	-2.255***	-5.264***	-2.145***	-2.976***	-1.696***	-2.306***	-2.485***
	(0.260)	(0.239)	(0.199)	(0.306)	(0.283)	(0.181)	(0.340)	(0.214)	(0.219)
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.025	0.041	0.031	0.046	0.033	0.044	0.034	0.044	0.038
N	74633	88310	146458	77259	74590	186000	57748	107168	151588

Panel B: Political risk index

$Flow_{isc,t}$:	Basic materials	Communication services	Consumer cyclical	Consumer defensive	Energy & Utilities	Financial Services & Real Estate	Healthcare	Industrials	Technology
L.$polrisk_{c,t}$	-2.008***	-1.431***	-3.212***	-2.905***	-1.222***	-2.263***	-1.449***	-1.648***	-2.744***
	(0.237)	(0.200)	(0.179)	(0.280)	(0.267)	(0.163)	(0.308)	(0.196)	(0.196)
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.025	0.041	0.033	0.045	0.033	0.044	0.034	0.043	0.038
N	74633	88310	146458	77259	74590	186000	57748	107168	151588

Panel C: Environmental risk index

$Flow_{isc,t}$:	Basic materials	Communication services	Consumer cyclical	Consumer defensive	Energy & Utilities	Financial Services & Real Estate	Healthcare	Industrials	Technology
L.$envrisk_{c,t}$	-1.999***	-1.774***	-2.770***	-4.710***	-1.701***	-2.828***	-1.783***	-2.219***	-2.795***
	(0.264)	(0.230)	(0.205)	(0.308)	(0.289)	(0.183)	(0.341)	(0.216)	(0.228)
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.025	0.041	0.032	0.046	0.033	0.044	0.034	0.043	0.038
N	74633	88310	146458	77259	74590	186000	57748	107168	151588

Notes: This table reports results from equation (4) estimated at the fund-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 15 countries, grouped by sectors of China asset holding. The dependent variable is the percentage change in the sectoral flow of institutional investors' investments in China. The main independent variable is the risk index, which is standardized for each country. The top, middle, and bottom panels show the results using economic, political, and environmental indices, respectively. All columns include a set of macroeconomic controls that can affect cross-border flows: the year-on-year real GDP growth differential between China and the investor's domicile economy, China's effective foreign exchange rate, the interest rate differential between China and the investor's domicile economy, the return of the Chinese stock market measured as the percentage change in the Shanghai Shenzhen CSI 300 index, and the volatility of the Chinese stock market measured as the volatility of the Shanghai Shenzhen CSI 300 index. All independent variables are lagged by one quarter. All columns include fund fixed effects. Standard errors are clustered at the fund level and are reported in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.

Table 10: The asymmetric effects of media narratives on investment flows

Dep. Var.:	$Flow_{ic,t}$			
	(1)	(2)	(3)	(4)
L.$pos_{c,t}$	-0.642**	0.923***	-0.604*	0.600*
	(0.238)	(0.255)	(0.242)	-0.256
L.$neg_{c,t}$	-1.765***	-2.959***	-1.940***	-2.800***
	-0.181	-0.195	-0.182	(0.194)
L.$Growthdiff_{c,t}$		0.253***		0.242***
		(0.018)		(0.018)
L.EX_t		0.275***		0.176***
		(0.044)		(0.046)
L.$Intdiff_{c,t}$		-1.213***		-0.910***
		(0.090)		(0.098)
L.Ret_t			-0.163	-1.952*
			(0.863)	-0.875
L.Vol_t			0.043***	0.024***
			(0.003)	(0.003)
$Yearend_t$		-0.416*	-0.607**	-0.554**
		(0.199)	(0.197)	-0.201
$Constant$	7.846***	9.972***	4.301***	7.151***
	(0.022)	(0.306)	(0.242)	(0.475)
Fund FE	Yes	Yes	Yes	Yes
Adj. R^2	0.045	0.046	0.046	0.047
N	307588	307526	307588	307526

Notes: This table reports results from equation (4) estimated at the fund-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 15 countries. The main independent variables are positive and negative sentiment indices. The positive index and negative index are standardized for each country. Column (2) and (4) include a set of macroeconomic controls that can affect cross-border flows (the year-on-year real GDP growth differential between China and the investor's domicile economy, China's effective foreign exchange rate, the interest rate differential between China and the investor's domicile economy), and column (3) and (4) include a set of financial controls (the return of the Chinese stock market measured as the percentage change in the Shanghai Shenzhen CSI 300 index, and the volatility of the Chinese stock market measured as the volatility of the Shanghai Shenzhen CSI 300 index). All independent variables are lagged by one quarter. All columns include fund fixed effects. Standard errors are clustered at the fund level and are reported in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% significance levels, respectively.

Appendix for Online Publication

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A Media List

Table A1: Media List

Region abbr	Region	Source	Date	Additional excluded months
AU	Australia	The Australian	Jan 01, 2007 to May 31, 2022	
AU	Australia	The Australian Financial Review	Sep 02, 2013 to May 31, 2022	Jun 2015 (*)
AU	Australia	The Canberra Times	Jan 01, 2007 to May 31, 2022, with a gap from Jan 1, 2010-Oct 21, 2010	
AU	Australia	Sydney Morning Herald	Jan 01, 2007 to May 31, 2022	
CA	Canada	The Globe and Mail	Jan 01, 2007 to May 31, 2022	
CA	Canada	Montreal Gazette	Jan 01, 2007 to May 31, 2022	
CA	Canada	The Vancouver Sun	Jan 01, 2007 to May 31, 2022	
CA	Canada	National Post	Jan 01, 2007 to May 31, 2022	
CA	Canada	Toronto Star	Jan 01, 2007 to May 31, 2022	
HK	Hong Kong	The Wall Street Journal Asia	Jan 02, 2007 to Oct 06, 2017	
HK	Hong Kong	China Daily (Hong Kong ed.)	Jul 22, 2013 to May 31, 2022, with a gap from Aug 21, 2016-Aug 23,2017, a gap from Jan 19, 2019-April 30, 2019, and a gap from Jan 2, 2020-Jan 2, 2022	May 2015 (*)
IN	India	The Times of India	Jan 01, 2007 to May 31, 2022	
IN	India	The Hindustan Times	Jan 01, 2007 to May 31, 2022	
IN	India	Indian Express	Apr 23, 2009 to May 31, 2022	
IE	Ireland	Irish Times	Jan 02, 2007 to May 31, 2022	
IE	Ireland	Sunday Independent	Jan 07, 2007 to May 29, 2022,	
IE	Ireland	Irish Independent	Jan 04, 2007 to May 30, 2022,	
MY	Malaysia	New Straits Times	Jan 01, 2007 to May 31, 2022	
NZ	New Zealand	The New Zealand Herald	Jan 01, 2007 to May 07, 2022, with a gap from Dec 13, 2013-Jan 13,2015	
PH	Philippine	Business Mirror	Jan 01, 2014 to May 31, 2022	
SG	Singapore	The Straits Times	Jan 01, 2011 to May 31, 2022	
SG	Singapore	The Business Timess	Jan 01, 2011 to May 31, 2022	
ZA	South Africa	The Mercury	March 31, 2008 to May 31, 2022 with a gap from Oct 13, 2012-May 1, 2015	Aug 2008, Sep 2008, Oct 2008, Nov 2008
ZA	South Africa	The Star	Mar 31, 2008 to May 31, 2022, with a gap from Oct 14, 2012-Dec 8, 2014	Aug 2008, Sep 2008, Oct 2008, Nov 2008
KR	South Korea	The Korea Times	Apr 04, 2007 to May 31, 2022	
TW	Taiwan	China Post	Sep 06, 2011 to Oct 03, 2017	Aug 2017, Sep 2017
TH	Thailand	Asia News Monitor	Jul 30, 2008 to May 31, 2022, with a gap from Aug 8, 2008-Dec 31, 2008 with a gap from Dec 30, 2010-July 19, 2011	July 2008 (*)
TH	Thailand	The Nation	Jan 23, 2012 to Apr 29, 2020 with a gap from Mar 12, 2019-Sep 31, 2019	Dec 2017,
UK	U.K.	Daily Mail	Jan 01, 2007 to May 31, 2022	
UK	U.K.	The Daily Telegraph	Jan 01, 2007 to May 31, 2022	
UK	U.K.	The Daily Mirror	Jan 01, 2007 to May 31, 2022	
UK	U.K.	Evening Standard	Jan 02, 2007 to May 31, 2022	
US	U.S.	Wall Street Journal	Jan 01, 2007 to May 31, 2022	
US	U.S.	New York Times	Jan 01, 2007 to May 31, 2022	
US	U.S.	The Washington Post	Jan 01, 2007 to May 31, 2022	
US	U.S.	usA Today	Jan 01, 2007 to May 31, 2022	
US	U.S.	Boston Globe	Jan 01, 2007 to May 31, 2022	
US	U.S.	The Los Angeles Times	Jan 01, 2007 to May 31, 2022	

Notes: This table shows the list of newspapers in each country used to construct all media indices. If a month is marked with * in the additional excluded months column, it means that month is not excluded, despite the total number of news articles being relatively lower than in adjacent months.

B Word list

Table A2: Rank of sentiment words count of news articles related to China in WSJ

negative	frequency	negative	frequency	positive	frequency	positive	frequency
against	107184	volatility	12039	strong	52419	efficient	5541
late	50086	easing	11651	better	46250	encouraging	5348
crisis	47716	declines	11567	good	46152	profitability	5126
cut	47691	dispute	11394	despite	38735	happy	4986
concerns	45649	conflict	11200	gains	30990	encouraged	4870
declined	38834	break	11131	boost	30523	gaining	4797
decline	31321	alleged	11088	great	25688	valuable	4541
lost	27616	worry	10874	able	25510	booming	4538
force	26899	accused	10738	leading	22752	succeed	4517
problems	25809	weakness	10632	gain	21133	efficiency	4393
problem	24667	protesters	10543	highest	20776	benefited	4305
closed	24258	losing	10340	greater	20201	strengthening	4295
losses	22077	closing	10241	gained	18267	strongest	4254
question	22033	corruption	10201	leadership	18223	friendly	4254
loss	21974	criticism	10085	popular	17677	favorite	4129
dropped	21394	warning	9750	positive	17545	transparency	3927
weak	21353	allegations	9738	stronger	16471	greatest	3776
slowdown	21065	damage	9256	win	15658	outstanding	3756
difficult	20583	worse	9160	progress	14556	prosperity	3744
threat	20292	threats	9154	opportunity	14231	lucrative	3562
bad	19815	slowed	9150	success	14107	strengthened	3512
concern	19093	shut	8979	improve	14106	popularity	3461
slow	18720	denied	8735	benefit	14071	enjoy	3338
challenge	17758	slower	8728	strength	12809	perfect	3223
investigation	17678	downturn	8557	boom	11820	stabilize	3194
slowing	17354	violence	8401	easy	11775	dream	3165
questions	17104	wrong	8321	advantage	11585	successfully	3163
opposition	16926	lose	8167	opportunities	11367	rebounded	3143
recession	16655	protest	7956	stability	10636	creative	3142
warned	16506	collapse	7917	alliance	10344	favorable	3077
claims	16106	criticized	7839	effective	9637	enjoyed	2976
challenges	16012	failure	7831	successful	9503	honor	2839
failed	15703	bankruptcy	7822	rebound	9106	achieved	2828
poor	15266	severe	7742	winning	8516	enable	2779
fears	15156	trouble	7740	innovation	8426	winners	2744
protests	14670	tightening	7659	premier	8366	improvements	2742
sharply	14646	suffered	7595	easier	8307	exclusive	2741
worries	14357	scrutiny	7439	boosted	8259	advances	2736
forced	14281	restructuring	7435	improved	8138	alliances	2714
hurt	14018	illegal	7410	stable	7987	favored	2713
negative	13708	incorrectly	7341	improving	7841	winner	2634
deficit	13338	turmoil	7176	attractive	7779	influential	2594
weaker	13307	volatile	7115	profitable	7232	succeeded	2349
worst	13239	stopped	7050	strengthen	6778	enthusiasm	2343
critical	13230	threatened	7032	easily	6605	advantages	2322
serious	12765	arrested	7018	resolve	6372	benefiting	2270
concerned	12590	crucial	6902	improvement	6212	enhance	2248
lack	12540	criminal	6882	achieve	6191	beautiful	2156
fear	12278	ill	6841	optimistic	6114	innovative	2109
unemployment	12208	declining	6750	confident	5652	collaboration	2084

Notes: This table lists the top 100 negative (columns 1-4) and top 100 positive (columns 5-8) tone words sorted by their frequency in all news articles related to China in WSJ from January 1, 2007 to May 31, 2022. The tone words are from Loughran and McDonald (2011).

Table A3: Rank of risk words count of news articles related to China in WSJ

word	frequency	word	frequency	word	frequency
risk	45803	risking	664	disquiet	103
risks	23068	unreliable	659	fitful	102
threat	20292	hazardous	652	riskiness	95
uncertainty	15049	jeopardize	650	dodgy	95
fear	12278	unsettled	642	indecision	89
chance	10234	peril	638	indecisive	84
bet	9281	variable	620	incalculable	78
possibility	8414	dubious	604	undetermined	77
unclear	6877	precarious	597	hairy	72
prospect	6840	unsure	545	untrustworthy	70
doubt	6451	erratic	539	variability	62
dangerous	6184	hazard	536	hesitating	61
risky	5608	jeopardy	535	defenseless	52
exposed	5157	wager	531	iffy	46
uncertain	4493	endanger	516	vagueness	44
danger	4002	queries	498	parlous	36
pending	3329	perilous	490	unreliability	33
riskier	3214	insecurity	477	equivocation	30
speculative	2960	wariness	454	vacillating	29
skepticism	2735	doubtful	435	unforeseeable	28
instability	2523	sticky	391	diffident	26
unknown	2497	undecided	320	gnarly	23
uncertainties	2425	menace	300	diffidence	23
likelihood	2332	unpredictability	281	oscillating	22
gamble	1971	wavering	270	fickleness	20
suspicion	1740	reservation	268	vacillation	19
unpredictable	1516	irregular	264	changeable	19
tricky	1512	riskiest	263	equivocating	12
dilemma	1454	imperil	234	undependable	10
tentative	1338	ambivalence	210	precariousness	9
probability	1254	treacherous	207	chancy	7
vague	1227	quandary	207	tentativeness	7
halting	1087	query	195	misgiving	3
faltering	1087	insecure	195	changeability	2
unstable	864	fluctuating	194	niggle	2
torn	856	hazy	189	qualm	1
hesitant	818	apprehension	187	incertitude	0
varying	800	ambivalent	160	unsureness	0
risked	726	hesitancy	132	unconfident	0
unresolved	699	dicey	129	fluctuant	0
unsafe	682	debatable	123	doubtfulness	0
Total synonyms found: 249,169					

Notes: This table shows the frequency of all single-word "risk", "risky", "uncertain", and "uncertainty" as given in the Oxford Dictionary (excluding "question", "questions", and "venture") in all news articles related to China in WSJ from January 1, 2007 to May 31, 2022.

C News Number Index

We follow the Baker et al. (2016) and construct a standardized number index. One challenge with the raw number counts is that the overall volume of articles varies across newspapers and time. To deal with this problem, we scale the raw counts by the total number of articles in the same newspaper and month. We use 2007-2019 data as the time interval used in standardization and normalization calculations. We standardize each monthly newspaper-level series to unit standard deviation from 2007 to 2019 and then average across all the newspapers within that country by both. Finally, we normalize the series to be a mean of 100 from 2007-2019. The step-by-step construction method is documented in Appendix D.1.

The index can be found in Figure A1, grouped by Major Advanced Economies (G7), Other Advanced Economies (Advanced Economies excluding G7 and Euro Area), and Emerging and Developing Economies following the IMF World Economic Outlook groups and aggreation information as of April 2023. We label the graphs with major global events and China-related events. News coverage related to China spikes during significant global events like the global financial crisis and COVID-19. Additionally, there is increased China-related media coverage during specific events such as the Beijing 2008 Olympics, the 2022 Olympics, China's new leadership, and the U.S.-China trade conflicts. Finally, there appear to be different trends in China-related coverage between emerging and developing economies and advanced economies.

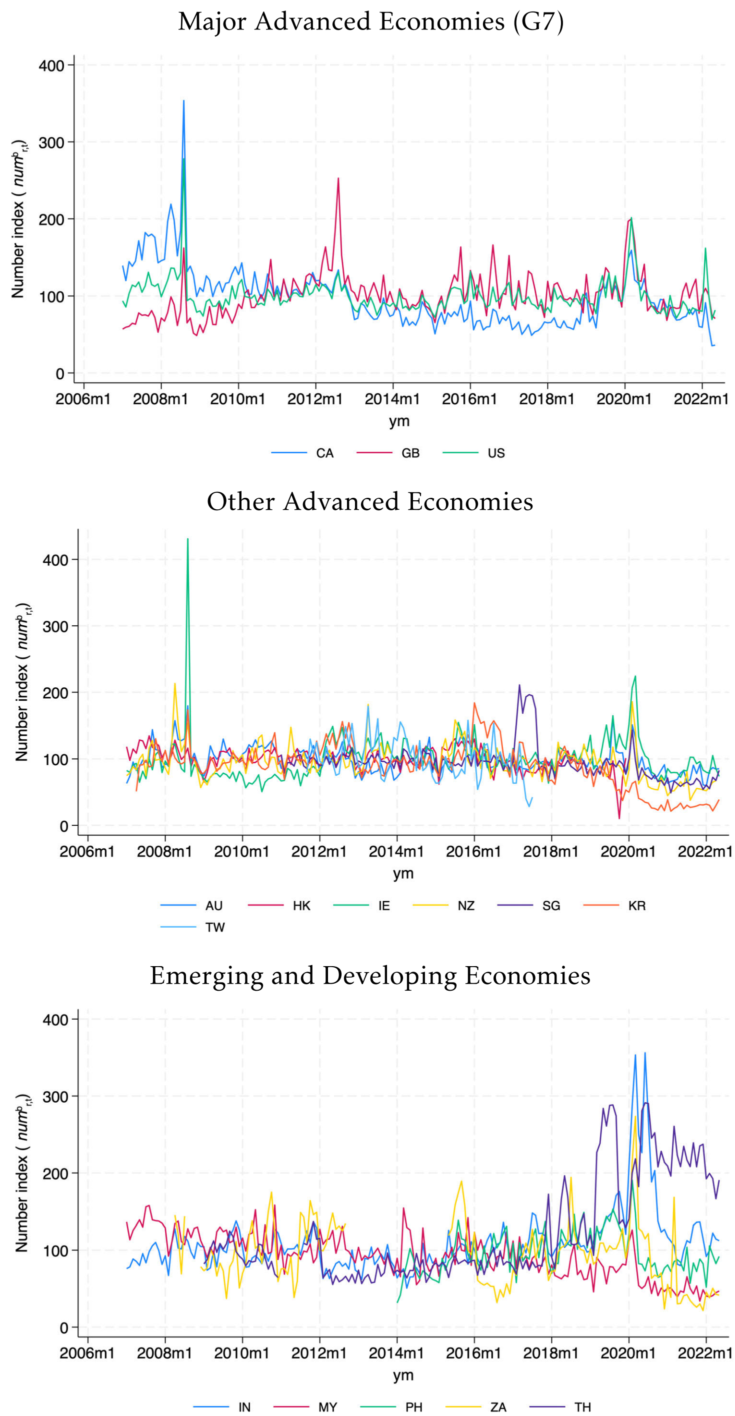


Figure A1: Number of China-related news articles: $num_{c,t}$

Notes: This figure plots the time series of the Number of China-related news articles ($num_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The number index reflects local media China-related news numbers and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index are provided in Section C. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

D Index Construction Steps

This section documents the step-by-step approach to constructing the number index, sentiment index, and risk index.

D.1 Number Index

To be precise, $num_{m,t}$ is the number of China related news for media m at quarter t, $all_{m,t}$ is the total number of news in media m at quarter t, and let T_1 denotes the time interval used in the standardization and T_2 denotes the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps:

1. Scale the China-related news number time series by the total number of news in the newspaper and calculate $num_{m,t}/all_{m,t}$
2. Compute the time-series variance σ_m^2 in the interval T_1 for each media m
3. Standardize the media time series by dividing through by the standard deviation σ_m^2 for all t. This operation yields for each newspaper a series $num_{m,t}^{sd}$ with unit standard deviation in the interval T_1
4. Compute the mean over newspapers of $num_{m,t}^{sd}$ in country t and obtain series $num_{c,t}^{sd}$
5. Compute M_r, the mean of $num_{c,t}^{sd}$ in the interval T_2
6. Multiply $num_{c,t}^{sd}$ by $100/M_r$ for all t to obtain the normalized time-series index $num_{c,t}^{b}$

D.2 Sentiment Index

To be precise, let T_1 denote the time interval used in the standardization, and T_2 denote the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps:

1. Compute the average number of positive and negative words in each article $posavg_{im,d}$ and $negavg_{im,d}$, respectively, as the sum of positive or negative words scaled by the total words in each article in media $pos_{im,d}/totalwords_{im,d}$ and $neg_{im,d}/totalwords_{im,d}$

2. Compute the total positive and negative words in each media each month $posavg^{p}_{m,t}$ and $negavg^{p}_{m,t}$ as the sum of the $posavg_{im,d}$ and $negavg_{im,d}$, respectively, of all the China-related news articles of each month t in each media m

3. Compute the scaled average number of positive and negative sentiment in each media each month $posavg_{m,t}$ and $negavg_{m,t}$ by dividing $posavg^{p}_{m,t}$ and $negavg^{p}_{m,t}$ by the total number of news articles in the newspaper m during the month t, $all_{m,t}$

4. Compute the time-series variance $\sigma^2_{pos,m}$ of $posavg_{m,t}$ and $\sigma^2_{neg,m}$ of $negavg_{m,t}$ in the interval T_1 for each media m

5. Standardize $posavg_{m,t}$ by dividing through by the standard deviation $\sigma^2_{pos,m}$ and $negavg_{m,t}$ by dividing through by the standard deviation $\sigma^2_{neg,m}$ for all t. This operation yields for each newspaper positive series $posavg^{sd}_{m,t}$ and negative series $negavg^{sd}_{m,t}$ with unit standard deviation in the interval T_1

6. Compute the standardized sentiment index $senavg^{sd}_{m,t}$ as the difference between standardized positive and negative index $posavg^{sd}_{m,t} - negavg^{sd}_{m,t}$ [24]

7. Compute the mean over newspapers of $senavg^{sd}_{m,t}$ in country t and obtain series $sen^{raw}_{c,t}$. Normalize the index further to be positive as $sen^{+}_{c,t}$ by adding a constant to the index $sen^{raw}_{c,t}$, which is the minus minimum value of the index plus one, $-sen^{min}_{c,t} + 1$

8. Compute M_r, the absolute value of the mean of $sen^{+}_{c,t}$ in the interval T_2

9. Multiply $sen^{+}_{c,t}$ by $100/M_r$ for all t to obtain the normalized time-series index $sen_{c,t}$

[24] The negative word list is significantly longer than the positive word list. If we calculate the indices first and then standardize them, all resulting values will be negative. Therefore, we standardize the positive and negative indices first, and then calculate the difference following Flynn and Sastry (2024). This approach aims to normalize the lengths of the index lists.

D.3 Risk Index

To be precise, let T_1 denotes the time interval used in the standardization and T_2 denotes the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps

1. Compute the average number of risk words in each article $riskavg_{im,d}$ as the sum of risk word count scaled by the total words in each article in media $risksum_{im,d}/totalwords_{im,d}$

2. Compute the total number of risk words in each media each month $riskavg^{p}_{m,t}$ as the sum of the $riskavg_{im,d}$ of all the China-related news articles of each month t in each media m

3. Compute the scaled average number of risk words in each media each month $riskavg_{m,t}$ by dividing $riskavg^{p}_{m,t}$ by the total number of news articles in the newspaper m during the month t, $all_{m,t}$

4. Compute the time-series variance $\sigma^2_{risk,m}$ of $riskavg_{m,t}$ in the interval T_1 for each media m

5. Standardize $riskavg_{m,t}$ by dividing through by the standard deviation σ^2_m for all t. This operation yields for each newspaper a series $riskavg^{sd}_{m,t}$ with unit standard deviation in the interval T_1

6. Compute the mean over newspapers of $riskavg^{sd}_{m,t}$ in country t and obtain series $risk^{sd}_{c,t}$

7. Compute M_r, the mean of $risk^{sd}_{c,t}$ in the interval T_2

8. Multiply $risk^{sd}_{c,t}$ by $100/M_r$ for all t to obtain the normalized time-series index $risk_{c,t}$

D.4 Positive Index

To be precise, let T_1 denotes the time interval used in the standardization and T_2 denotes the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps

1. Compute the average number of positive words in each article $posavg_{im,d}$ as the sum of positive word count scaled by the total words in each article in media $pos_{im,d}/totalwords_{im,d}$

2. Compute the total number of positive words in each media each month $posavg^{p}_{m,t}$ as the sum of the $posavg_{im,d}$ of all the China-related news articles of each month t in each media m

3. Compute the scaled average number of positive words in each media each month $posavg_{m,t}$ by dividing $posavg^{p}_{m,t}$ by the total number of news articles in the newspaper m during the month t, $all_{m,t}$

4. Compute the time-series variance $\sigma^2_{pos,m}$ of $posavg_{m,t}$ in the interval T_1 for each media m

5. Standardize $posavg_{m,t}$ by dividing through by the standard deviation σ^2_m for all t. This operation yields for each newspaper a series $posavg^{sd}_{m,t}$ with unit standard deviation in the interval T_1

6. Compute the mean over newspapers of $posavg^{sd}_{m,t}$ in country t and obtain series $pos^{sd}_{c,t}$

7. Compute M_r, the mean of $pos^{sd}_{c,t}$ in the interval T_2

8. Multiply $pos^{sd}_{c,t}$ by $100/M_r$ for all t to obtain the normalized time-series index $pos_{c,t}$

D.5 Negative Index

To be precise, let T_1 denotes the time interval used in the standardization and T_2 denotes the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps

1. Compute the average number of negative words in each article $negavg_{im,d}$ as the sum of negative word count scaled by the total words in each article in media $negsum_{im,d}/totalwords_{im,d}$

2. Compute the total number of negative words in each media each month $negavg_{m,t}^{p}$ as the sum of the $negavg_{im,d}$ of all the China-related news articles of each month t in each media m

3. Compute the scaled average number of negative words in each media each month $negavg_{m,t}$ by dividing $negavg_{m,t}^{p}$ by the total number of news articles in the newspaper m during the month t, $all_{m,t}$

4. Compute the time-series variance $\sigma_{neg,m}^2$ of $negavg_{m,t}$ in the interval T_1 for each media m

5. Standardize $negavg_{m,t}$ by dividing through by the standard deviation σ_m^2 for all t. This operation yields for each newspaper a series $negavg_{m,t}^{sd}$ with unit standard deviation in the interval T_1

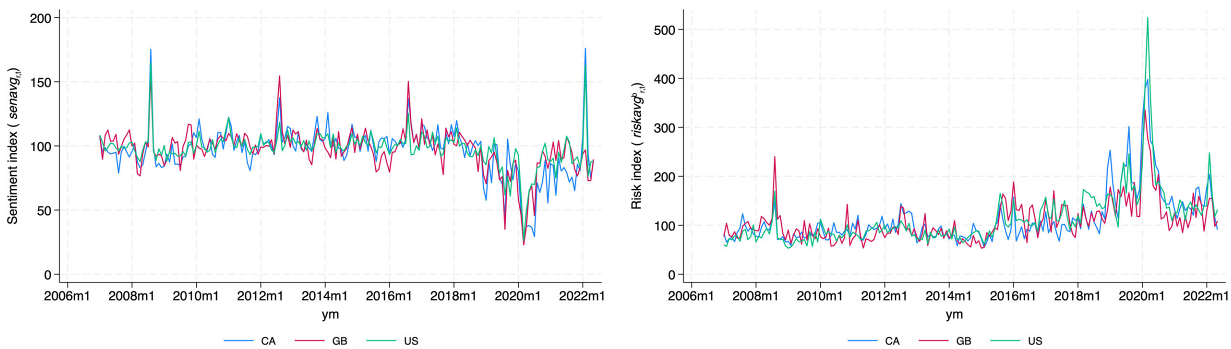
6. Compute the mean over newspapers of $negavg_{m,t}^{sd}$ in country t and obtain series $neg_{c,t}^{sd}$

7. Compute M_r, the mean of $neg_{c,t}^{sd}$ in the interval T_2

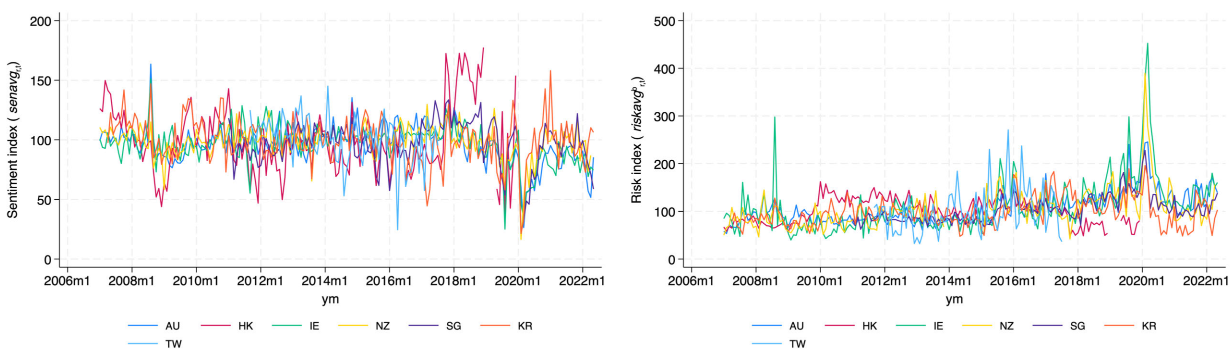
8. Multiply $neg_{c,t}^{sd}$ by $100/M_r$ for all t to obtain the normalized time-series index $neg_{c,t}$

E Index Plots by Country

(A) Major Advanced Economies (G7)



(B) Other Advanced Economies (AE)



(C) Emerging and Developing Economies (EM)

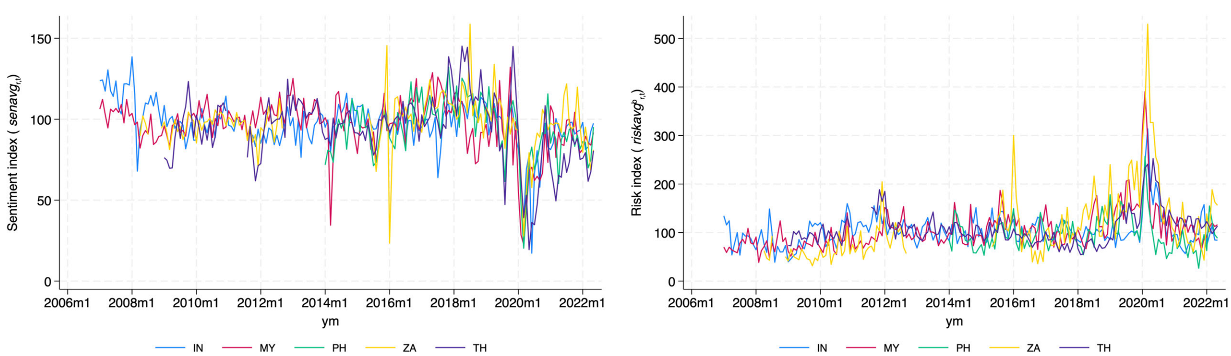


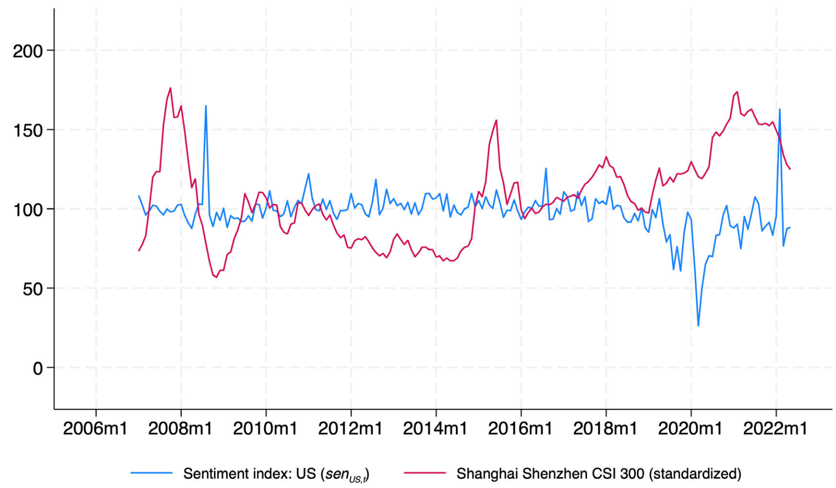
Figure A2: Sentiment index and risk index

Notes: This figure plots the time series of the sentiment index ($sen_{c,t}$, left) and risk index ($risk_{c,t}$, right), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The detailed methodologies for constructing this index is provided in Section 2.2.

F Additional Sentiment and Risk Measures

F.1 U.S. media indices with financial market measures

(A) U.S. sentiment index & SSE Comp. Index



(B) U.S. risk index & SSE Vol. Index

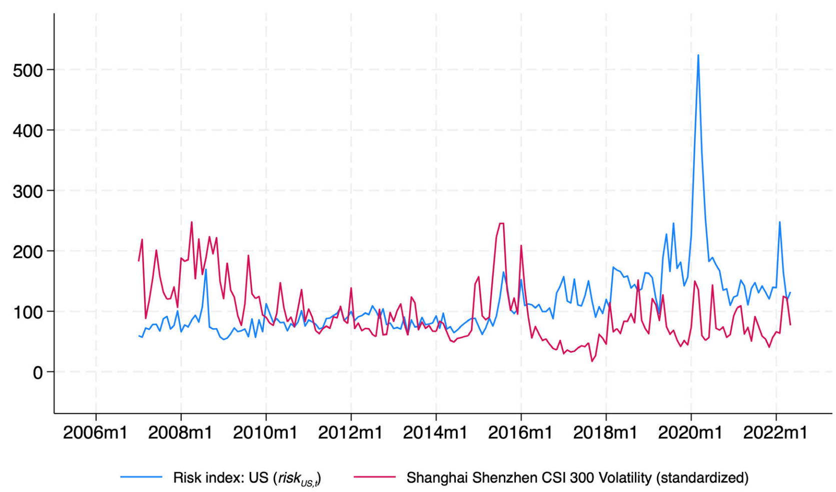


Figure A3: U.S. narrative indices and Chinese stock market indices

Notes: This graph shows the time series of the U.S. sentiment index alongside the China stock market return index, Shanghai Shenzhen CSI 300 (A), and the U.S. risk index alongside the China stock return volatility indices, Shanghai Shenzhen CSI 300 Volatility Index (B). Both the stock market return and volatility indices are standardized to a mean of 100 for the period 2017-2019.

G Variable Definitions

Table A4 shows the definitions and source of variables used in equation (4).

Table A4: Variable definitions

Variable	Def	Source
$Growthdiff_{c,t}$	The GDP growth difference between China and the investor's domicile country, where GDP is measured as real quarterly growth on a year-over-year basis.	CEIC
EX_t	China's exchange rate, calculated as the percentage change from quarter to quarter.	BIS
$Intdiff_{c,t}$	Interest rate differential between China and the fund domicile country, which is constructed using short-term interest rates from the *OECD*. If a country's short-term interest rates are unavailable, we substitute with the lending interest rate differential from the *IMF*. In cases where both rates are missing, we default to using China's short-term interest rates.	OECD, IMF International Financial Statistics (IFS)
Ret_t	Stock market return, calculated as the percentage change in the quarterly average of the monthly Shanghai Shenzhen CSI 300 index. For comparison purposes, we standardize the monthly Shanghai Shenzhen CSI 300 index to have a mean of 100 over the period from 2007 to 2019.	Bloomberg
Vol_t	Stock market return, constructed as the quarterly average of the monthly volatility of the Shanghai Shenzhen CSI 300 index. We calculate the Shanghai Shenzhen CSI 300 volatility as the monthly volatility of daily values of the index. For comparison purposes, we further standardize the monthly volatility index to a mean of 100 over the period from 2007 to 2019.	Bloomberg

Notes: This table shows the definitions and source of variables used in equation (4).

H Categorical Bigrams

Table A5 shows the top 100 economic bigrams. Table A6 shows the top 100 political bigrams. Table A7 shows the top 100 environment bigrams.

Table A5: Top 100 economic bigrams

Bigram	Weight $\times 10^5$	Frequency	Bigram	Weight $\times 10^5$	Frequency
the euro	42.28	4510	of growth	14.36	1532
emerging markets	33.92	3619	from in	14.16	1511
gross domestic	31.42	3352	year earlier	14.08	3003
domestic product	31.21	3329	the dow	13.77	2937
the economy	30.79	15828	emerging market	13.61	1452
economist at	30.22	3224	its currency	13.57	1448
growth in	26.65	5685	world economy	13.51	1441
the yuan	26.42	2818	its economy	13.49	1439
the imf	25.93	2766	economists say	13.35	1424
fed s	25.48	2718	the recession	13.27	1416
international monetary	23.28	2484	goods and	13.22	1410
euro zone	23.08	2462	tax cuts	13.20	1408
monetary fund	22.93	2446	largest economy	13.18	1406
interest rate	22.74	2426	economic slowdown	12.95	1382
second quarter	21.22	2264	growth the	12.92	1378
central banks	21.16	2257	first quarter	12.90	2752
the fed	20.22	10397	rates and	12.78	1363
monetary policy	19.65	2096	the treasury	12.47	1330
s p	19.49	4159	the recovery	12.43	1326
financial markets	19.42	2072	the dollar	12.36	6355
consumer spending	18.06	1927	the stock	12.32	2628
bank s	17.92	1912	s exports	12.27	1309
policy makers	17.86	1905	spending and	12.13	1294
global financial	17.53	1870	for economic	12.04	1284
a recession	17.43	1859	chinese economy	11.91	1271
chief economist	17.25	1840	the fund	11.62	1240
global growth	17.15	1830	european central	11.54	1231
the labor	17.02	1816	strategist at	11.53	1230
percent in	16.83	3591	latin america	11.45	1222
mr trump	16.75	8612	commodity prices	11.40	1216
oil prices	16.60	3542	banks to	11.34	1210
slowdown in	16.54	1764	s financial	11.32	1208
central bank	16.43	8448	goldman sachs	11.31	1207
financial system	16.28	1737	growth rate	11.28	1203
s growth	16.18	1726	exchange rate	11.23	1198
interest rates	16.05	8251	the debt	11.19	1194
economic growth	15.97	8210	the markets	11.13	1187
the currency	15.86	1692	economic activity	11.13	1187
demand for	15.86	3383	banks and	11.12	1186
unemployment rate	15.69	1674	world economic	11.02	1176
economy has	15.41	1644	inflation and	10.96	1169
trade deficit	15.37	1640	economy to	10.95	1168
s economy	15.31	7869	foreign exchange	10.95	1168
fourth quarter	14.94	1594	of trade	10.91	1164
percentage point	14.84	1583	the federal	10.89	5600
growth is	14.81	1580	as investors	10.84	1156
economic recovery	14.69	1567	of last	10.71	1143
pace of	14.64	1562	the financial	10.71	5506
economy in	14.55	1552	a sharp	10.64	1135
an economist	14.36	1532	markets in	10.62	1133

Notes: This table shows the top 30 economic, political, and environmental bigrams with the highest weight in the construction of the respective categorical sentiment and risk indices. The frequency column reports the number of occurrences of the bigram across all bigrams in the respective categorical word library. The methodology is detailed in Section 7.1.

Table A6: Top 100 political bigrams

Bigram	Weight $\times 10^5$	Frequency	Bigram	Weight $\times 10^5$	Frequency
mr trump	32.31	22106	putin s	10.49	1489
the police	21.88	3107	dalai lama	10.36	1471
party s	19.88	5645	xi s	10.34	2935
the communist	19.55	5552	he told	10.28	1460
pro democracy	18.95	2690	the border	10.28	1459
of hong	17.57	2494	for president	10.23	1453
mrs clinton	16.98	2411	a campaign	10.21	1450
mr romney	16.15	2293	news media	10.18	1445
hillary clinton	16.02	2275	tiananmen square	10.09	1433
chinese communist	14.95	2122	after he	10.06	1429
s political	14.94	2121	in office	10.04	1426
the presidential	14.36	2039	rule of	9.99	1419
the authorities	13.70	1945	the foreign	9.97	1415
the hong	13.42	1906	soviet union	9.95	1413
his campaign	13.37	1899	security adviser	9.89	1404
kim jong	13.33	1892	in prison	9.86	1400
the taliban	13.14	1865	the mainland	9.84	1397
ambassador to	12.99	1845	to speak	9.80	1392
s campaign	12.88	1829	accused of	9.74	1383
social media	12.67	3599	mitt romney	9.66	1372
about his	12.58	1786	a republican	9.64	1369
cold war	12.55	1782	the vote	9.62	1366
the protests	12.33	1750	a president	9.58	1360
of trump	12.26	1741	the dalai	9.55	1356
served as	12.25	1740	president elect	9.52	1352
chief of	12.19	1731	state media	9.49	1347
democratic party	12.11	1720	government in	9.45	1342
the soviet	12.10	1718	ties to	9.44	1341
mr xi	12.04	8240	the pentagon	9.42	1337
state department	11.94	3392	republican party	9.42	1337
page a	11.90	1689	he can	9.39	1333
in afghanistan	11.89	1688	trump was	9.35	1328
party and	11.76	1670	university in	9.35	1328
to beijing	11.66	1655	north korean	9.32	2648
clinton s	11.60	1647	law and	9.23	1310
and former	11.56	1641	the trump	9.22	6308
of law	11.42	1621	of staff	9.13	1296
mr bo	11.35	1611	romney s	9.11	1294
the post	11.25	1597	in xinjiang	9.09	1290
mr wang	11.06	1571	news agency	9.08	1289
mr chen	11.06	1571	the gop	9.08	1289
that trump	11.03	1566	as his	9.06	1286
the opposition	10.95	1555	had not	9.03	1282
the streets	10.93	1552	mr hu	8.99	1276
mr liu	10.85	1541	party has	8.99	1276
foreign ministry	10.66	1513	of national	8.96	1272
security law	10.63	1509	ties with	8.86	1258
the regime	10.60	1505	him in	8.84	1255
leader of	10.56	1500	kong and	8.83	1254
mr obama	10.54	7215	house and	8.80	1250

Notes: This table shows the top 100 political bigrams with the highest weight in the construction of the political sentiment and risk indices. The frequency column reports the number of occurrences of the bigram across all bigrams in the political word library. The methodology is detailed in Section 7.1.

Table A7: Top 100 environment bigrams

Bigram	Weight $\times 10^5$	Frequency	Bigram	Weight $\times 10^5$	Frequency
carbon dioxide	54.70	3623	a barrel	15.00	1987
greenhouse gas	54.30	3597	and solar	14.96	991
on climate	42.57	2820	energy companies	14.93	989
climate change	41.20	13151	wind and	14.87	985
gas emissions	40.91	2710	demand for	14.68	1945
renewable energy	39.15	2593	international energy	14.55	964
fossil fuels	35.79	2371	for oil	14.28	946
power plants	35.15	2328	fired power	14.27	945
the climate	34.83	2307	barrels a	14.10	1868
of climate	34.59	2291	electric cars	14.09	933
carbon emissions	33.76	2236	degrees celsius	14.06	931
global warming	32.58	4316	to climate	13.99	927
nuclear power	31.57	2091	to curb	13.81	915
of energy	31.52	2088	a climate	13.80	914
clean energy	30.57	2025	s climate	13.80	914
greenhouse gases	30.42	2015	change is	13.71	908
of carbon	27.61	1829	protection agency	13.60	901
s energy	27.02	1790	price of	13.57	1798
the planet	24.15	1600	of solar	13.45	891
the environment	23.82	1578	plant in	12.98	860
solar panels	23.70	1570	of nuclear	12.97	859
oil prices	23.55	3120	the carbon	12.94	857
the environmental	23.52	1558	the earth	12.62	836
energy agency	22.25	1474	emissions of	12.55	831
fossil fuel	21.68	1436	coal and	12.53	830
the energy	20.40	2703	air pollution	12.48	827
of coal	20.31	1345	energy efficiency	12.39	821
environmental protection	19.76	1309	the gulf	12.27	813
and gas	19.75	2616	power plant	12.14	804
coal fired	19.69	1304	for energy	12.08	800
electric vehicles	19.23	1274	s p	12.02	1592
the paris	18.27	2420	and climate	11.94	791
oil companies	18.24	1208	the plant	11.78	780
cap and	17.89	1185	an energy	11.76	779
emissions by	17.89	1185	oil and	11.74	3747
of oil	17.63	2335	energy sources	11.68	774
the atmosphere	17.62	1167	oil production	11.61	769
change and	17.41	1153	and natural	11.58	767
solar power	17.27	1144	percent to	11.57	1533
natural gas	16.44	5248	a carbon	11.52	763
emissions from	16.43	1088	and india	11.47	1520
tons of	16.18	1072	that iran	11.47	760
the oil	15.98	2117	s oil	11.41	1512
gas prices	15.87	1051	production of	11.41	756
of greenhouse	15.53	1029	the kyoto	11.40	755
dioxide emissions	15.38	1019	emissions in	11.35	752
million barrels	15.38	2037	global climate	11.29	748
emissions and	15.35	1017	used in	11.11	736
paris agreement	15.20	1007	mr trump	11.06	3529
gas and	15.14	1003	solar panel	10.90	722

Notes: This table shows the top 100 environmental bigrams with the highest weight in the construction of the environmental sentiment and risk indices. The frequency column reports the number of occurrences of the bigram across all bigrams in the environmental word library. The methodology is detailed in Section 7.1.

I Categorical Index Construction Steps

This section documents the step-by-step approach to constructing the categorical sentiment index and risk index.

I.1 Categorical Sentiment Index

To be precise, let T_1 denotes the time interval used in the standardization and T_2 denotes the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps

1. Compute the average number of positive and negative sentiment indices by category in each media each month $Categorypos^p_{m,t}$ and $Categoryneg^p_{m,t}$ as the sum of the $Categorypos_{im,d}$ and $Categoryneg_{im,d}$ of all the China-related news articles of each month t in each media m, respectively

2. Compute the scaled average number of positive and negative sentiment in each media each month $Categorypos_{m,t}$ and $Categoryneg_{m,t}$ by multiplying $Categorypos^p_{m,t}$ and $Categoryneg^p_{m,t}$ by the total number of news articles in the newspaper m during the month t, $all_{m,t}$, respectively

3. Compute the time-series variance $\sigma^2_{pos,m}$ of $Categorypos_{m,t}$ and $\sigma^2_{neg,m}$ of $Categoryneg_{m,t}$ in the interval T_1 for each media m

4. Standardize $Categorypos_{m,t}$ by dividing through by the standard deviation $\sigma^2_{pos,m}$ for all t and $Categoryneg_{m,t}$ by dividing through by the standard deviation of $\sigma^2_{neg,m}$ for all t. This operation yields for each newspaper categorical series $Categorypos^{sd}_{m,t}$ and $Categoryneg^{sd}_{m,t}$ with unit standard deviation in the interval T_1

5. Compute the standardized sentiment index $Categorysen^{sd}_{m,t}$ as the difference between standardized positive and negative index $Categorypos^{sd}_{m,t} - Categoryneg^{sd}_{m,t}$

6. Compute the mean over newspapers of $Categorysen_{m,t}^{sd}$ in country t and obtain series $Categorysen_{c,t}^{raw}$. Normalize the index further to be positive as $Categorysen_{c,t}^{+}$ by adding a constant to the index $Categorysen_{c,t}^{raw}$, which is the minus minimum value of the index plus 1, $-Categorysen_{c,t}^{min} + 1$

7. Compute $CategoryM_r$, the mean of $Categorysen_{c,t}^{+}$ in the interval T_2

8. Multiply $Categorysen_{c,t}^{+}$ by $100/CategoryM_r$ for all t to obtain the normalized time-series index $Categorysen_{c,t}$

where *Category* stands for *pol*, *econ*, and *env*.

I.2 Categorical Risk Index

To be precise, let T_1 denotes the time interval used in the standardization and T_2 denotes the time interval used in normalization calculations. (In our current setting $T_1 = T_2$.) We do the following steps

1. Compute the average number of risk words by category in each media m in each month t, $Categoryrisk_{m,t}^{p}$, as the sum of the $Categoryrisk_{im,d}$ of all the China-related news articles of each month t in each media m

2. Compute the scaled average number of risk words in each media each month $Categoryrisk_{m,t}$ by multiplying $Categoryrisk_{m,t}^{p}$ by the total number of news articles in the newspaper m during the month t, $all_{m,t}$, respectively

3. Compute the time-series variance σ_m^2 of $Categoryrisk_{m,t}$ in the interval T_1 for each media m

4. Standardize $Categoryrisk_{m,t}$ by dividing through by the standard deviation σ_m^2 for all t. This operation yields for each newspaper categorical series $Categoryrisk_{m,t}^{sd}$ with unit standard deviation in the interval T_1

5. Compute the mean over newspapers of $Categoryrisk^{sd}_{m,t}$ in country t and obtain series $Categoryrisk^{raw}_{c,t}$

6. Compute $CategoryM_r$, the mean of $Categoryrisk^{raw}_{c,t}$ in the interval T_2

7. Multiply $Categoryrisk^{raw}_{c,t}$ by $100/CategoryM_r$ for all t to obtain the normalized time-series index $Categoryrisk_{c,t}$

where $Category$ stands for pol, $econ$, and env.

J Categorical Sentiment and Risk Indices at the Country Level

Figures A4, A5, and A6 display the economic, political, and environmental sentiment indices, respectively. Figure A7, A8, and A9 present the economic risk index, political risk index, and environmental risk index, respectively, for major advanced economies (G7), other advanced economies, and emerging and developing economies.

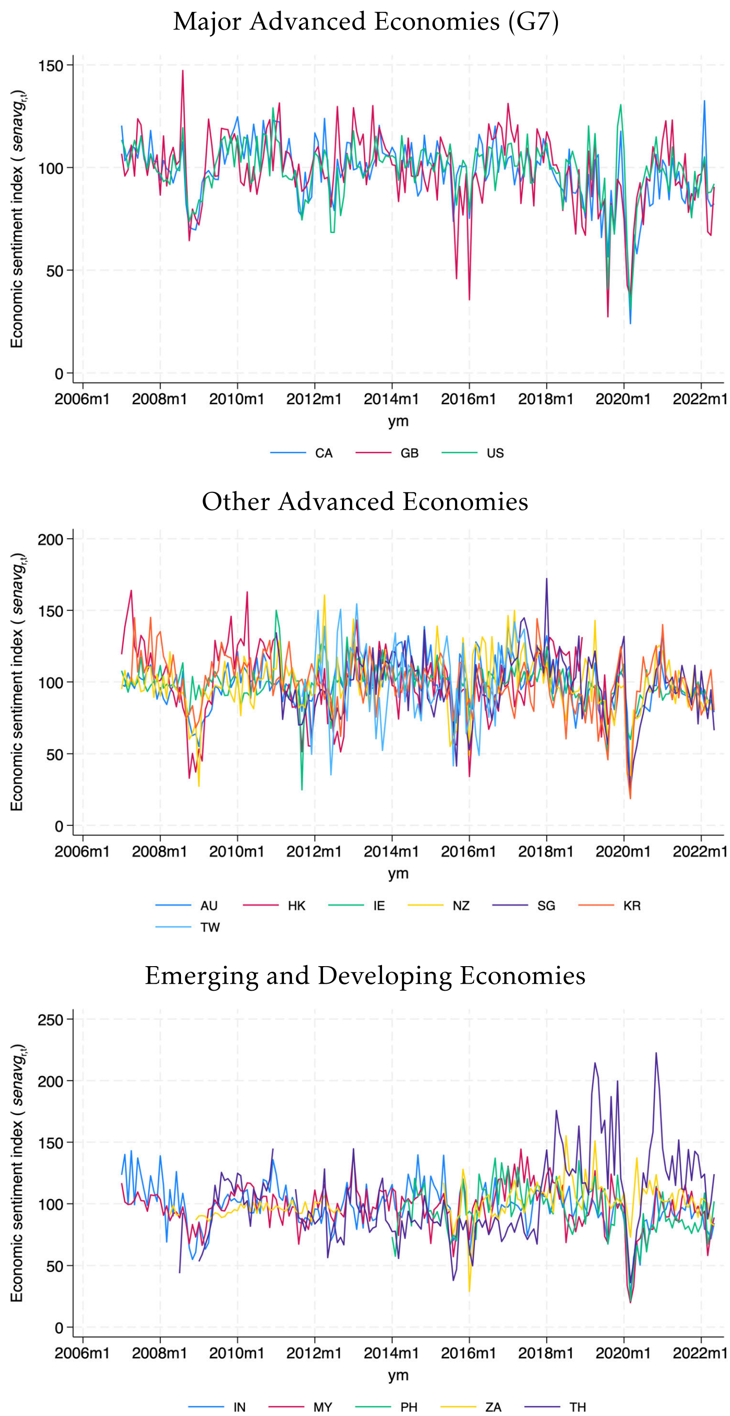


Figure A4: Economic sentiment index: $econsen_{c,t}$

Notes: This figure plots the time series of the economic sentiment index ($econsen_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The economic sentiment index reflects local media economic sentiment perception of China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

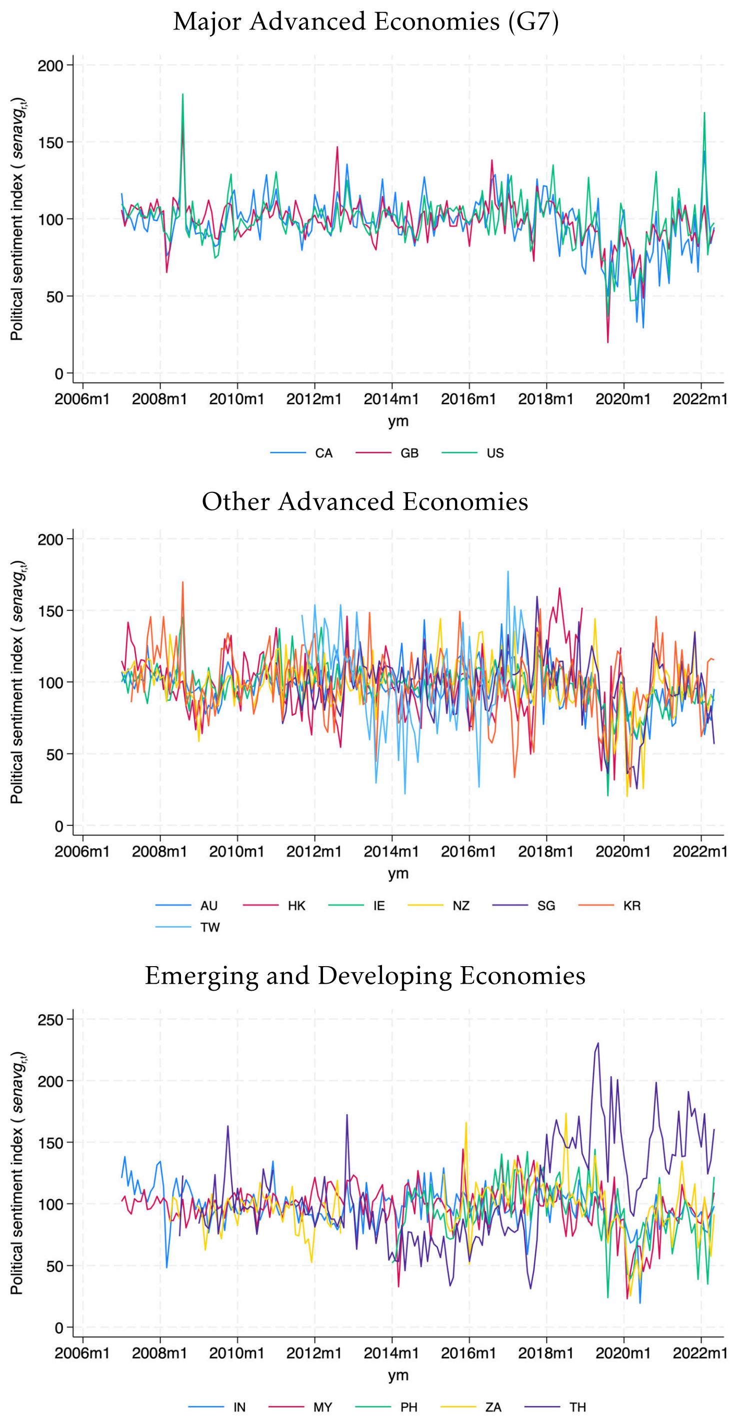


Figure A5: Political sentiment index: $polsen_{c,t}$

Notes: This figure plots the time series of the political sentiment index ($polsen_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The political sentiment index reflects local media political sentiment perception of China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

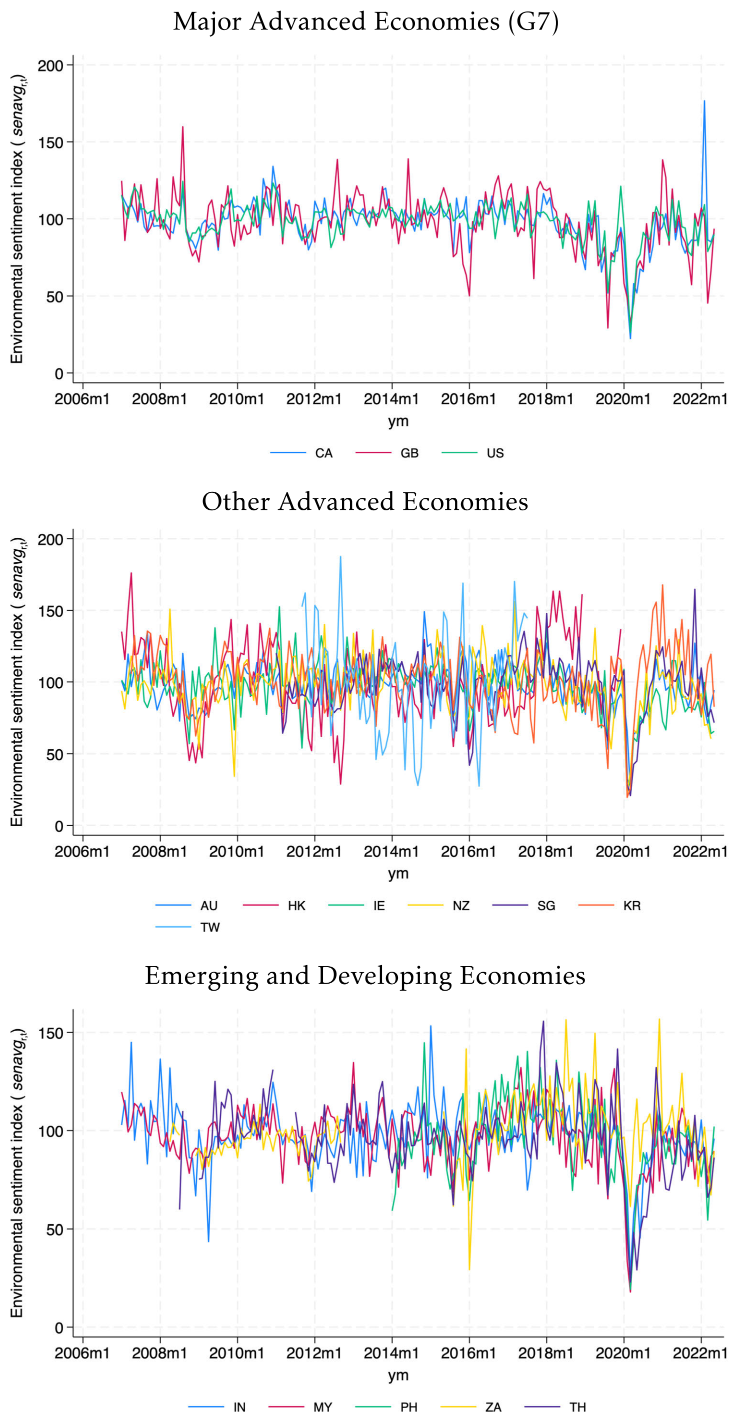


Figure A6: Environmental sentiment index: $envsen_{c,t}$

Notes: This figure plots the time series of the environmental sentiment index ($envsen_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The environmental sentiment index reflects local media environmental sentiment perception of China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

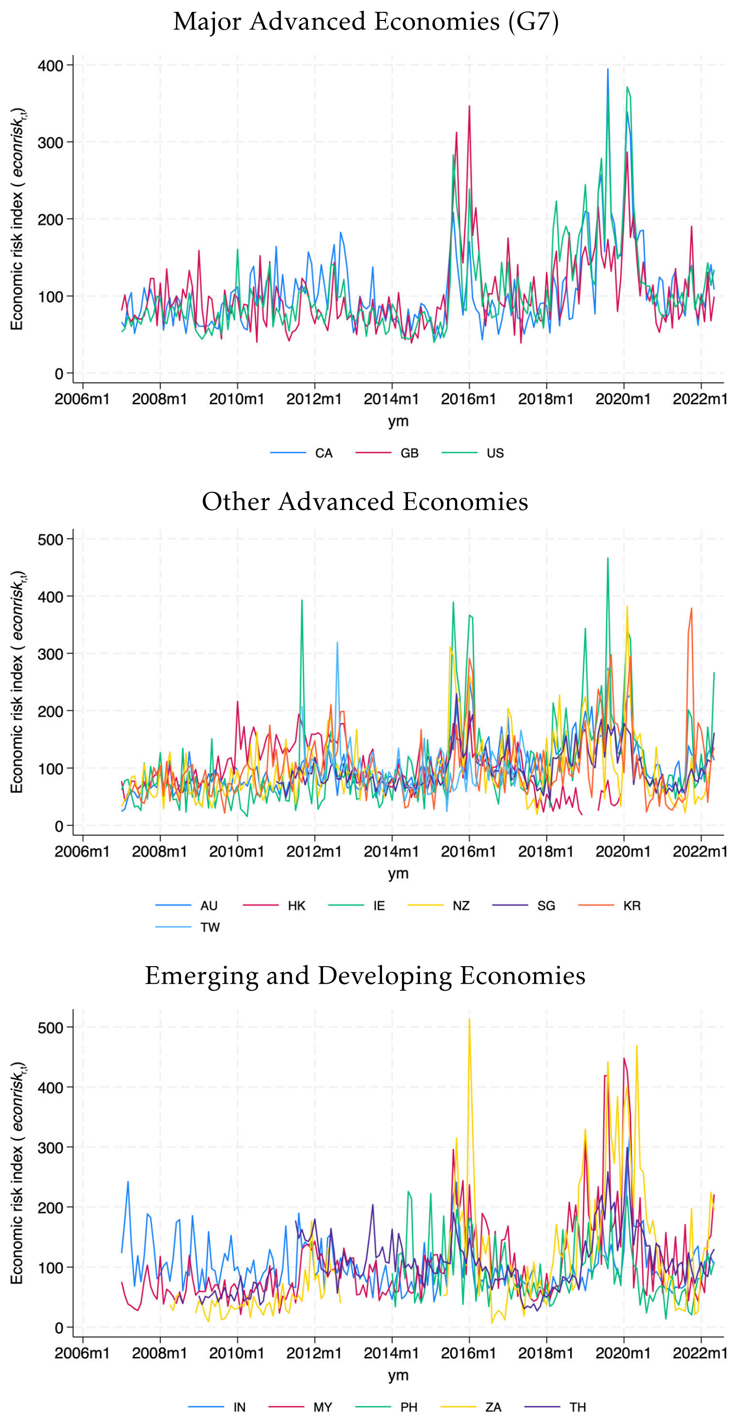


Figure A7: Economic risk index: $econrisk_{c,t}$

Notes: This figure plots the time series of the economic risk index ($econrisk_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The economic risk index reflects local media economic risk perception of China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

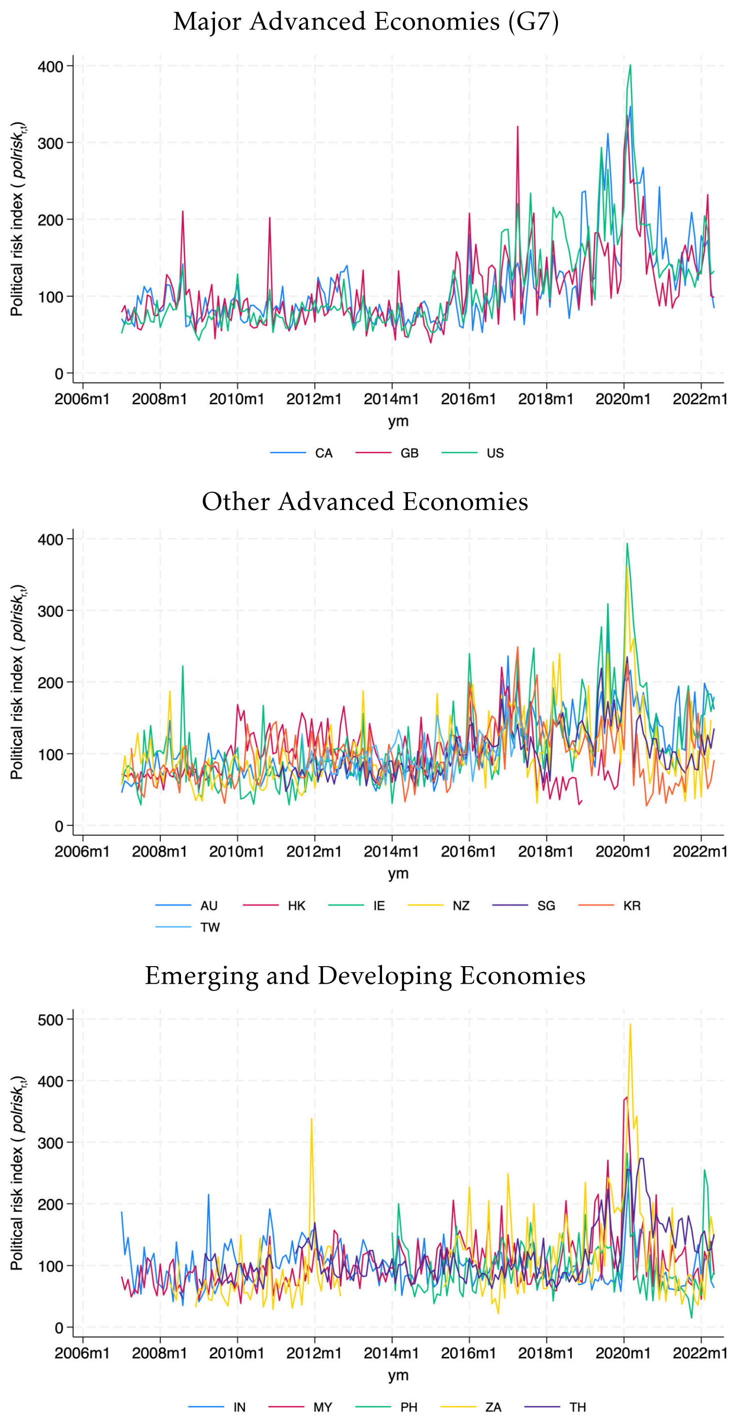


Figure A8: Political risk index: $polrisk_{c,t}$

Notes: This figure plots the time series of the political risk index ($polrisk_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The political risk index reflects local media political risk perception of China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

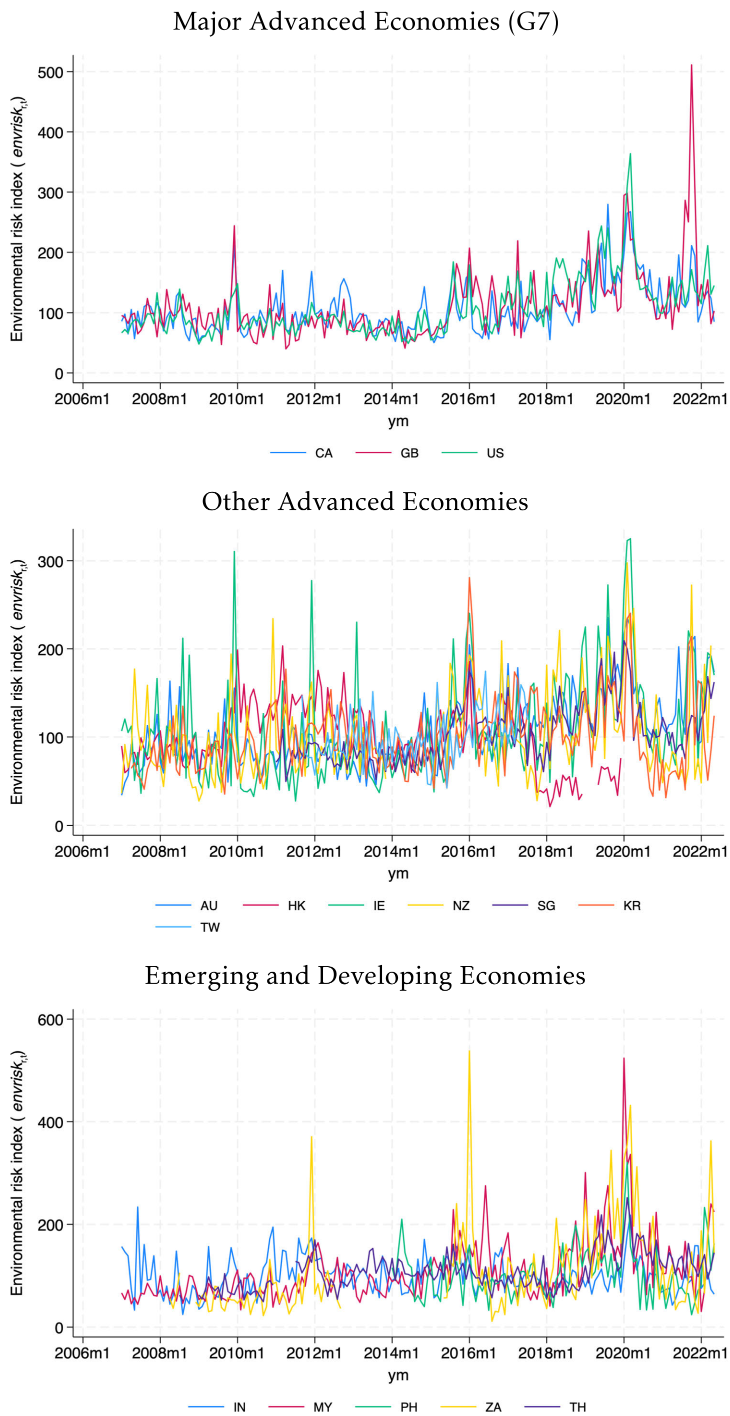


Figure A9: Environmental risk index: $envrisk_{c,t}$

Notes: This figure plots the time series of the environmental risk index ($envrisk_{c,t}$), grouped by Major Advanced Economies (G7), Other Advanced Economies, and Emerging and Developing Economies. The environmental risk index reflects local media environmental risk perception of China and is constructed through textual analysis of all China-related news in local newspapers. The detailed methodologies for constructing this index is provided in Section 7.2. All data series are normalized to have a mean of 100 for the period from 2007 to 2019.

K Sector Definitions

Table A8: Sector definitions and example firms

Sector	Def	Companies
Basic Materials	Companies that manufacturer chemicals, building materials and paper products. This sector also includes companies engaged in commodities exploration and processing.	Anhui Conch Cement Co Ltd, China Shenhua Energy Co Ltd, China National Building Material Co Ltd
Communication Services	Companies that provide communication services using fixed-line networks or those that provide wireless access and services. This sector also includes companies that provide internet services such as access, navigation and internet related software and services.	China Mobile Ltd, China Telecom Corp Ltd, China Communications Services Corp Ltd
Consumer Cyclical	This sector includes retail stores, auto & auto parts manufacturers, companies engaged in residential construction, lodging facilities, restaurants and entertainment companies.	Alibaba Group Holding Ltd, JD.com Inc, Li Ning Co Ltd
Consumer Defensive	Companies engaged in the manufacturing of food, beverages, household and personal products, packaging, or tobacco. Also include companies that provide services such as education & training services.	New Oriental Education & Technology Group Inc, China Mengniu Dairy Co Ltd, China Resources Beer (Holdings) Co Ltd
Energy	Companies that produce or refine oil and gas, oil field services and equipment companies, and pipeline operators.	CNOOC Ltd, China Petroleum & Chemical Corp, PetroChina Co Ltd
Utilities	Electric, gas, and water utilities.	ENN Energy Holdings Ltd, China Gas Holdings Ltd, China Yangtze Power Co Ltd
Financial Services	Companies that provide financial services which includes banks, savings and loans, asset management companies, credit services, investment brokerage firms, and insurance companies.	Ping An Insurance (Group) Co. of China Ltd, China Construction Bank Corp, Industrial And Commercial Bank Of China
Real Estate	This sector includes mortgage companies, property management companies and REITs.	China Overseas Land & Investment Ltd, China Resources Land Ltd, Shimao Property Holdings Ltd
Health Care	This sector includes biotechnology, pharmaceuticals, research services, home healthcare, hospitals, long-term care facilities, and medical equipment and supplies.	Sinopharm Group Co Ltd, Jiangsu Hengrui Medicine Co Ltd, Aier Eye Hospital Group Co Ltd
Industrials	Companies that manufacture machinery, hand-held tools and industrial products. This sector also includes aerospace and defense firms as well as companied engaged in transportations and logistic services.	Shanghai International Airport Co Ltd, China Merchants Port Holdings Co Ltd, Jiangsu Expressway Co Ltd
Technology	Companies engaged in the design, development, and support of computer operating systems and applications. This sector also includes companies that provide computer technology consulting services. Also includes companies engaged in the manufacturing of computer equipment, data storage products, networking products, semiconductors, and components.	Tencent Holdings Ltd, Baidu Inc ADR, 58.com Inc

Notes: This table provides the definitions of each sector from Morningstar along with the corresponding Chinese companies within those sectors.

L Institutional Investor's Cross-Border Investment in China

We use data on institutional investors' holdings from Morningstar, spanning from January 1, 2007, to May 31, 2022. Figure A10 illustrates the annual trends in these investments, categorized by investor demographics, asset types, currencies, fund types, and sectors. Employing the domicile grouping method outlined by Maggiori et al. (2020) and Coppola et al. (2021), we find that institutional investors from the U.S., the European Economic and Monetary Union (EMU), the U.K., and Canada predominantly hold Chinese assets, both in terms of the number of investors and the total value of investments. [25] The breakdown in Figure A10 indicates that the majority of holdings are equities, primarily in Hong Kong dollars and U.S. dollars. There has been a significant increase in investments denominated in Chinese Renminbi in recent years. Open-ended funds are the foremost vehicles for holding Chinese assets, followed by exchange-traded funds and money market funds. The sectors attracting the most investment are technology, financial services, and consumer cyclicals.

[25] Using raw domicile information, the primary holders are from the U.S., Luxembourg, and Ireland, as detailed in Figure A11.

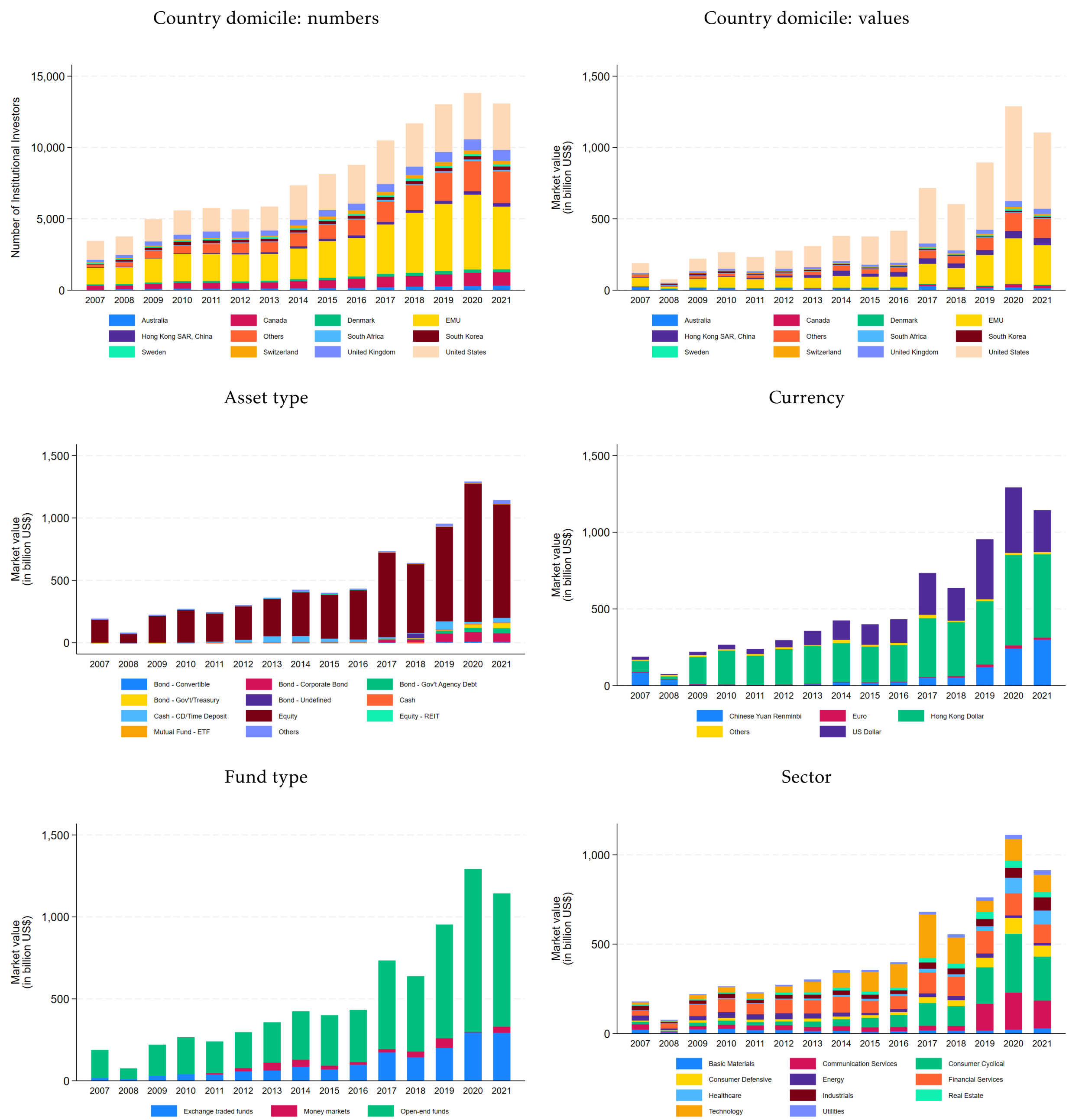
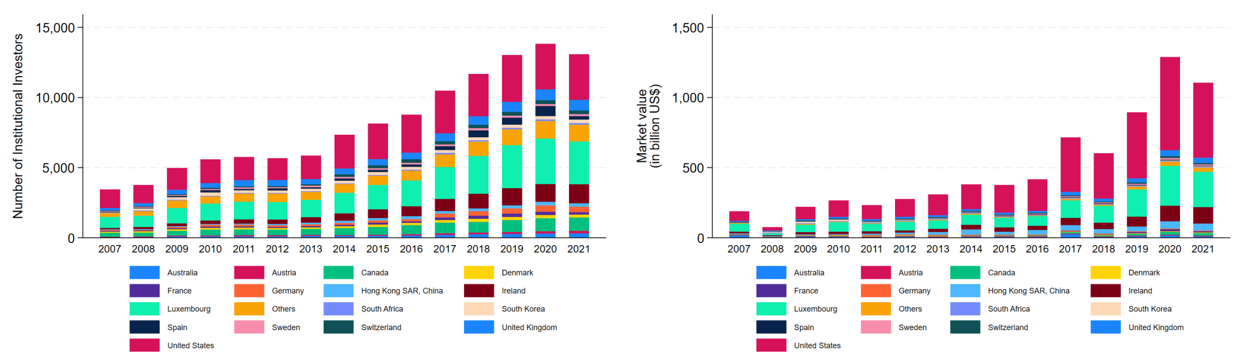


Figure A10: Decomposition of Institutional Investors' Investment in China

Notes: The figure shows the decomposition of institutional investors' investments in China for all funds from Morningstar over the period 2007-2021.The plot on the top left displays the number of institutional investors, and the plot on the right shows the total investment value by these investors. We reclassify domicile decomposition using EMU following Maggiori et al. (2020) and Coppola et al. (2021). The countries included in the EMU in their data are Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovenia, and Spain. Each country is included in the sample only after adopting the euro: Malta in 2008, Slovenia in 2007, and the remaining countries in 2002. The mid left panel displays the asset type decomposition, the mid right panel shows the currency decomposition, the bottom left plot illustrates the fund type decomposition, and the bottom right plot presents the sector decomposition.

Since the majority of Chinese asset holdings come from open-ended funds, and given that exchange-traded funds and money market funds are generally less active, our empirical analysis focuses specifically on open-ended funds.

Table A9 presents the summary statistics for the Morningstar variables. The count of institutional investors with Chinese assets has escalated significantly over time, increasing from 1,649 in the first quarter of 2007 to 15,872 in the first quarter of 2022. Despite this substantial growth, the median value of Chinese asset holdings by open-ended funds remains relatively modest, fluctuating from 1.5 million USD (representing 1.0% of total assets under management) in 2007Q1 to 3.4 million USD (1.9% of total assets under management) in 2022Q1.[26]



Numbers Values

Figure A11: Domiciles of institutional investors: annual data

Notes: The figure shows the annual domicile decomposition of all funds investing in China from Morningstar over the period 2007-2021. The plot on the top left displays the number of institutional investors, and the plot on the right shows the total investment value by these investors.

[26] In recent decades, China has advanced its capital account liberalization through various measures, such as the Qualified Foreign Institutional Investor (QFII) program, stock connect programs, offshore listings, etc. A critical question arises: Are the capital account restrictions limiting investors' ability to allocate as much capital as they desire in Chinese assets? The empirical evidence presented by Chen (2021) indicates that institutional investors' actual investments in China via the QFII program are significantly lower than their approved quotas. In this paper, we posit it is without loss of generality to assume that investors are not bound by capital account constraints.

Table A9: Summary statistics of the Morningstar data

	AUM (billion USD)		China holdings: Value (billion USD)		China holdings: Share (% of AUM)		Number of Institutions
Quarter	Median	90th Percentile	Median	90th Percentile	Median	90th Percentile	
2007q1	0.1870	1.6321	0.0015	0.0206	0.9726	4.4978	1649
2007q2	0.2017	1.8328	0.0019	0.0266	1.1613	6.0328	1944
2007q3	0.2178	1.9086	0.0027	0.0495	1.4376	9.6581	2140
2007q4	0.1857	1.7414	0.0032	0.0815	1.8764	17.6724	3345
2008q1	0.1646	1.6718	0.0024	0.0668	1.6225	17.4813	3236
2008q2	0.1404	1.5236	0.0023	0.0589	1.6731	19.1132	3645
2008q3	0.1172	1.2481	0.0018	0.0442	1.5600	17.9909	3466
2008q4	0.0783	0.8254	0.0013	0.0295	1.6811	18.3007	3625
2009q1	0.0735	0.7762	0.0013	0.0302	1.7640	17.5007	3604
2009q2	0.0853	0.8942	0.0018	0.0415	2.2643	19.2716	4199
2009q3	0.1028	1.1576	0.0022	0.0569	2.2437	19.2229	4148
2009q4	0.0995	1.1487	0.0026	0.0656	2.7021	23.6549	4784
2010q1	0.1115	1.2587	0.0026	0.0655	2.5448	23.1721	4542
2010q2	0.0926	1.0428	0.0022	0.0570	2.7136	23.5008	4880
2010q3	0.1154	1.3409	0.0027	0.0708	2.6826	22.7827	4694
2010q4	0.1084	1.2809	0.0025	0.0646	2.5626	21.6343	5353
2011q1	0.1191	1.4077	0.0027	0.0659	2.4863	21.2363	5137
2011q2	0.1100	1.3284	0.0026	0.0615	2.5475	22.6741	5460
2011q3	0.0976	1.1672	0.0019	0.0482	2.1841	20.5587	5126
2011q4	0.0940	1.1659	0.0023	0.0520	2.5508	24.3367	5422
2012q1	0.1112	1.3875	0.0027	0.0646	2.5487	23.0767	5155
2012q2	0.0949	1.1695	0.0024	0.0567	2.5906	24.5929	5316
2012q3	0.1125	1.3222	0.0025	0.0612	2.4072	22.6475	4982
2012q4	0.1037	1.2285	0.0027	0.0656	2.7057	25.9430	5278
2013q1	0.1240	1.4182	0.0026	0.0664	2.3591	23.2106	5050
2013q2	0.1135	1.3381	0.0025	0.0632	2.4768	24.3340	5319
2013q3	0.1384	1.6000	0.0030	0.0762	2.5173	25.1146	5005
2013q4	0.1365	1.6198	0.0032	0.0771	2.4993	26.6676	5436
2014q1	0.1421	1.7153	0.0031	0.0720	2.2367	23.2476	5181
2014q2	0.1415	1.7563	0.0031	0.0728	2.3306	23.6458	5585
2014q3	0.1564	2.0147	0.0030	0.0764	2.1121	23.1496	5829
2014q4	0.1538	1.9944	0.0029	0.0751	2.1302	25.4181	6725
2015q1	0.1626	2.1585	0.0031	0.0791	1.9830	25.1653	6599
2015q2	0.1548	1.9425	0.0031	0.0755	2.0506	26.9435	7535
2015q3	0.1442	1.9313	0.0027	0.0587	1.7665	25.2302	7064
2015q4	0.1431	1.8279	0.0028	0.0640	2.0423	27.5791	7384
2016q1	0.1507	1.8921	0.0026	0.0622	1.9488	25.3769	6557
2016q2	0.1403	1.7635	0.0025	0.0601	1.9192	25.1110	7046
2016q3	0.1530	1.9576	0.0030	0.0715	2.0505	26.4027	6812
2016q4	0.1482	1.8409	0.0028	0.0633	1.8883	25.3001	7871
2017q1	0.1692	2.1372	0.0032	0.0694	1.9304	25.3484	8179
2017q2	0.1693	2.1449	0.0032	0.0751	2.0126	25.6875	8707
2017q3	0.1838	2.2852	0.0035	0.0843	1.9731	26.9951	8771
2017q4	0.1879	2.2743	0.0035	0.0875	1.9448	27.1812	9450
2018q1	0.1913	2.2863	0.0034	0.0881	1.9010	27.0736	9082
2018q2	0.1768	2.1458	0.0032	0.0797	1.8786	27.4658	10535
2018q3	0.1704	2.0789	0.0027	0.0699	1.7003	25.8469	10190
2018q4	0.1528	1.7827	0.0025	0.0613	1.7996	26.1126	10524
2019q1	0.1640	1.9633	0.0027	0.0727	1.8792	26.8917	10899
2019q2	0.1707	2.0507	0.0029	0.0743	1.9256	26.9725	11124
2019q3	0.1712	2.0807	0.0031	0.0793	1.9912	27.0241	11154
2019q4	0.1768	2.1880	0.0034	0.0886	2.1251	29.1430	11589
2020q1	0.1494	1.7774	0.0030	0.0800	2.2568	33.1574	11362
2020q2	0.1673	2.0413	0.0035	0.0936	2.3581	34.7608	11645
2020q3	0.1799	2.1786	0.0037	0.1056	2.4072	34.4742	11680
2020q4	0.1980	2.4659	0.0040	0.1148	2.3640	32.0258	12314
2021q1	0.1937	2.4642	0.0040	0.1144	2.3403	31.2892	11686
2021q2	0.1985	2.5005	0.0039	0.1126	2.2670	30.6470	11504
2021q3	0.2049	2.7170	0.0037	0.1048	1.9837	28.0774	12011
2021q4	0.2284	2.7655	0.0040	0.1039	1.9119	29.1235	11241
2022q1	0.2064	2.7372	0.0034	0.0910	1.8709	28.4041	15872

Notes: The table shows the summary statistics of open-ended funds that have holdings of Chinese assets in Morningstar.