Beyond the Fundamentals: Cross-Country Media Narrative Dispersion and Global Capital Flows*

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Abstract

This paper provides the first empirical evidence that cross-country variation in domestic media narratives about a destination country shapes global institutional investment flows. Using modern natural language processing methods, including transformer-based sentiment models and LLMs, applied to large-scale newspaper text from multiple countries, we measure narrative disagreement across investor countries about the same foreign economy. Drawing on more than one million newspaper articles from 39 outlets across 16 economies, we construct country-specific measures of media attention and sentiment toward China, an increasingly important investment destination with severe information frictions. We document large and persistent cross-country dispersion in sentiment, even when media cover the same topics. A counterfactual decomposition reveals that this dispersion is driven almost entirely by differences in within-topic sentiment rather than topic attention, indicating heterogeneous framing of common information. Further analysis shows that narrative disagreement reflects both slow-moving country-specific priors and heterogeneous responses to new information. Linking narratives to behavior, we find that domestic media sentiment significantly influences cross-border portfolio flows to China after controlling for fundamentals. By systematically measuring narrative disagreement and linking it to international portfolio allocation, our findings establish domestic media narratives as an important channel shaping belief formation and global capital flows.

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1 Introduction

Economic agents rely on narratives, stories that organize and interpret complex economic events, when making decisions under limited attention and information frictions (Shiller, 2017, 2020). News media play a central role in shaping these narratives by selecting, framing, and interpreting information through editorial "gatekeeping" decisions (Shoemaker and Vos, 2009; Nimark and Pitschner, 2019; Chahrour, Nimark and Pitschner, 2021). A growing literature shows that media attention and sentiment affect asset prices, trading activity, and investor behavior (e.g., Tetlock, 2007; Engelberg and Parsons, 2011; Manela and Moreira, 2017; Bybee et al., 2024a; Calomiris and Mamaysky, 2019; Baker et al., 2021). These forces are likely to be particularly salient in cross-border settings, where investors face severe information and interpretation frictions when evaluating foreign economies (Van Nieuwerburgh and Veldkamp, 2009).

Compared with domestic investing, cross-border portfolio allocation requires processing large volumes of unfamiliar and often opaque information, complicated by language barriers, institutional differences, and policy uncertainty. As a result, institutional investors may be especially reliant on intermediaries, such as domestic news media, to filter and interpret developments abroad. Despite the importance of media narratives in shaping investment dynamics, existing evidence remains overwhelmingly domestic in scope, focusing on media coverage of domestic assets or macroeconomic conditions, or examining sentiment toward different countries without studying heterogeneity in media narratives about the same country [1]. Consequently, we still lack evidence on whether media narratives about the *same foreign economy* differ systematically *across investor countries*

[1] A growing literature uses textual analysis of news to construct sentiment, uncertainty, and risk indices in an international setting. Early work by Calomiris and Mamaysky (2019) demonstrates how news content and context extracted from global media sources can be used to explain asset price movements. Related studies construct country-level indices of economic uncertainty or risk using domestic newspapers, including the Economic Policy Uncertainty index of Baker et al. (2016), the World Uncertainty Index of Ahir et al. (2022), and the Geopolitical Risk index of Caldara and Iacoviello (2022). While these studies exploit international news coverage, they do not examine sentiment disagreement across countries about a common destination.

and whether such differences matter for cross-border capital allocation.

Using large language models applied to large-scale newspaper text from multiple countries, we address this gap by providing the first systematic measurement of media narratives about the same economy across investor domicile countries. In particular, we construct novel cross-country indices of media-based narratives about China and examine their effects on international portfolio flows. Using the full text of more than one million newspaper articles from multiple countries, we build measures of media attention and sentiment toward China as portrayed in investors' home-country media. To our knowledge, this is the first study to systematically construct and compare media-based narrative indices about a single destination economy across a broad set of investor countries and to link cross-country heterogeneity in narratives to capital flows.

We focus on China, an increasingly important destination for global institutional investors and a setting in which information frictions are especially pronounced. Investors face well-known challenges in accessing timely and reliable data on China, which are exacerbated by opacity in policymaking and periodic reductions in data dissemination.[2] Even when data are available, interpretation is costly due to language barriers, institutional complexity, and frequent regulatory changes. In this environment, domestic media narratives can play a central role in shaping investors' decisions by influencing both which aspects of China receive attention and how available information is interpreted.

Media-driven narratives influence investors' decisions at both the extensive and intensive margins. At the extensive margin, the volume of China-related news shapes the level of attention devoted to China by global investors. At the intensive margin, each article can affect investors by shaping their sentiment toward China. To capture these dimensions, we construct two country-level indices: an attention index and a sentiment index, using large language models applied to more than one million articles published in 39 English-language newspapers across 16 economies between 2007 and 2022. The

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

attention index captures the share of news allocated to China while the sentiment index reflects the intensity of positive and negative sentiments in local newspapers about China. 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 about the *same* country.

We begin by documenting substantial cross-country dispersion in media sentiment about China. Some countries consistently portray China in a negative tone, while others adopt markedly more positive portrayals. This variation in aggregate sentiment can arise through two distinct channels. First, countries may differ in the topics they emphasize when reporting on China, with some topics being inherently more negative than others. Second, even conditional on similar topic coverage, media outlets may differ in how they frame and interpret the same topics. The richness of our dataset allows us to construct topic-level attention and sentiment indices in a cross-country setting, going beyond aggregate sentiment measures used in prior work. This granularity enables a systematic decomposition of narrative disagreement into differences in topic attention and within-topic sentiment, providing new evidence on sources of variation in international media's narratives about China.

We conduct a decomposition exercise to assess the relative importance of topic coverage and within-topic sentiment in explaining cross-sectional variation in aggregate media sentiment about China. For each investor country, we begin by expressing the aggregate sentiment index about China as a weighted average of within-topic sentiment, where topic shares serve as weights. We then construct two counterfactual sentiment indices: one that holds topic coverage fixed across investor countries while allowing within-topic sentiment to vary, and another that holds within-topic sentiment fixed while allowing topic coverage to vary. Comparing the cross-country variance of these counterfactual indices with that of the observed aggregate sentiment index allows us to quantify the contribution of each channel. We find that nearly all of the cross-country variation in aggregate sentiment is driven by differences in within-topic sentiment.

The dominant role of within-topic sentiment variation suggests that cross-country disagreement in media narratives about China reflects differences in how the same information is framed, rather than differences in which aspects of China are covered. This observation raises a natural question: do these differences arise from heterogeneous reactions to new information, or do they reflect persistent, country-specific priors about China? To address this question, we decompose each country's topic-level sentiment index into two components. The first is a country-specific term capturing average priors of domicile-country investors toward a given China-related topic. The second isolates how current, common information about a topic is incorporated into topic-level sentiment. This decomposition allows us to assess whether cross-country narrative disagreement is driven primarily by heterogeneous baseline views or differences in the interpretation of new information.

The variance decomposition reveals substantial heterogeneity across topics in the sources of cross-country disagreement. For some topics, cross-country differences in within-topic sentiment are driven primarily by persistent country-specific components, indicating the dominant role of slow-moving priors. For other topics, however, a meaningful share of the cross-sectional variance is explained by heterogeneity in countries' responses to common topic-level information, pointing to differential interpretation of the same underlying news. On average, country-specific terms account for the majority of the variation in sentiment across investor countries, but the relative importance of priors versus interpretation varies systematically across topics. This pattern suggests that disagreement in media narratives about China reflects a combination of stable baseline framing and topic-dependent differences in how new information is processed. In this sense, countries interpret China through persistent narrative lenses, while allowing for cross-country divergence in interpretation for particular topics.

These findings raise a natural question: do cross-country differences in media narratives translate into differences in cross-border capital flows to China? To address this question, we combine our narrative measures with portfolio holdings data for open-ended mutual funds from Morningstar. Using quarterly fund-level data for approximately 20,000 funds domiciled in sixteen economies, we find that domestic media sentiment toward China has a statistically and economically significant effect on portfolio allocation decisions, even after controlling for China's macroeconomic and financial fundamentals. Holding constant these fundamentals, countries whose media portray China more negatively subsequently allocate less capital to Chinese assets, while more positive sentiment predicts stronger portfolio flows to China. The magnitude of these effects is economically meaningful: a one–standard deviation increase in the sentiment index is associated with a 0.96% increase in quarterly investment flows into China, corresponding to an annualized increase of 3.82%.

We assess the robustness of this baseline result along several dimensions. First, we examine whether our findings are driven by reliance on English-language newspapers. To do so, we construct multilingual sentiment indices using FinBERT-style models applied to major domestic newspapers in Germany, France, Spain, Switzerland, and Austria in their native languages. The cross-language estimates remain positive, statistically significant, and economically meaningful. Importantly, both the sign and interpretation of the coefficients are unchanged, confirming that our baseline results are not an artifact of English-language reporting but instead reflect a broader, language-invariant narrative channel shaping cross-border investment decisions. Second, we exploit the full text of articles and measure article-level sentiment using a traditional bag-of-words approach. The results remain robust when sentiment is constructed using this alternative methodology.

To provide further evidence the role of interpretation in shaping media narratives, we exploit the Arab Spring as a plausibly exogenous global geopolitical shock. The Arab Spring triggered a worldwide reassessment of political stability, governance, and regime durability, elevating the salience of geopolitical risk in media narratives well beyond the countries directly affected. Although China's economic fundamentals were unchanged, this shift in global political narratives led media outlets to reinterpret China through a more geopolitical risk lens. Consistent with this mechanism, we show that following the Arab Spring, countries whose media environments are more oriented toward geopolitical reporting experience a pronounced deterioration in sentiment toward China, despite no corresponding differential change in media attention. These narrative shifts are accompanied by relative declines in portfolio flows to Chinese assets, supporting a narrative-based transmission mechanism in which global shocks affect cross-border investment through country-specific framing and interpretation rather than changes in country fundamentals.

Finally, we study asymmetries in the effects of media narratives and the role of higher-order narrative measures. Consistent with a large literature on negativity bias (Holbrook, Krosnick, Visser, Gardner and Cacioppo, 2001; Soroka, 2006), we find that adverse media narratives about China exert a significantly stronger influence on institutional portfolio allocation than favorable narratives. In particular, increases in negative media sentiment are associated with economically meaningful reductions in capital flows to Chinese assets, while positive narratives have little incremental effect. This asymmetry suggests that downside information plays a dominant role in shaping cross-border investment decisions, especially in settings characterized by limited transparency. Beyond first-moment effects, we also identify an independent role for media-implied risk. Increases in media-based risk perceptions about China, which capture heightened uncertainty rather than average sentiment, predict additional declines in investment flows even after controlling for macroeconomic and financial fundamentals. These results suggest that domestic media shape international capital allocation not only through average narrative tone, but also through second-moment perceptions of risk, reinforcing the importance of media narratives as a channel of belief formation in global finance.

Related Literature. Our paper contributes to the literature on news media, narratives, and financial market outcomes. While a large body of work shows that media affects financial market outcomes (e.g., Tetlock, 2007; Engelberg and Parsons, 2011; Manela and Moreira, 2017; Bybee et al., 2024a; Calomiris and Mamaysky, 2019; Baker et al., 2021), this literature has remained overwhelmingly domestic in scope, focusing on media coverage of domestic assets or macroeconomic conditions.[3] Despite this extensive literature and the potential importance of media narratives in international settings, we still lack evidence on how media narratives about the *same foreign economy* differ across *multiple investor countries* and whether such differences matter for global capital allocation. We contribute to this literature by being the first to construct cross-country media-based narrative indices about the same destination economy using newspapers from multiple investor countries. We show that media narratives about the same economy are not uniform across countries, but instead differ systematically across investor countries and shape global capital flows.

Our paper also contributes to the growing text-as-data literature that uses advances in natural language processing to measure sentiment, risk, and uncertainty from large textual corpora (Baker et al., 2016; Handley and Li, 2020; Ahir et al., 2022; Hassan et al., 2019, 2024; Arteaga-Garavito et al., 2024; Caldara and Iacoviello, 2022; van Binsbergen et al., 2024).[4] This literature has generated aggregate measures but it has largely focused on a single media environment and has not studied disagreement across investors exposed to different domestic information intermediaries. At the same time, a growing literature

[3]Existing research has also examined the impact of news media on investment dynamics and business cycles within closed economies (Gulen and Ion, 2016; Hassan, Hollander, Van Lent and Tahoun, 2019; Chahrour, Nimark and Pitschner, 2021; Flynn and Sastry, 2024; Bybee, Kelly, Manela and Xiu, 2024b; Hu, 2024).

[4]Baker, Bloom and Davis (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, Bloom and Furceri (2022) produce country-level uncertainty indices from Economist Intelligence Unit reports. Hassan, Hollander, Van Lent and Tahoun (2019) and Hassan, Schreger, Schwedeler and Tahoun (2024) use U.S. firms' earnings call transcripts and 10-K filings to measure political risks and perceived country risks. Arteaga-Garavito, Colacito, Croce and Yang (2024) construct climate attention indices from newspaper tweets, while Caldara and Iacoviello (2022) develop a geopolitical risk index using U.S. newspaper articles. van Binsbergen, Bryzgalova, Mukhopadhyay and Sharma (2024) exploits long historical newspaper archives to measure economic sentiment over very long time horizons. See Hoberg and Manela (2025) for a review of this literature.

on belief dispersion shows that investors can disagree even when facing similar information, due to heterogeneous priors, attention, or interpretation (Cookson et al., 2020; Cookson and Niessner, 2020; Cookson et al., 2023, 2024). We bridge these literatures by introducing a media-based, cross-country measure of narrative disagreement about the same foreign economy and by decomposing this disagreement into differences in topic attention and within-topic sentiment. Methodologically, our analysis relies on modern natural language processing tools, including transformer-based sentiment models and large language models, applied to large-scale newspaper text from multiple countries. We further contribute by developing a unified multilingual sentiment measurement framework based on language-specific FinBERT-style transformer models, enabling comparable narrative measurement across domestic media environments without relying on translation or English-only reporting. This integration allows us to study belief dispersion in an international setting and to link it directly to cross-border capital flows, an economic margin that has not been studied in the disagreement literature.

Finally, our paper contributes to the literature on determinants of cross-border capital flows.[5] We identify a previously overlooked determinant: local media narratives in investors' domicile countries. Existing studies emphasize information frictions as a key driver of international investment (Van Nieuwerburgh and Veldkamp, 2009; Andrade and Chhaochharia, 2010; Karolyi, Ng and Prasad, 2020), but typically treat these frictions as latent or proxy them with geographic, institutional, or technological distance. In contrast, we provide a direct, investor-facing measure of the information and interpretation environment, capturing not only the availability of information but also how common information is framed and interpreted in domestic media. By documenting that media

[5] 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, Lins and Warnock, 2009), currency returns (Froot and Ramadorai, 2005), proximity and cultural similarities-induced home bias (Chan, Covrig and Ng, 2005), currency denomination (Maggiori, Neiman and Schreger, 2020), diversification and learning motives (Agarwal, Gu and Prasad, 2020), information and transaction technology (Portes and Rey, 2005), tax haven status (Coppola, Maggiori, Neiman and Schreger, 2021), and economic uncertainty (Alok, Javadekar, Kumar and Wermers, 2022).

narratives influence capital flows over and above traditional macro-financial drivers,[6] our findings add a new dimension to the study of international investment behavior: belief formation shaped by domestic media narratives, rather than fundamentals alone.

2 Measuring Media Narratives at the Micro Level

In this section, we describe our methodology for quantifying media narratives about China using natural language processing (NLP) techniques. We begin by outlining the data collection process and then detail the construction of our narrative indices. For each country in the sample, we generate time series measures that capture both the volume of China-related media coverage at the extensive margin and the sentiment of that coverage at the intensive margin. In addition, we construct topic-level attention and sentiment indices that measure the prominence of specific topics in investor-country media reporting about China and the sentiment associated with those topics.

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). In addition, we include the *Financial Times*, both as one of the U.K. media outlets and as the primary media source for European Economic and Monetary Union (EMU) countries excluding Ireland.[7]

[6] The literature on capital flows to emerging markets documents the role of interest rate differentials, U.S. monetary policy, and global risk aversion (Lee and Engel, 2024; Ahmed and Zlate, 2014; Ghosh, Qureshi, Kim and Zalduendo, 2014; Forbes and Warnock, 2012; Hutchison and Noy, 2006).

[7] We define the EMU following Maggiori, Neiman and Schreger (2020) and Coppola, Maggiori, Neiman and Schreger (2021). The EMU countries in their data include Austria, Belgium, Finland, France, Germany,

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.

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 1,484,526 China-related news articles from 39 newspapers across 16 economies, covering the period from January 1, 2007 to May 31, 2022.

To mitigate potential language bias arising from the exclusive use of English-language newspapers, we incorporate seven additional newspapers in German, French, and Spanish, covering countries including Germany, France, Spain, Switzerland, and Austria. Table A2 reports the set of non-English newspapers included in this extended analysis.

2.2 Index Construction

Using natural language processing method, we construct four key narrative indices: an attention index, an aggregate sentiment index, a topic-level share index, and a topic-level sentiment index. Together, these indices capture time variation in media narratives about China as reflected in news coverage across countries. At the extensive margin, the attention index, denoted by $num_{c,t}$, measures the volume of China-related news and quantifies the overall level of media attention to China. At the intensive margin, we compute an average

Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovenia, and Spain. Each country enters the sample only after adopting the euro: Malta in 2008, Slovenia in 2007, and the remaining countries in 2002.

sentiment index, $sen_{c,t}$, at the article level, which captures changes in the tone of reporting about China. We further construct attention and sentiment indices using non-English newspapers as a robustness check. Using large-language models, we further decompose China-related news into twelve thematic topics and construct corresponding indices at the topic level. The topic share index, $share^k_{c,t}$, measures the proportion of China-related news devoted to topic k relative to all China-related news in a given country and month, capturing how media attention is allocated across topics. The topic sentiment index, $sen^k_{c,t}$, measures the average sentiment associated with topic k, reflecting how positively or negatively that topic is portrayed. Taken together, these measures provide a comprehensive characterization of both the breadth and the intensity of media narratives about China across countries and over time.

2.2.1 Aggregate-level Index

Attention Index. We follow a methodology similar to Baker, Bloom and Davis (2016) to construct the attention index, $num_{c,t}$, for investors domiciled in country c in month t, which serves as a measure of China related news volume at the extensive margin. For each media outlet m, we scale the number of China related articles published in month t, denoted by $num_{m,t}$, by the total number of articles published by the same outlet in that month, denoted by $all_{m,t}$. This normalization controls for differences in overall news output across media outlets. We then compute the country level attention index by averaging these scaled measures across all media outlets within each country.

Sentiment Index. We construct a sentiment index, $sen_{c,t}$, for each country c in month t using the FinBERT methodology, which applies transformer-based sentiment classification models pre-trained or fine-tuned on financial text. For the English-language analysis, we use the `ProsusAI/finbert` model, an industry-standard BERT variant trained on financial news and earnings call transcripts. A detailed description of the model and implementation is provided in Appendix C.

The model classifies text into three sentiment categories, positive, neutral, and negative, each accompanied by a confidence score. We apply the classifier to a truncated version of each article consisting of the headline followed by the first 480 characters of the body text. This window captures the portion of the article where narrative framing and evaluative language are typically concentrated, while avoiding dilution from descriptive detail or repetition later in the article.[8] This approach preserves the most sentiment-relevant content while maintaining comparability across a large corpus of documents and multiple language settings.

After extracting article-level sentiment labels from the `ProsusAI/FinBERT` model, we convert qualitative classifications into a numeric time series by assigning a value of +1 to positive articles, 0 to neutral articles, and −1 to negative articles. Each article-level sentiment value is multiplied by the model-assigned confidence score, so that classifications made with greater certainty receive proportionally more weight. We then aggregate to the newspaper-month level by taking the mean across all articles published by a given newspaper within a month. To obtain a country-level series, we further average the monthly newspaper values across all newspapers available for that country. The resulting monthly sentiment index reflects the weighted balance of positive and negative language in national media coverage and is comparable across countries.

Table 1 reports summary statistics for the sentiment index constructed using the FinBERT method ($sen_{c,t}$). The correlation between this FinBERT-based index and the traditional bag-of-words–based sentiment index is 0.82, indicating a high degree of consistency across methods.[9]

[8]BERT-based models, including FinBERT, operate under fixed input length constraints, and the average article in our dataset contains approximately 695 words. Beyond this mechanical consideration, truncation reflects a deliberate design choice. Restricting attention to the headline and opening text ensures consistent treatment across outlets and languages and aligns with journalistic conventions, in which the headline and lead paragraph convey the most salient sentiment and narrative framing.

[9]We further construct a sentiment index using bag-of-words–based method and a risk index. The methodology is reported in Appendix B.

Cross-Language Sentiment Index. In our baseline construction, we rely on English-language newspapers for the natural language processing analysis to ensure direct comparability across countries, as cross-language differences in vocabulary, morphology, and contextual usage could otherwise complicate the interpretation of sentiment indices. At the same time, the FinBERT-based methodology provides a natural framework for extending the analysis beyond English. Transformer-based sentiment models can be fine-tuned separately for different languages while preserving a common polarity structure, namely `positive`, `neutral`, and `negative`, which allows us to incorporate non-English text in a manner that remains systematically comparable across countries. This extension is particularly relevant for European economies, where leading national newspapers are typically published in local languages and where key economic and political narratives may be more accurately reflected in domestic-language media.

Implementing this multilingual extension requires selecting appropriate FinBERT-style models for each language. We evaluate a range of candidates for German, French, and Spanish, focusing on domain alignment, calibration quality, and consistency with the FinBERT labeling framework. Appendix C documents the model-selection process and reports the final packages adopted for each language. Because these models share the same polarity structure as the English FinBERT, they enable a unified narrative-measurement framework across countries and languages.

We include seven additional newspapers in German, French, and Spanish, covering Germany, France, Spain, Switzerland, and Austria. We construct sentiment indices from these sources and incorporate them into our empirical analysis. Importantly, this multilingual extension is not merely a robustness exercise but also constitutes a methodological contribution of independent interest. By comparing sentiment derived from English-language reporting with sentiment extracted from dominant domestic-language news ecosystems, we directly assess whether cross-country variation in our baseline indices is driven by linguistic or editorial differences or instead reflects deeper structural differences in national media narratives.

2.2.2 Topic-level Index

We further classify all news articles in our dataset into twelve mutually exclusive subject categories using a large language model. These categories capture the primary dimensions along which global media report on China and provide a structured representation of the thematic content embedded in news coverage. The twelve topics are defined as follows:

1. **Trade & Supply Chain:** Exports, imports, tariffs, sanctions, supply-chain disruptions, logistics, commodity trade, and sourcing.
2. **Domestic Economy & Growth:** GDP, inflation, consumption, investment, unemployment, industrial production, macroeconomic performance, and stimulus policies.
3. **Financial Markets, Banking & FX:** Stocks, bonds, currencies, interest rates, central banking, monetary policy, capital flows, and banking developments.
4. **Real Estate, Debt & Financial Stability:** Property markets, mortgages, developers, credit risks, and broader financial fragility concerns.
5. **Technology, Innovation & Industry Policy:** Technology firms, semiconductors, artificial intelligence, telecommunications, industrial upgrading, automation, and state-led industrial policy initiatives.
6. **Governance, Regulation & Institutions:** Government policy actions, regulatory interventions, administrative measures, leadership decisions, and institutional reforms.
7. **Environment, Climate & Energy:** Pollution, climate change, renewable energy, fossil fuels, mining, and natural resource issues.
8. **Diplomacy & Geopolitics:** Foreign relations, great-power competition, military relations, alliances, interstate conflicts, and China's positioning in global politics.
9. **Society, Labor & Demographics:** Population trends, migration, education, workforce issues, inequality, and civil-society developments.
10. **Security, Surveillance & Human Rights:** National security, policing, censorship, surveillance technologies, detentions, and human-rights disputes.
11. **Health, Pandemics & Public Safety:** Disease outbreaks, vaccines, COVID-19, medical systems, and public-safety concerns.
12. **Firms, Industries & Corporate Strategy:** Corporate decisions, earnings, mergers and acquisitions, product launches, supply–demand conditions, and business strategies.

Instead of relying on traditional unsupervised approaches such as Latent Dirichlet Allocation (LDA), which often produce unstable clusters and require subjective interpretation, we classify articles using a pre-defined taxonomy that aligns with key economic, political, and social domains. The classification is performed using the `gpt-4.1-mini` model, which interprets headlines with high semantic accuracy and applies the taxonomy consistently. For each article, only the headline is provided to the model together with a concise description of the twelve categories, and the model returns a single topic label. This procedure yields a transparent and replicable mapping from raw text to economically meaningful subjects.[10] The exact prompt and the full category definitions are reported in Appendix E.

For the *Financial Times* (FT) archive, we follow the same taxonomy and classification procedure, but due to data usage restrictions,[11] classification is implemented via a local deployment of the `mistral-7b-instruct.Q4_0` model using the `llama.cpp` inference framework. While smaller than commercial cloud models, this architecture offers fast inference, robust semantic understanding of headlines, and full compatibility with constrained environments, making it a practical and secure solution for large-scale, title-based classification. To mitigate potential misclassification arising from the limitations of a local model, we use both the article title and the first two sentences of each *Financial Times* article when assigning subject classifications.

Using an LLM provides several methodological advantages relative to LDA. Because the taxonomy is fixed and conceptually grounded, topic assignments remain stable across newspapers, time periods, and subsamples, whereas LDA topics change as corpus composition evolves. The LLM also incorporates contextual and domain-specific knowledge that improves semantic differentiation, allowing it to distinguish, for example, macroeconomic

[10] To reduce computational time and cost, we classify articles using only their titles rather than full text. Random subsample tests confirm that title-based and full-text classifications produce near identical results.

[11] The FT license agreement limits how content may be used in conjunction with AI systems. Specifically, classification must be conducted on locally hosted models entirely controlled by the user, and results cannot be used to train or adapt any general-purpose large language model. The full content cannot be transferred to third-party cloud models or services.

developments from financial market interventions or diplomatic communication from national security concerns, distinctions that LDA often merges into broad clusters. The procedure also scales efficiently: classifying approximately 180,000 Wall Street Journal articles required about four hours and a modest monetary cost, making the approach feasible for our multi-million–article dataset. Since all articles are classified under the same taxonomy, the resulting subject indices are directly comparable across countries and over time, which is essential in an international setting.

Formally, we construct a topic share index and a topic sentiment index for each topic k in each country c at time t.

Topic Share Index. The topic share index, $share_{c,t}^{k}$, measures the proportion of media attention devoted to topic k in country c and month t relative to all China related news. For each newspaper, we compute the share of articles classified as topic k in month t relative to the total number of China related articles published by that newspaper in the same month. This index captures how reporting capacity is allocated to topic k out of all China related coverage. We then average these newspaper level shares across all newspapers in country c to obtain the monthly index.

Topic Sentiment Index. The topic sentiment index $sen_{c,t}^{k}$ captures the intensive margin of narrative tone for topic k in country c in month t. For each newspaper, we compute the average FinBERT sentiment score of articles classified as topic k in that month, which reflects the within-subject tone conditional on coverage. We then take the average of these values across all newspapers in country c to obtain the monthly index.

3 Stylized Facts

3.1 Visualizing the Indices

Figure 1 shows that both the attention and sentiment indices track major global and China-related episodes closely, confirming that our narrative measures capture systematic shifts in international reporting. Attention to China rises sharply around well-known events, including the Global Financial Crisis, the 2015–2016 stock market crash, the escalation of U.S.-China trade tensions, and the onset of the COVID-19 pandemic, while sentiment turns markedly more negative during these periods. Notably, the cross-country interquartile range narrows during these major episodes, indicating that media outlets across different economies tend to converge in both the volume and tone of their China coverage when global uncertainty spikes. Outside of crisis periods, however, the dispersion widens again, reflecting persistent cross-country heterogeneity in how China is framed in the news.

Figure 3 presents the evolution of topic-level media narratives about China between 2007 and 2022. Both the topic share and sentiment indices display substantial time variation, with noticeable increases in coverage and shifts in tone during major global or China-related events. For example, attention to Health, Pandemics & Public Safety (Topic 11) rises sharply around 2020, consistent with the outbreak of COVID-19, while coverage of Financial Markets, Banking & FX (Topic 3) spikes during the 2015–2016 stock market turmoil. Sentiment patterns similarly reflect key episodes: sentiment within economic and financial topics deteriorates during the Global Financial Crisis and again during the 2018–2020 trade tensions, whereas technology-related sentiment (Topic 5) remains relatively stable over time. Across topics, the interquartile range shows considerable cross-country heterogeneity, though dispersion narrows temporarily during large global shocks when reporting becomes more synchronized.

3.2 Cross-Country Narrative Dispersion

Topic Share Dispersion. Across countries, the topical composition of China-related reporting exhibits clear and systematic patterns. Panel (a) of Figure 4 shows that three topics, Diplomacy & Geopolitics (Topic 8), Society, Labor & Demographics (Topic 9), and Firms, Industries & Corporate Strategy (Topic 12), receive consistently higher coverage shares than other categories across most economies. These topics account for a substantial portion of China-related reporting, indicating that global media outlets tend to frame China primarily through geopolitical relations, domestic social developments, and corporate or industrial dynamics.

At the same time, the heatmap reveals notable cross-country clustering in narrative emphasis. Economies geographically close to China, such as Korea, India, Thailand, and Taiwan, devote relatively more coverage to Diplomacy & Geopolitics (Topic 8), reflecting the salience of regional security and bilateral relations. Advanced western economies, including the United States, United Kingdom, and Canada, allocate disproportionately large shares to Diplomacy & Geopolitics (Topic 8) and Society, Labor & Demographics (Topic 9), consistent with a more political and socio-institutional framing of China. By contrast, Asian economies with deeper commercial exposure to China, such as Hong Kong, Malaysia, Singapore, and Korea, place greater weight on Firms, Industries, & Corporate Strategy (Topic 12), and Financial Markets, Banking & FX (Topic 3), indicating a more economic and business-oriented lens on China's global role.

Topic Sentiment Dispersion. Panel (b) of Figure 4 highlights pronounced cross-topic and cross-country heterogeneity in sentiment toward China. First, there are strong systematic differences across topics: Security, Surveillance & Human Rights (Topic 10) is uniformly negative across all countries, and especially so in the United States, United Kingdom, Canada, Australia, and New Zealand, making it the single most negative narrative category. Governance (Topic 6) and Health & Public Safety (Topic 11) also exhibit consistently negative sentiment across the sample. By contrast, Firms, Industries & Corporate Strategy (Topic 12) and Technology, Innovation & Industry Policy (Topic 5) are among the few categories with generally positive sentiment, with particularly favorable views in Malaysia, the Philippines, and Thailand, although Topic 12 shows notable exceptions for the United States and United Kingdom, where sentiment is markedly more negative.

Second, several topics exhibit substantial cross-country disagreement in tone. Sentiment toward Domestic Economy & Growth (Topic 2), Financial Markets, Banking & FX (Topic 3), and Real Estate, Debt & Financial Stability (Topic 4) varies widely across countries. Southeast Asian economies, including Malaysia, the Philippines, and Thailand, tend to report these topics with a more positive tone, whereas advanced Western economies report them much more negatively, indicating divergent assessments of China's economic conditions.

Third, when comparing sentiment across all topics, a clear geographic divide emerges: Asian economies such as Malaysia, the Philippines, and Thailand consistently display more positive sentiment toward China, while the United States, United Kingdom, Canada, and Australia are systematically more negative. This persistent cross-country asymmetry highlights distinct national narrative environments, with implications for how investors in different countries interpret China-related information.

4 Understanding Cross-Country Narrative Dispersion

This section examines the sources of cross-country dispersion in media narratives about China. While aggregate sentiment toward China varies substantially across investor countries, such variation can arise for conceptually distinct reasons. Countries may differ in the extent to which their media devote attention to different aspects of China, what we refer to as *topic attention* (or topic coverage), or they may differ in how they evaluate and frame the same topics, as reflected in within-topic sentiment. Distinguishing between these channels is important for understanding whether cross-country narrative disagreement primarily reflects differences in information selection or differences in interpretation. To this end, we develop a variance decomposition of aggregate sentiment that isolates the contribution of topic attention and within-topic sentiment to cross-country dispersion.

4.1 Topic Attention versus Within-Topic Sentiment

We conduct a counterfactual variance decomposition to separate variation arising from differences in topic attention, i.e., the allocation of media attention across certain topic, from variation arising from differences in sentiment conditional on topic. We do so by constructing counterfactual sentiment indices that hold one component fixed at its cross-country mean while allowing the other to vary across countries. Comparing the cross-country variance of these counterfactual indices to the variance of observed aggregate sentiment allows us to quantify the relative contribution of topic attention, within-topic sentiment, and their interaction to overall narrative disagreement.

Let $S_{c,t}$ denote the aggregate sentiment toward China in country c at time t, constructed as a weighted average of topic-level sentiment, where weights reflect topic attention. Formally,

$$S_{c,t} = \sum_{k=1}^{K} w_{c,t}^{k} s_{c,t}^{k},$$

where $w_{c,t}^{k}$ denotes the share of media coverage devoted to topic k in country c at time t, corresponding to the topic share index $share_{c,t}^{k}$, and $s_{c,t}^{k}$ denotes sentiment toward topic k in country c at time t, corresponding to the topic sentiment index $sen_{c,t}^{k}$.

To isolate cross-country variation in sentiment $S_{c,t}$ driven purely by differential topic attention across investor countries' media, we construct a counterfactual sentiment index that holds within-topic sentiment fixed at its cross-country mean. Formally,

$$S_{c,t}^{\text{att}} = \sum_{k=1}^{K} w_{c,t}^{k} \bar{s}_{t}^{k}, \qquad \bar{s}_{t}^{k} \equiv \frac{1}{C} \sum_{c=1}^{C} s_{c,t}^{k}.$$

where $w^k_{c,t}$ denotes the share of media attention devoted to topic k in country c at time t, and $\bar{s}^k_t$ is the cross-country average sentiment for topic k at time t. By construction, this index varies across countries solely because of differences in topic attention, abstracting from cross-country differences in sentiment conditional on topic.

Conversely, holding topic attention fixed at its cross-country mean, we define the within-topic-sentiment-only counterfactual index as

$$S^{\text{tone}}_{c,t} = \sum_{k=1}^{K} \bar{w}^k_t s^k_{c,t}, \qquad \bar{w}^k_t \equiv \frac{1}{C} \sum_{c=1}^{C} w^k_{c,t}.$$

where $\bar{w}^k_t$ is the cross-country average topic attention weight for topic k at time t, and $s^k_{c,t}$ denotes country-specific sentiment toward topic k. This index varies across countries solely because of differences in sentiment conditional on topic, holding the allocation of attention across topics fixed.

Next, we study the relative contribution of the two counterfactual indices to the variance of the country-level sentiment index. Formally, let $\text{Var}_t(\cdot)$ denote the cross-country variance at a given time t. We compute:

$$V_t = \text{Var}_t(S_{c,t}); \qquad V^{\text{att}}_t = \text{Var}_t\left(S^{\text{att}}_{c,t}\right); \qquad V^{\text{tone}}_t = \text{Var}_t\left(S^{\text{tone}}_{c,t}\right).$$

For each time period t, V_t measures the total cross-country dispersion in aggregate sentiment toward China, while V^{att}_t and V^{tone}_t measure the portions of that dispersion generated by cross-country differences in topic attention and within-topic sentiment, respectively, as captured by the corresponding counterfactual sentiment indices.

Using these quantities, we define the variance shares attributable to topic attention and within-topic sentiment as

$$\text{Share}^{\text{att}}_t = \frac{V^{\text{att}}_t}{V_t}, \qquad \text{Share}^{\text{tone}}_t = \frac{V^{\text{tone}}_t}{V_t}.$$

These shares measure the fraction of cross-country variation in aggregate sentiment at time t that can be attributed to differences in topic attention and differences in sentiment conditional on topic, respectively.

Because topic attention and within-topic sentiment may not be independent across countries, the variation in aggregate sentiment will also depend on the interaction between the two components. We therefore define a residual interaction component as

$$\text{Residual}_t = 1 - \text{Share}_t^{\text{att}} - \text{Share}_t^{\text{tone}}, \tag{1}$$

which captures cross-country variation arising from the interaction between topic attention and within-topic sentiment.

Figure 5 summarizes the results of the variance decomposition. We find that the overwhelming majority of cross-country dispersion in aggregate sentiment toward China is driven by differences in within-topic sentiment rather than by differential topic coverage across countries. In contrast, variation in topic attention contributes only a small fraction of overall narrative disagreement. This finding indicates that cross-country differences in media narratives about China do not primarily reflect what countries choose to write about, but rather how they evaluate and frame the same underlying topics. Put differently, investor-country media largely focus on similar sets of China-related issues, yet attach systematically different sentiment to those issues. As a result, disagreement in aggregate narratives arises mainly from differences in tone conditional on topic, rather than from differences in the allocation of attention across topics.

4.2 Heterogeneous Priors versus Heterogeneous Interpretation

While the preceding analysis establishes that cross-country narrative dispersion is driven primarily by differences in within-topic sentiment, it does not yet explain the source of these differences. Conceptually, within-topic sentiment can vary across countries for two distinct reasons. First, countries may differ in their baseline framing of a given topic, reflecting slow-moving, country-specific beliefs or priors about China that persist over time. Second, countries may differ in how they interpret and respond to new, common information within a topic, generating heterogeneous reactions to the same underlying events. Distinguishing between these channels is crucial for understanding whether narrative disagreement reflects stable belief differences or time-varying differences in interpretation. In this section, we decompose within-topic sentiment into a persistent country-specific component and a country-specific response to common topic-level information, allowing us to assess the relative importance of heterogeneous priors versus heterogeneous interpretation across topics.

To this end, we develop an econometric framework that decomposes cross-country variation in media narratives about China into differences in persistent country-specific priors and differences in how countries translate common information into sentiment. For each topic k, investor country c, and month t, let $S^k_{c,t}$ denote the media sentiment index capturing country c's narrative stance toward China on topic k, corresponding to the topic sentiment index $sen^k_{c,t}$ defined in the previous section. We model $S^k_{c,t}$ as a function of a country-specific prior, narrative persistence, and a country-specific interpretation of a common topic-level information signal:

$$S^k_{c,t} = \alpha^k_c + \rho^k_c S^k_{c,t-1} + \beta^k_c C^k_t + u^k_{c,t}. \tag{2}$$

The coefficient α^k_c captures country–topic–specific prior reflecting long-run narrative stance toward China in each topic. The autoregressive coefficient ρ^k_c captures narrative persistence arising from editorial inertia, slow belief updating, or institutional continuity in media coverage. The sensitivity parameter β^k_c measures how strongly country i's media narrative responds to common information about China on topic k.

The common information signal C^k_t proxies for information about China on topic k

that is broadly available to global investors and media outlets at time t. In the baseline specification, we construct C_t^k the first principal component extracted from the panel of country-level topic-k sentiment indices.

Under this specification, cross-country heterogeneity in narratives arises from three distinct sources. First, differences in α_c^k reflect heterogeneity in time-invariant country-specific priors, such as political attitudes, media ideology, or time-invariant perceptions of certain topics in China. Second, differences in ρ_c^k reflect heterogeneity in narrative persistence and adjustment speed. Third, differences in β_c^k reflect heterogeneity in how sensitive countries are to common information about China.

To assess the relative importance of priors and sensitivities in explaining cross-country dispersion in narratives, we construct counterfactual fitted narrative indices that selectively shut down one source of heterogeneity at a time while holding others fixed.

Let $\bar{\alpha}^k = \frac{1}{N}\sum_c \alpha_c^k$ and $\bar{\beta}^k = \frac{1}{N}\sum_c \beta_c^k$ denote the cross-country averages of priors and sensitivities for topic k.

Sensitivity-only heterogeneity. We construct a counterfactual narrative index that preserves heterogeneity in sensitivities while imposing a common prior:

$$\tilde{S}_{c,t}^{k,\text{sensitivity}} = \bar{\alpha}^k + \rho_c^k S_{c,t-1}^k + \beta_c^k C_t^k. \tag{3}$$

Cross-country variation in $\tilde{S}_{c,t}^{k,\text{sensitivity}}$ therefore arises solely from differences in responsiveness to common information and narrative persistence.

Prior-only heterogeneity. Conversely, we construct a counterfactual narrative index that preserves heterogeneity in priors while imposing a common sensitivity:

$$\tilde{S}_{c,t}^{k,\text{prior}} = \alpha_c^k + \rho_c^k S_{c,t-1}^k + \bar{\beta}^k C_t^k. \tag{4}$$

In this case, cross-country variation reflects differences in baseline narrative stance and persistence, holding responsiveness to common information fixed.

For each topic k, we quantify the contribution of priors and sensitivities to cross-country narrative dispersion by comparing the cross-sectional variance of the counterfactual indices with the variance of the fitted baseline narrative index:

$$\hat{S}^k_{c,t} = \alpha^k_c + \rho^k_c S^k_{c,t-1} + \beta^k_c C^k_t. \tag{5}$$

Specifically, we compute the time-averaged cross-sectional variance of $\tilde{S}^{k,\text{prior}}_{c,t}$ and $\tilde{S}^{k,\text{sensitivity}}_{c,t}$, and express each as a share of the variance of $\hat{S}^k_{c,t}$. Because priors and sensitivities may be correlated across countries, these components need not sum to one; the residual reflects covariance between priors and sensitivities.[12]

The parameters $\{\alpha^k_c, \rho^k_c, \beta^k_c\}$ are estimated separately for each country and topic using time-series regressions. Because the variance decomposition relies on estimated parameters, we account for generated-regressor uncertainty using a time-series bootstrap. Specifically, we resample months with replacement, re-estimate all parameters, recompute counterfactual narrative indices, and recalculate variance shares in each bootstrap draw. We report bootstrap means for all variance-decomposition results.

Prior, Sensitivity and Persistence. *Prior.* We plot the estimated $\{\hat{\alpha}^k_c, \hat{\rho}^k_c, \hat{\beta}^k_c\}$ across countries and topics in Figure 6. Panel (a) visualizes the estimated country–topic priors $\hat{\alpha}^k_c$ which capture long-run narrative stances toward China that are orthogonal to both short-run information shocks and narrative persistence. Several systematic patterns emerge. Across topics, priors are markedly negative in Topics 6 (Governance, Regulation, and Institutions), 10 (Security, Surveillance, and Human Rights), and 11 (Health, Pandemics, and Public Safety), with Topic 10 exhibiting by far the most negative priors across nearly all countries. These topics are closely tied to political institutions, civil liberties, and security concerns, where China is persistently framed in an adverse light irrespective

[12]Narrative persistence (ρ^k_i) varies substantially across countries and topics, but we treat persistence as a propagation mechanism rather than a separate source of cross-sectional variance.

of contemporaneous news. In contrast, Topics 5 (Technology, Innovation, and Industry Policy) and 12 (Firms, Industries, and Corporate Strategy) display the most positive priors, reflecting a more favorable long-run narrative associated with China's role in global production, industrial upgrading, and firm-level performance. Across countries, we observe pronounced heterogeneity in baseline narrative stance. Media in several Asian economies, notably Malaysia, Singapore, and Thailand, exhibit systematically more positive priors across most topics, whereas major Western economies such as the United States, Australia, and the United Kingdom display uniformly negative priors. Importantly, these cross-sectional patterns align closely with the average sentiment measures documented earlier. This consistency shows that while average sentiment reflects unconditional mean tone, the estimated priors $\hat{\alpha}_c^k$ isolate the persistent component of narrative bias after netting out common information shocks and dynamic adjustment. The close correspondence therefore indicates that long-run narrative stances are a first-order driver of observed sentiment differences across countries and topics, rather than being an artifact of short-run news fluctuations. We formally test this in the next variance decomposition section.

Sensitivity. Panel (b) of Figure 6 plots the estimated sensitivities to common information, $\hat{\beta}_c^k$, which measure how strongly country c's media narrative responds to shared topic-level news about China. Across topics, sensitivities are modest but systematically higher in Topics 1–3 (Trade & Supply Chain; Domestic Economy & Growth; Financial Markets, Banking & FX) than in most other domains. These topics are more directly tied to observable economic fundamentals and high-frequency global information, leading to more synchronized narrative updating across countries when new information arrives. Across countries, Asian economies, particularly Taiwan, South Korea, Malaysia, and the Philippines, exhibit substantially higher sensitivities to China-related news than Western economies such as the United States, Australia, and Canada. This pattern is especially pronounced in Topic 5 (Technology, Innovation, and Industry Policy) and Topic 10 (Security, Surveillance, and Human Rights), where Asian media narratives adjust sharply in response to common information shocks, while Western narratives remain comparatively inert. One interpretation is that countries with deeper economic, technological, or geopolitical exposure to China place greater informational weight on shared signals, whereas media in Western economies rely more heavily on stable priors or domestic framing when covering China-related developments. Finally, cross-country heterogeneity in sensitivity is most pronounced in Topic 4 (Real Estate, Debt, and Financial Stability), Topic 5 (Technology, Innovation, and Industry Policy), Topic 7 (Environment, Climate, and Energy), and Topic 10 (Security, Surveillance, and Human Rights), domains characterized by greater ambiguity, normative content, or strategic interpretation. In these areas, common information about China does not map cleanly into a single narrative implication, leaving greater scope for country-specific framing, institutional filters, and geopolitical considerations to shape how news is incorporated.

Persistence. Panel (c) of Figure 6 reports the estimated narrative persistence parameters $\hat{\rho}_c^k$. Across topics, persistence is highest in Topic 12 (Firms, Industries & Corporate Strategy) and Topic 2 (Domestic Economy & Growth), indicating that narratives in these domains evolve gradually and exhibit substantial editorial inertia. These topics are characterized by continuous reporting, reliance on slow-moving fundamentals, and incremental reassessment rather than episodic reframing. By contrast, narratives in more episodic or shock-driven domains, such as Topic 4 (Real Estate, Debt & Financial Stability), Topic 5 (Technology, Innovation & Industry Policy), Topic 7 (Environment, Climate & Energy), Topic 10 (Security, Surveillance & Human Rights), and Topic 11 (Health, Pandemics & Public Safety), exhibit lower persistence, reflecting faster updating and greater sensitivity to breaking news.Across countries, Hong Kong media displays the highest narrative persistence across a broad range of topics, followed by Australia, Canada, the United States, and Thailand. This pattern is consistent with stronger editorial continuity, sustained exposure to China-related coverage, and stable framing conventions in these media environments.

Variance decomposition: Prior versus Sensitivity. Results from this decomposition exercise are shown in Figure 7. Two patterns stand out. First, for most topics, cross-country dispersion in sentiment is dominated by persistent country-specific components, indicating that slow-moving priors account for a large share of narrative disagreement. This is particularly pronounced for topics such as trade and supply chains, domestic economic conditions, financial markets, geopolitics, and corporate strategy, where priors explain roughly 80–95% of the cross-sectional variance.

Second, the relative importance of heterogeneous responses to common information varies substantially across topics. For topics related to governance, institutions, the environment, security and human rights, and public health, cross-country differences in sensitivity to common shocks account for a sizable, and in some cases dominant, share of sentiment dispersion. For example, in security and human rights and health-related narratives, variation in countries' responses to common information explains more than half of the total cross-country variance.

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.

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

$$Flow_{ic,t} = \beta_0 + \beta_1 Index_{c,t-1} + \beta_2 num_{c,t-1} + X'_{c,t-1}\Phi + \alpha_i + \alpha_t + \varepsilon_{ic,t} \tag{6}$$

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.[13]

$Index_{c,t-1}$ denotes the media narrative based sentiment index for investors in domicile country c at time $t-1$, and serves as our main variable of interest. We also include $num_{c,t-1}$ to control for the effect of narrative coverage at the extensive margin on investment flows.[14] $X_{c,t-1}$ is a vector of macroeconomic controls, lagged one quarter, that may affect fund flows to China. These include the year-over-year GDP growth differential between China and the investor's domicile country ($Growthdiff_{c,t-1}$); the bilateral exchange rate between the renminbi and the domicile country's currency ($EX_{c,t-1}$), where an increase reflects a depreciation of the renminbi; the interest rate differential between China and the domicile country ($Intdiff_{c,t-1}$); and relative equity market performance, measured by the excess return of the Chinese stock market over the domicile country's market

[13]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 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.

[14]Since the indices are constructed at a monthly frequency, we use the arithmetic average over the three months of the quarter ending in $t-1$ in equation 6.

($Retdiff_{c,t-1}$); and the volatility of the Chinese stock market over the volatility of the domicile country's market ($Volratio_{t-1}$).[15] To facilitate cross-country comparisons, we standardize the sentiment and risk indices for each country. The specification includes fund fixed effects (α_i) and quarter-year fixed effects (α_t). Standard errors are clustered at the fund level to adjust for potential serial correlation in the error term $\varepsilon_{ic,t}$.

Table 2 reports baseline estimates from alternative specifications of equation (6) using different combinations of control variables. Columns (1) through (4) show that more positive domestic media sentiment toward China is associated with higher fund flows into Chinese assets. As shown in column (4), after controlling for macroeconomic and financial fundamentals, as well as fund and quarter fixed effects, a one standard deviation increase in the domestic media sentiment index is associated with a 0.96% increase in quarterly investment flows to China, which corresponds to an annualized increase of 3.82%.

The inclusion of quarter fixed effects ensures that these results are not driven by common global shocks, highlighting that cross-country differences in media sentiment play an important role in explaining heterogeneity in capital flows. Consistent with the earlier cross-country variance decomposition, which shows that most narrative variation arises from sentiment rather than attention, we find that the volume of China-related news coverage does not have a statistically significant relationship with investment flows once sentiment is controlled for. This result indicates that investment decisions respond primarily to the tone of media narratives at the intensive margin, rather than to changes in the overall quantity of China-related reporting.

5.1 Robustness Analysis: Bag-of-word Method

We further construct bag-of-word sentiment indices ($sen^{bag}_{c,t}$) using the method described in Appendix B, in which we count the number of positive and negative words in each news article based on the word lists developed by Loughran and McDonald (2011). Panel A

[15]Definitions and data sources for all control variables are provided in Table A3 in Appendix D.

of Table 3 reports the results using these bag of words indices. As shown in column (4), after controlling for financial and macroeconomic fundamentals, a one standard deviation increase in China related news is associated with a 0.93% increase in quarterly investment flows into Chinese assets, which corresponds to a 3.72% increase on an annualized basis. These estimates are consistent with and comparable in magnitude to our baseline results, providing additional support for the robustness of our index construction.

5.2 Robustness Analysis: Cross-language FinBERT Analysis

Benson et al. (2025) show that language differences in news coverage can matter for asset prices and market outcomes. Hence, we restimate our baseline analysis replacing the English language narrative indices with indices constructed using local language FinBERT models in German, French, and Spanish applied to domestic newspapers. Panel (B) of Table 3 reports results from this analysis. We find that domestic language narratives about China are also strongly predictive of cross border investment flows. As shown in column (4), after controlling for macroeconomic and financial fundamentals as well as fund and quarter fixed effects, a one standard deviation increase in the domestic language sentiment index is associated with a 0.75% increase in quarterly flows to China, corresponding to an annualized increase of approximately 2.98%. The estimated effect is highly statistically significant and economically meaningful, with a magnitude that is slightly smaller than, but comparable to, the baseline English language results.[16]

[16] One explanation for the modestly lower coefficients in the cross language specification is that domestic language newspapers exhibit less variation in their coverage of China. German, French, and Spanish language outlets tend to be more domestically oriented and devote a smaller share of reporting to China relative to global English language media such as the *Wall Street Journal*, the *Financial Times*, or major United States national newspapers. As a result, fluctuations in China related narratives are more muted in local language media markets, which mechanically limits the variation captured by the sentiment indices. This structural feature implies that multilingual sentiment indices display lower cross country dispersion, even though their informational content remains highly relevant. When the underlying variance of narratives is smaller, the estimated elasticity of capital flows is naturally attenuated, despite the relationship being precisely estimated and statistically strong. Moreover, international investors, particularly those allocating to emerging markets, rely heavily on English language financial news when forming global investment views. Consequently, English based indices capture a broader and more globally salient information set, which helps explain their somewhat larger estimated effects.

The strong statistical significance and consistent signs across languages reinforce that the results are not driven by linguistic artifacts or the choice of media language. Instead, they point to a robust underlying mechanism through which media narratives, whether expressed in global English outlets or domestic language media, shape cross border capital flows to China.

5.3 Robustness Analysis: Extracting Media Narrative Shocks

In the previous section, we show that media narratives about China from investors' domicile countries influence cross-border fund flows into Chinese assets, even after controlling for a range of macroeconomic and financial variables. However, the constructed media indices may still reflect a combination of underlying fundamentals in China along with the narrative framing that shapes how these fundamentals are perceived and interpreted. To address this concern, in this section, we conduct robustness checks by isolating media narrative shocks that are orthogonal to macroeconomic and financial fundamentals.

To isolate the narrative component ($narrativeshocks_{c,t}$) from the sentiment and risk indices, we estimate the following equation:

$$Index_{c,t} = g(fundamentals_t) + \varepsilon_{c,t},$$

where $index_{c,t}$ is the sentiment index constructed for domicile country c, $g(\cdot)$ is a function of current and lagged Chinese fundamentals, and $\varepsilon_{c,t}$ captures the narrative shocks, i.e., deviations from what fundamentals alone would predict.

In particular, we use a recursive vector autoregression (VAR) with Cholesky decomposition to identify $\varepsilon_{c,t}$. The baseline VAR specification is:

$$\boldsymbol{A}\boldsymbol{Y_t} = \sum_{j=1}^{p} \boldsymbol{C_j}\boldsymbol{Y_{t-j}} + \boldsymbol{\varepsilon_t}$$

where $\boldsymbol{A}$ and $\boldsymbol{C_j}$ are $K \times K$ matrices of parameters, ε_t is a $K \times 1$ vector of innovation with

$\varepsilon_t \sim N(0, \boldsymbol{\sigma})$ and $E[\varepsilon_t \varepsilon_s^{'}] = \boldsymbol{O}_K$ for all $s \neq t$. For the variables, the Cholesky restrictions result in the exclusion restriction on contemporaneous response in the matrix $\boldsymbol{A}$ to fit a just-identified model, with $\boldsymbol{A}$ to be a lower triangular matrix.

We include three lags ($p = 3$) based on the combined results of lag-order selection statistics, including final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (BIC), and the Hannan and Quinn information criterion (HQIC).

The vector $\boldsymbol{Y_t}$ includes the following variables, all in log form unless otherwise noted: the constructed media sentiment and risk indices; the stock composite index ($Comp_t$), measured by the monthly average of the Shanghai Shenzhen CSI 300 index, capturing the overall performance of the Chinese stock market; the volatility index (Vol_t), defined as the monthly volatility of the CSI 300; China's RMB effective exchange rate index (EX_t); the monthly year-over-year Consumer Price Index (CPI) of China (CPI_t), which reflects inflation dynamics; and the seasonally adjusted industrial production index (IP_t), representing real economic activity.[17]

We order the variables in $\boldsymbol{Y_t}$ based on standard macro-financial assumptions. (1) The media index is placed first, under the assumption that narrative shocks can contemporaneously affect all other variables, but are not themselves contemporaneously affected by them. (2) The stock composite index follows, as stock returns react immediately to news and are considered highly responsive. (3) The volatility index is ordered next, as it typically reacts to returns but exhibits more persistence and slower transmission to other variables. (4) The exchange rate index is placed fourth, reflecting its sensitivity to financial variables while assuming it does not contemporaneously influence real economic activities. (5) The CPI is then included, based on its slower-moving nature and limited immediate responsiveness to financial shocks. (6) Finally, the industrial production index appears

[17] The media narrative index and the stock return are used in levels rather than logs because both series can take negative values. The stock return is already expressed as a log-difference of prices, and the sentiment index is centered around zero; therefore logging these variables is neither meaningful nor feasible.

last, as it is assumed to be the most sluggish among the variables and does not respond contemporaneously to any of the preceding shocks.[18]

The first element of ε_t, corresponding to the media index, is interpreted as the media narrative shock. We estimate this structural VAR separately for each country and for both sentiment and risk indices to generate country-level media narrative shock series.

We repeat the baseline analysis using media narrative shocks identified from the recursive VAR model rather than the original narrative indices. Panel C of Table 3 reports the results. As shown in column (4), a one standard deviation increase in the media sentiment shock about China is associated with a 1.47% increase in quarterly investment flows into Chinese assets, which corresponds to an annualized increase of 5.88%. Consistent with the findings from the cross-country narrative decomposition, these results suggest that media narratives influence cross-border capital flows not only through fundamentals reflected in the indices, but also through the framing and interpretation of those fundamentals. This evidence supports a narrative-based transmission mechanism in which deviations in media sentiment that are orthogonal to macroeconomic and financial conditions have independent effects on international portfolio allocation.

5.4 Event Study Analysis: Arab Spring as a Global Narrative Shock

The baseline results document a strong association between domestic media sentiment toward China and cross-border investment flows. A key remaining question is whether this relationship reflects differences in how common global information is interpreted through domestic media narratives, rather than unobserved country-specific exposure to China. This section addresses this question by exploiting a plausibly exogenous global geopolitical shock to study how media narratives and capital flows respond across countries.

The Arab Spring triggered a worldwide reassessment of political stability, governance, and regime durability, elevating the salience of geopolitical risk in media narratives well

[18]Our results are robust to alternative ordering schemes, including placing the stock return index first, followed by the media and volatility indices.

beyond the countries directly affected. Although China's economic fundamentals were unchanged, this shift in global political narratives led media outlets to reinterpret China through a more geopolitical and risk-oriented lens. We examine whether this common global shock generated differential changes in media narratives about China across investor countries and whether such narrative shifts were accompanied by changes in cross-border investment.

Our identification leverages cross-country heterogeneity in pre-existing exposure to geopolitical news. The key idea is that countries whose media environments are structurally more oriented toward geopolitical reporting may respond to the same global shock by re-framing narratives about China along geopolitical dimensions, rather than by reallocating attention toward China. This approach allows us to isolate differential narrative responses to a common event while holding constant the underlying information set. Consistent with this mechanism, we show that following the Arab Spring, countries with greater exposure to geopolitical reporting experience a pronounced deterioration in sentiment toward China, despite no corresponding differential change in media attention. These narrative shifts are accompanied by relative declines in portfolio flows to Chinese assets, supporting a narrative-based transmission mechanism in which global shocks affect cross-border investment through country-specific framing and interpretation rather than changes in information availability or China's underlying fundamentals.

5.4.1 Measuring Geopolitical News Exposure

We construct a country-level measure of exposure to geopolitical news based on newspaper coverage. For each newspaper in our dataset, we identify geopolitical-related articles using the keyword list developed by Caldara and Iacoviello (2022). We then compute, for each newspaper, the share of geopolitical-related articles as a%age of all articles published over the full sample period from 2007 to 2022. This measure captures persistent differences in editorial focus toward geopolitical issues rather than short-run responses to specific events.

We aggregate this measure to the country level by averaging across newspapers within each country. Countries are then ranked according to their average geopolitical news share, and we define an indicator

$$HighGeoPolitics_c = \mathbb{1}\{\text{GeoExposure}_c > \text{median}\},$$

which equals one for countries with above-median geopolitical news exposure and zero otherwise. Importantly, this classification is time-invariant and reflects long-run media orientation rather than responses to the Arab Spring itself.

5.4.2 Media Narrative Response to the Arab Spring

To examine how media narratives about China respond to the Arab Spring, we define a post-event indicator $Post_t$ equal to one for all months from January 2011 onward. We estimate the following difference-in-differences specification at the country–month level:

$$index_{c,t} = \alpha + \beta\,(Post_t \times HighGeoPolitics_c) + \gamma_c + \delta_t + \varepsilon_{c,t}, \tag{7}$$

where $index_{c,t}$ denotes alternative country-level media narrative indices about China, including a China-related attention index and an aggregate sentiment index. Country fixed effects γ_c absorb time-invariant differences in media systems and baseline attitudes toward China, while month fixed effects δ_t capture global shocks common to all countries.

Panel A of Table 5 reports the results from this first-stage analysis across different event windows. We find no statistically significant differential change in media attention to China following the Arab Spring for countries with high geopolitical news exposure. In contrast, we observe a pronounced and persistent decline in aggregate sentiment toward China among these countries. The sentiment effect emerges gradually and becomes statistically significant over longer horizons, consistent with a re-framing of narratives rather than a mechanical reallocation of media coverage.

5.4.3 Capital Flow Response

We next examine whether these differential narrative responses are associated with subsequent changes in cross-border investment. Using fund-level data, we estimate:

$$Flow_{ic,t} = \theta\left(Post_t \times HighGeoPolitics_c\right) + \alpha_i + \alpha_t + X'_{c,t-1}\Phi + \varepsilon_{ic,t}, \tag{8}$$

where $Flow_{ic,t}$ measures fund i's capital flow to Chinese assets in quarter t. The specification includes fund fixed effects α_i, which absorb time-invariant investment mandates and fund characteristics, and quarter fixed effects α_t, which capture global investment conditions. The vector $X_{c,t}$ includes a set of macroeconomic and financial controls same as the baseline specification.

Results reported in Panel B of Table 5 suggest that, following the Arab Spring, funds domiciled in countries with high geopolitical news exposure reduce their investments in Chinese assets significantly more than funds from countries with lower exposure. The divergence in capital flows becomes economically and statistically significant over medium- to long-run horizons, even after controlling for macroeconomic fundamentals and fund-specific factors.

These results suggest that the Arab Spring triggered a global shift in geopolitical narratives that disproportionately affected countries whose media environments are more oriented toward geopolitical reporting. While media attention to China does not change differentially across countries, sentiment toward China deteriorates significantly in high-geopolitical-exposure countries, and this deterioration is accompanied by a relative decline in institutional investment flows into Chinese assets. These findings are consistent with a narrative-based transmission mechanism in which global geopolitical shocks reshape the tone and interpretation of media coverage about China, influencing investor perceptions and portfolio allocation decisions independently of China's underlying economic fundamentals.

6 Asymmetric and Higher-Moment Effects of Media Narratives

Asymmetric Effects of Media Narratives. A large literature documents that news media disproportionately emphasize negative events, exhibiting a systematic bias toward unfavorable reporting (Goidel and Langley, 1995; Damstra and Boukes, 2021; van Binsbergen, Bryzgalova, Mukhopadhyay and Sharma, 2024). At the same time, extensive evidence suggests that individuals tend to react more strongly to negative than to positive information (Holbrook, Krosnick, Visser, Gardner and Cacioppo, 2001; Soroka, 2006). Motivated by these findings, we examine whether cross-border institutional investors respond asymmetrically to positive versus negative media narratives about China. In particular, we ask whether negative narratives exert a stronger influence on portfolio allocation decisions, or whether positive narratives play a more salient role in shaping investment flows given prevailing pessimistic priors about emerging markets.

To distinguish between positive and negative news, we construct two separate indices based on word frequencies.[19] Using the positive and negative word lists from Loughran and McDonald (2011), the positive media narrative index, $pos_{c,t}$, is computed as the frequency of positive words in each article scaled by article length, averaged across all articles within a given media outlet, and then averaged across all outlets within each country. The negative media narrative index, $neg_{c,t}$, is constructed analogously using negative word frequencies.[20]

Panel A of Table 4 reports the results from specifications that jointly include the positive and negative media narrative indices. Consistent with conventional predictions

[19]Similarly, Rey, Stavrakeva and Tang (2024) define two risk news indices, "risk on" and "risk off," to study the relationship between exchange rates and the global network of equity holdings.

[20]As an alternative approach, we construct positive news indices using only articles with positive sentiment scores and negative news indices using only articles with negative sentiment scores. Our results are robust to this alternative construction.

based on negativity bias, we find that negative narratives exert a statistically significant influence on capital flows, whereas positive narratives do not. As shown in column (4), a one standard deviation increase in the negative sentiment index is associated with a 0.69% decline in quarterly fund flows into Chinese assets, while the estimated effect of the positive sentiment index is small and statistically insignificant. These results indicate that adverse media narratives play a dominant role in shaping cross-border institutional investment decisions.

This asymmetry is consistent with the idea that negative news carries greater salience in investors' information processing, particularly in cross-border settings characterized by uncertainty and limited transparency. In an environment where media coverage already exhibits a structural bias toward adverse events, negative narratives may amplify downside concerns and trigger portfolio reallocation away from Chinese assets. By contrast, positive narratives appear insufficient to offset entrenched negative perceptions, suggesting that downside information is more influential than upside signals in driving international portfolio flows.

Higher Moment Effects of Media Narratives. Hassan, Hollander, Van Lent and Tahoun (2019) argue that changes in sentiment reflect shifts in expected average outcomes, corresponding to the first moment of the distribution, whereas changes in risk capture variation or uncertainty around those outcomes, corresponding to the second moment. To examine higher moment effects of media narratives, we follow the approach in Hassan, Hollander, Van Lent and Tahoun (2019) and construct a risk index, denoted by $risk_{c,t}$ for investors domiciled in country c in month t. The detailed construction of this index is described in Appendix B. This risk index captures country specific perceptions of uncertainty about China as reflected in each country's media coverage.

As shown in Panel B of Table 4 column (8), after controlling for cross country macroeconomic and financial fundamentals, a one standard deviation increase in the risk perception index is associated with a 0.66% quarterly decline in fund flows into Chinese assets. This result indicates that heightened perceived risk conveyed by media in investors' domicile countries has a statistically and economically meaningful negative effect on cross border investment flows.

7 Conclusion

This paper studies how media narratives about a common foreign economy differ across investor countries and how such differences shape international capital allocation. Using a large corpus of newspapers from multiple investor countries, we construct novel measures of media attention and sentiment toward China and document substantial, persistent cross-country dispersion in media sentiment, even when outlets cover the same underlying events. These findings demonstrate that narratives about a foreign economy are not global or uniform, but instead reflect country-specific framing and interpretation.

A central contribution of the paper is to unpack the sources of this narrative disagreement. By decomposing aggregate sentiment into topic attention and within-topic sentiment, we show that nearly all cross-country variation in sentiment is driven by differences in interpretation rather than differences in what countries choose to cover. Further decompositions reveal that narrative disagreement reflects both slow-moving country-specific priors and heterogeneous responses to new information, with their relative importance varying across topics. Taken together, these results provide direct evidence that investors in different countries interpret the same foreign economy through distinct narrative lenses.

We then link narrative disagreement to behavior by showing that domestic media sentiment toward China predicts cross-border portfolio flows, even after controlling for fundamentals and global financial conditions. This evidence highlights domestic media narratives as a distinct channel shaping belief formation and international portfolio choice, complementing existing work that treats information frictions as latent or proxied by distance, institutions, or familiarity. More broadly, our findings suggest that disagreement in international finance is not solely the result of differential information access, but also reflects systematic differences in how common information is framed and interpreted by domestic information intermediaries.

Our results open several avenues for future research. First, media-based measures of narrative disagreement could be used to study cross-country differences in reactions to global shocks, policy announcements, or geopolitical events. Second, extending the analysis to other destination economies would shed light on whether narrative disagreement is more pronounced in environments characterized by opacity or policy uncertainty. Finally, linking media narratives to asset prices and risk premia across borders would further illuminate the role of belief formation in global financial markets. Overall, this paper shows that understanding international capital flows requires not only measuring fundamentals, but also accounting for the narratives through which investors interpret them.

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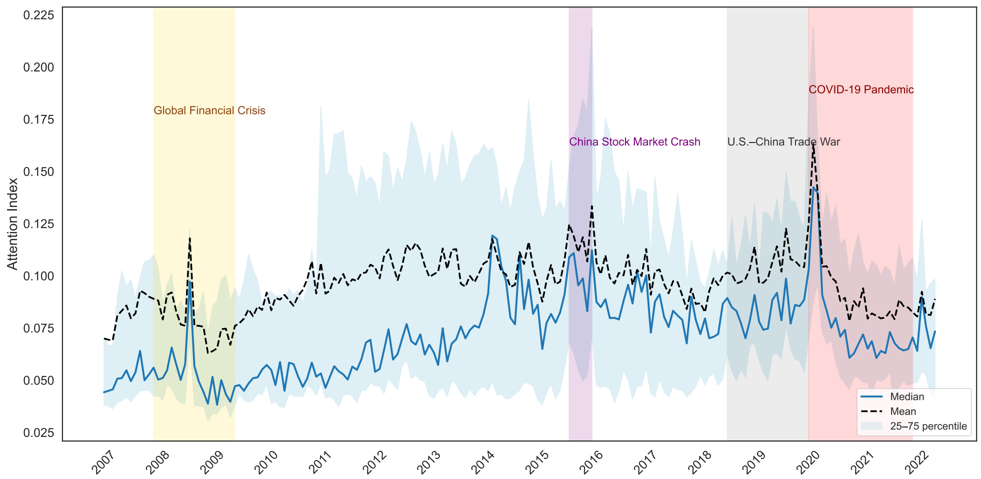
Figures and Tables

(a) Attention index



(b) Sentiment index

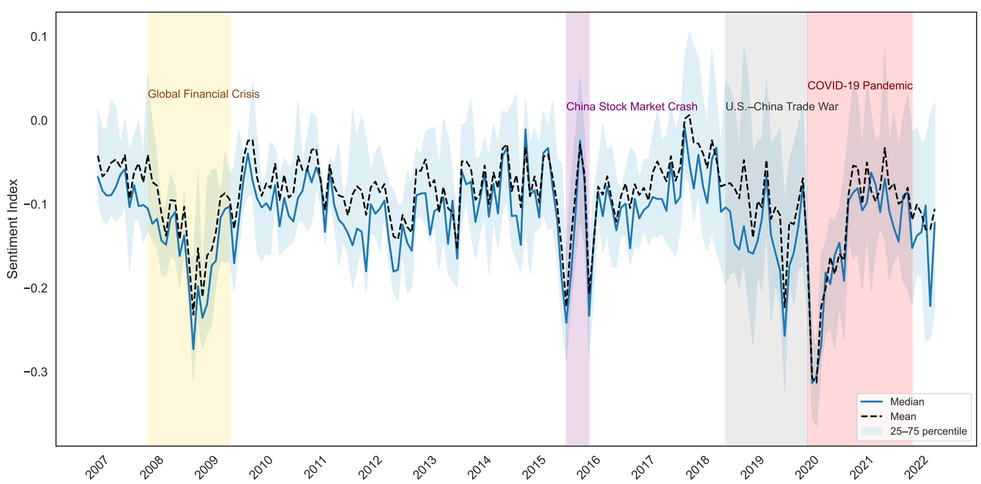
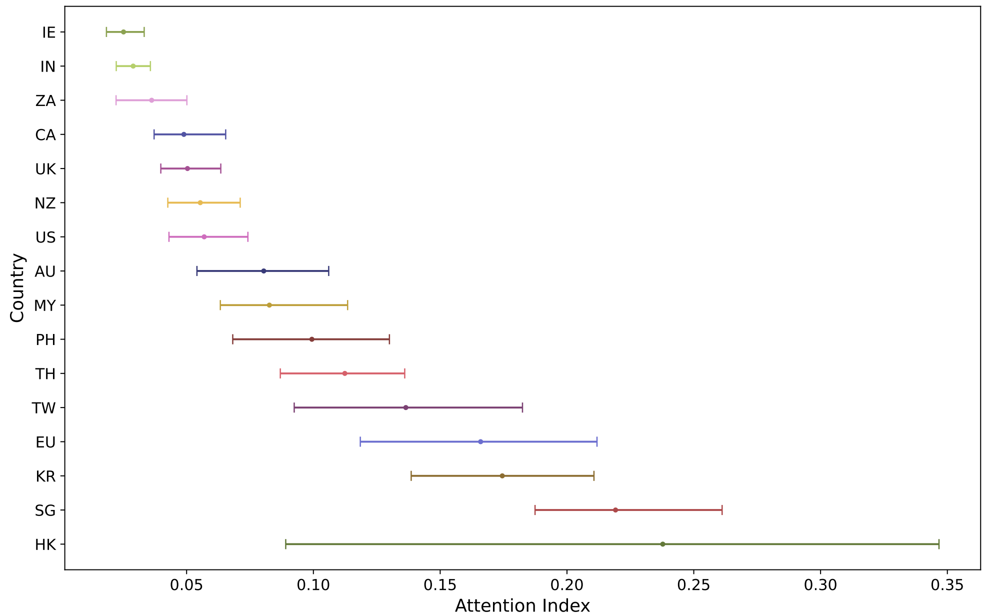


Figure 1: China Attention and Sentiment Indices

Notes: This figure plots the cross-country distribution of (a) the attention index and (b) the sentiment index for China over the period 2007–2022, constructed using the methodology described in Section 2. The black dashed line shows the cross-country mean, the solid blue line shows the median, and the shaded blue band represents the interquartile range (25th–75th%iles).

(a) Attention index



(b) Sentiment index

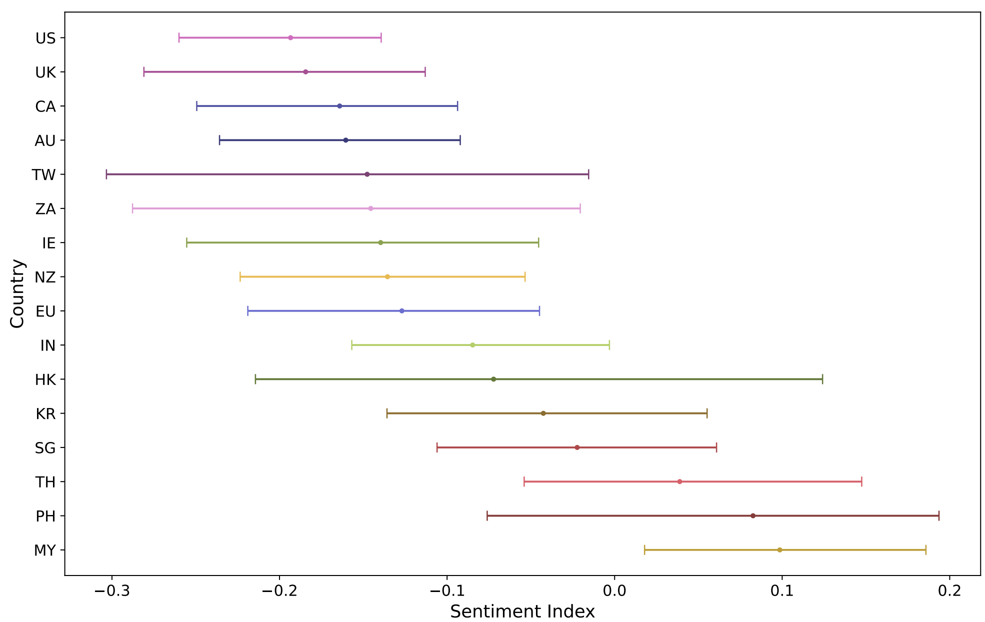
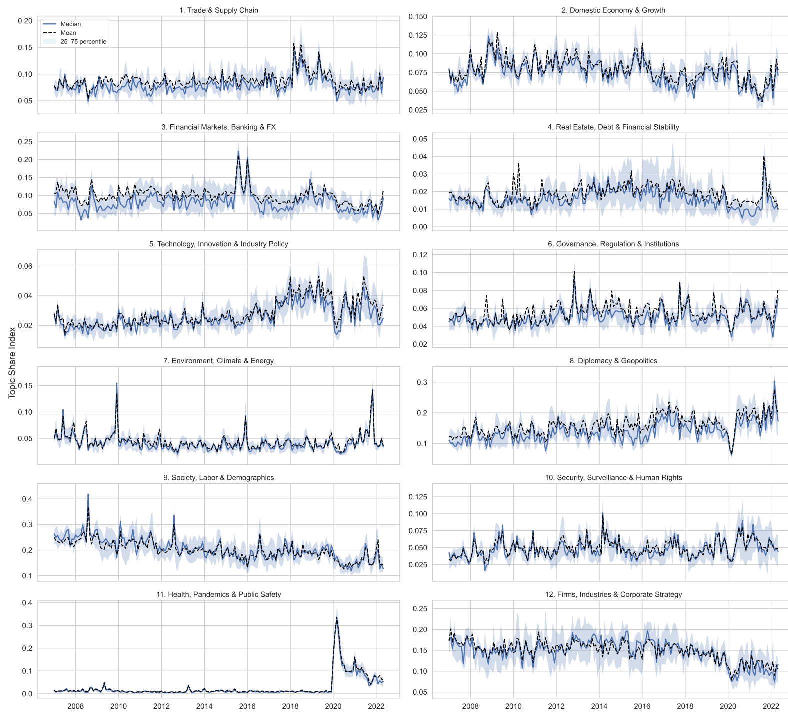


Figure 2: Cross-country 90th percentile ranges by index type

Notes: This figure illustrates the average cross-country dispersion in media narratives about China over the period 2007–2022. For each country in the sample, we plot the 90-th percentile range, defined as the difference between the 5th and 95th%iles, of (a) the China-related attention index and (b) the China-related sentiment index, averaged over the sample period. All indices are constructed using the methodology described in Section 2.

(a) Topic share index



(b) Topic sentiment index

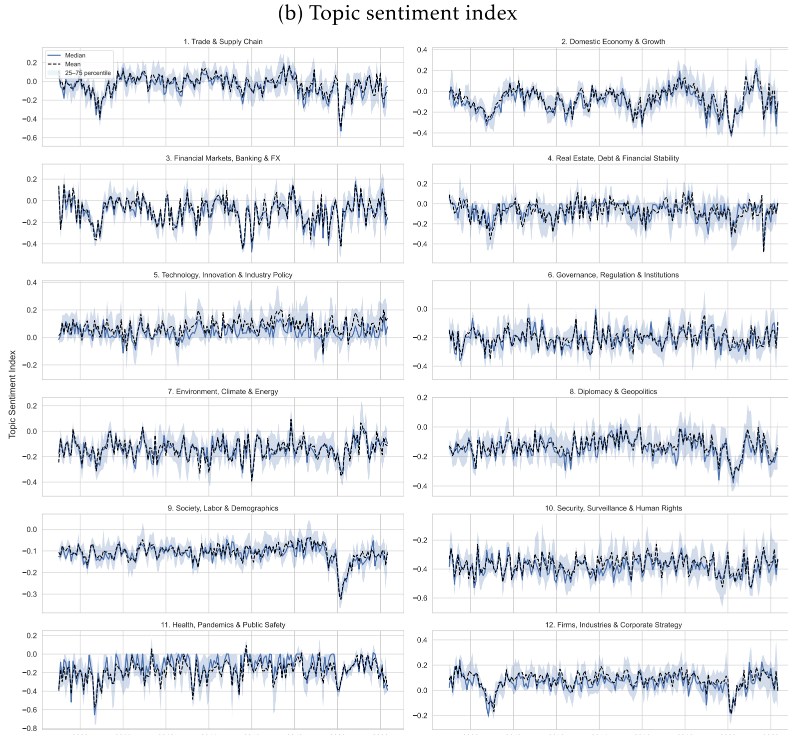
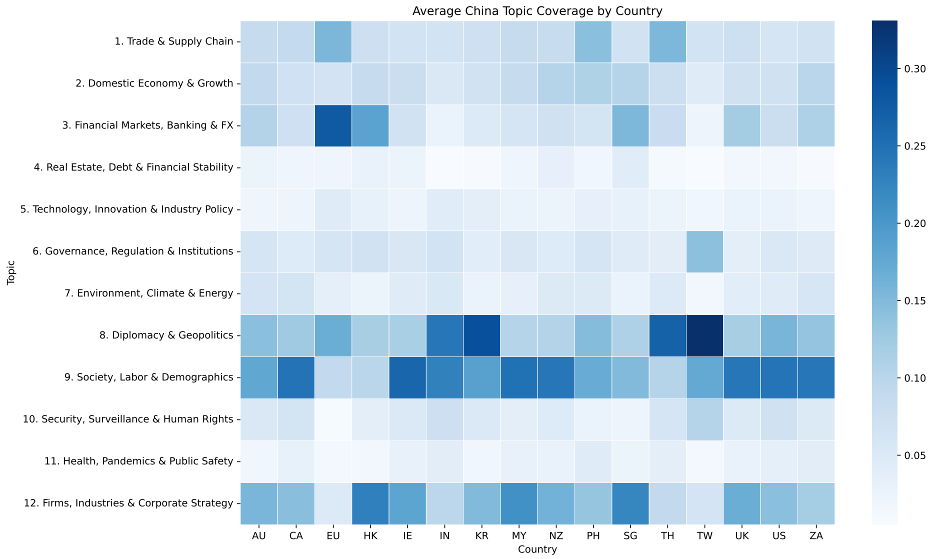


Figure 3: Topic Share and Sentiment Indices

Notes: This figure plots the cross-country distribution of (a) the topic share index and (b) the topic sentiment index for China over the period 2007–2022, constructed using the methodology described in Section 2. The black dashed line shows the cross-country mean, the solid blue line shows the median, and the shaded blue band represents the interquartile range (25th–75th%iles).

(a) Average Topic Share Index



(b) Average Topic Sentiment Index

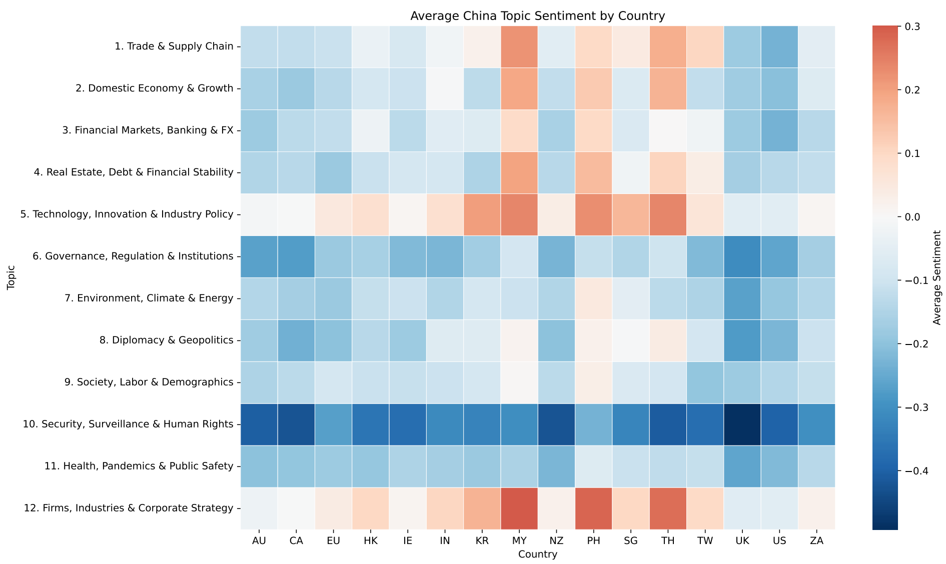


Figure 4: Average Topic Share and Sentiment by Country

Notes: This figure plots (a) the average topic share index and (b) the average topic sentiment index by country (horizontal axis) and topic (vertical axis) over the full sample period, constructed using the methodology described in Section 2. In panel (a), darker shading indicates a higher relative share of reporting devoted to each topic within all China-related news articles. In panel (b), red shading reflects more positive sentiment and blue shading reflects more negative sentiment, with darker colors indicating stronger sentiment intensity in either direction.

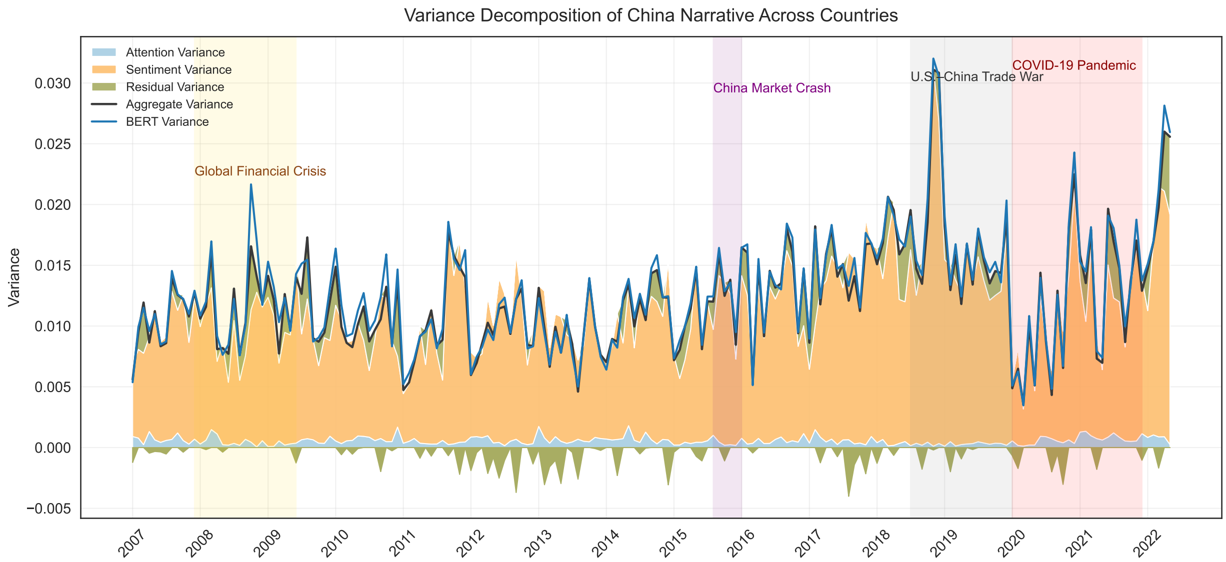
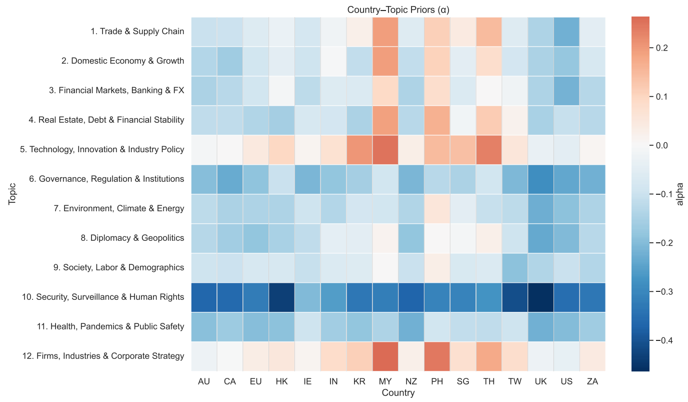


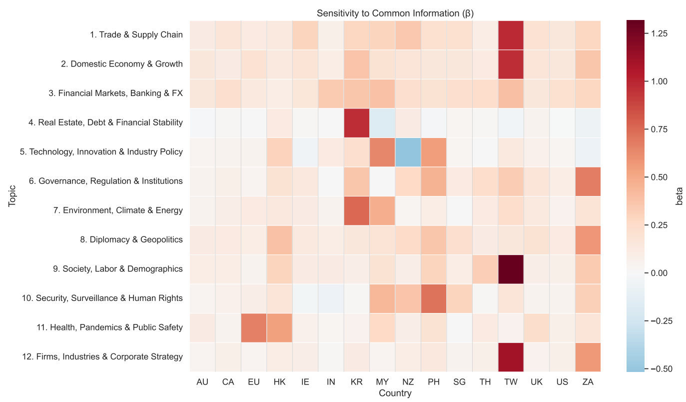
Figure 5: Variance Decomposition of China Narratives Across Countries

Notes: This figure reports a variance decomposition of cross country dispersion in aggregate media sentiment toward China. For each month, aggregate sentiment is constructed as a weighted average of topic level sentiment, where the weights reflect the allocation of media attention across topics in each country. The solid line shows the total cross country variance of aggregate sentiment. The shaded areas decompose this variance into three components. The attention component captures variation arising from cross country differences in topic coverage, holding sentiment within each topic fixed at its cross country average. The sentiment component captures variation arising from cross country differences in sentiment conditional on topic, holding topic attention fixed at its cross country average. The residual component reflects the interaction between topic attention and within topic sentiment. All variances are computed across countries at a monthly frequency over the period from 2007 to 2022. A detailed description of the methodology is provided in Section 4.1.

(a) Country-Topic Priors (α_c^k)



(b) Sensitivity to Common Information (β_c^k)



(c) Narrative Persistence (ρ_c^k)

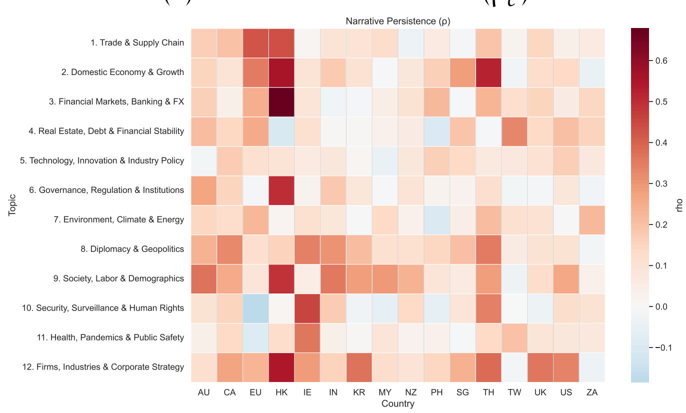


Figure 6: Average Country-Topic Priors, Sensitivity, and Persistence

Notes: This figure plots the $\hat{\alpha}_c^k$ (a), $\hat{\rho}_c^k$ (b), $\hat{\beta}_c^k$ (c) estimated using equation (2) by each country and topic. $\hat{\alpha}_c^k$ captures the country c's prior about that the topic k. $\hat{\rho}_c^k$ captures narrative persistence arising from editorial inertia, slow belief updating, or institutional continuity in media coverage. The sensitivity parameter $\hat{\beta}_c^k$ measures how strongly country c's media narrative responds to common information about China on topic k.

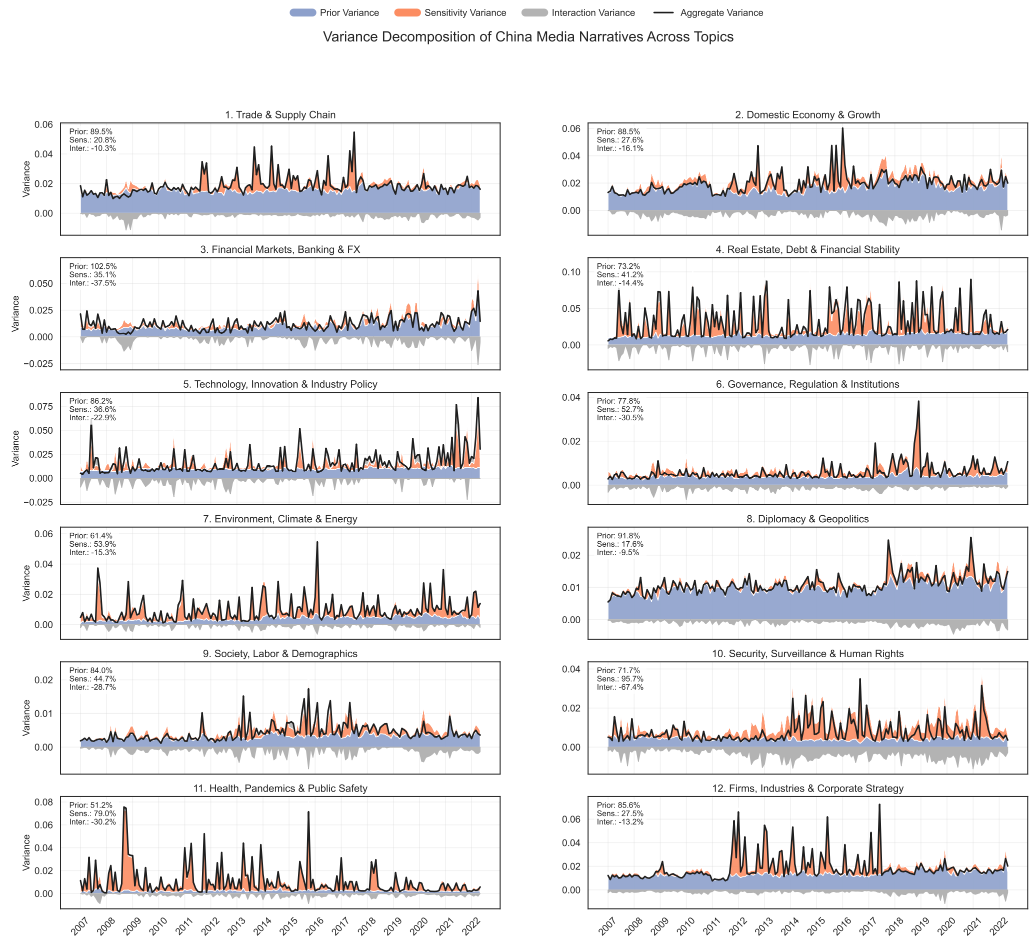


Figure 7: Prior-Sensitivity Variance Decomposition of Topic Sentiment Index

Notes: This figure presents a variance decomposition of cross-country dispersion in media sentiment toward China across twelve topic categories as documented in Section 4.2. For each topic, the figure plots the time series of cross-sectional variance in fitted narrative sentiment and decomposes it into three components: variance attributable to persistent country-specific baseline framing (priors), variance attributable to heterogeneous responses to common topic-level information (sensitivities), and a residual interaction component reflecting covariance between these two channels. Colored areas represent the contributions of priors, sensitivities, and their interaction, while the black line traces total cross-country variance. Reported%ages summarize the average share of total variance explained by each component over the sample period.

Table 1: Summary statistics

Panel A: Narrative indices								
	mean	**sd**	**p5**	**p25**	**p50**	**p75**	**p95**	**count**
(1) Aggregate-level Index:								
$num_{c,t}$	0.10	0.07	0.02	0.04	0.07	0.14	0.24	2587
$sen_{c,t}$	-0.09	0.12	-0.27	-0.17	-0.11	-0.02	0.14	2587
$sen^{bag}_{c,t}$ (×100)	-0.96	0.42	-1.63	-1.23	-0.96	-0.70	-0.23	2587
$risk_{c,t}$ (×100)	0.16	0.04	0.09	0.13	0.15	0.18	0.23	2587
$pos_{c,t}$	0.01	0.00	0.01	0.01	0.01	0.01	0.01	2587
$neg_{c,t}$	0.02	0.00	0.01	0.02	0.02	0.02	0.02	2587
(2) Topic-level Index: Topic Share Index ($share^k_{c,t}$):								
1.Trade & Supply Chain	0.09	0.04	0.04	0.06	0.08	0.11	0.17	2587
2.Domestic Economy & Growth	0.08	0.04	0.03	0.06	0.08	0.10	0.14	2587
3.Financial Markets, Banking & FX	0.10	0.08	0.02	0.04	0.08	0.13	0.27	2587
4.Real Estate, Debt & Financial Stability	0.02	0.02	0.00	0.01	0.02	0.03	0.05	2587
5.Technology, Innovation & Industry Policy	0.03	0.02	0.01	0.02	0.03	0.04	0.06	2587
6.Governance, Regulation & Institutions	0.05	0.03	0.02	0.04	0.05	0.06	0.11	2587
7.Environment, Climate & Energy	0.04	0.03	0.01	0.02	0.04	0.06	0.09	2587
8.Diplomacy & Geopolitics	0.16	0.09	0.06	0.10	0.14	0.20	0.34	2587
9.Society, Labor & Demographics	0.20	0.08	0.07	0.14	0.20	0.25	0.33	2587
10.Security, Surveillance & Human Rights	0.05	0.03	0.01	0.03	0.05	0.07	0.10	2587
11.Health, Pandemics & Public Safety	0.03	0.05	0.00	0.00	0.01	0.02	0.13	2587
12.Firms, Industries & Corporate Strategy	0.15	0.07	0.04	0.10	0.15	0.19	0.27	2587
(3) Topic-level Index: Topic sentiment Index ($sen^k_{c,t}$):								
1.Trade & Supply Chain	-0.03	0.25	-0.41	-0.20	-0.03	0.12	0.37	2609
2.Domestic Economy & Growth	-0.07	0.25	-0.44	-0.23	-0.09	0.06	0.37	2609
3.Financial Markets, Banking & FX	-0.09	0.27	-0.50	-0.25	-0.10	0.04	0.38	2609
4.Real Estate, Debt & Financial Stability	-0.08	0.31	-0.56	-0.24	-0.05	0.04	0.46	2609
5.Technology, Innovation & Industry Policy	0.08	0.22	-0.23	-0.03	0.03	0.19	0.47	2609
6.Governance, Regulation & Institutions	-0.20	0.18	-0.48	-0.31	-0.21	-0.09	0.08	2609
7.Environment, Climate & Energy	-0.14	0.23	-0.48	-0.27	-0.14	0.00	0.23	2609
8.Diplomacy & Geopolitics	-0.13	0.17	-0.38	-0.25	-0.14	-0.01	0.15	2609
9.Society, Labor & Demographics	-0.11	0.11	-0.29	-0.17	-0.11	-0.05	0.08	2609
10.Security, Surveillance & Human Rights	-0.37	0.20	-0.67	-0.49	-0.39	-0.26	0.00	2609
11.Health, Pandemics & Public Safety	-0.18	0.29	-0.74	-0.33	-0.13	0.00	0.22	2609
12.Firms, Industries & Corporate Strategy	0.08	0.19	-0.18	-0.03	0.06	0.19	0.41	2609

Panel B: Other Variables								
	mean	**sd**	**p5**	**p25**	**p50**	**p75**	**p95**	**count**
Ret_t	0.00	0.08	-0.13	-0.04	0.00	0.04	0.13	185
Vol_t	0.02	0.01	0.01	0.01	0.01	0.02	0.03	185
$Flow_{ic,t}$	7.36	49.19	-32.56	-4.67	0.00	6.92	58.62	344253
$Growthdiff_{c,t}$	5.08	4.66	-1.23	2.83	4.75	7.30	12.52	915
$EX_{c,t}$	3.34	3.37	0.01	0.21	1.85	5.90	9.45	915
$Intdiff_{c,t}$	0.72	2.88	-5.09	-0.80	0.97	2.74	5.13	903
$Retdiff_{c,t}$	0.00	0.04	-0.07	-0.03	0.00	0.02	0.10	915
$Volratio_{c,t}$	1.68	0.76	0.76	1.12	1.53	2.03	3.17	915

Notes: This table reports summary statistics for all variables used in the empirical analysis. All media indices are measured at a monthly frequency and cover the period from January 2007 to May 2022. For each country c and month t, $num_{c,t}$ denotes the news attention index on China, and $sen_{c,t}$ denotes the aggregate media sentiment index on China. The variable $sen^{bag}_{c,t}$ is a sentiment index constructed using the bag of words method, while $risk_{c,t}$ captures country level risk perceptions about China reflected in domestic media coverage. The variables $pos_{c,t}$ and $neg_{c,t}$ measure positive and negative media narratives, respectively. The topic share index $share^k_{c,t}$ characterizes the share of topic k among all China related news covered by media outlets in country c in month t, and $sen^k_{c,t}$ measures the sentiment associated with topic k. Stock return, denoted by Ret_t, is measured as the monthly average of daily returns on the Shanghai Shenzhen CSI 300 index. Stock market volatility, denoted by Vol_t, is computed as the monthly volatility of daily returns on the same index. The variable $Flow_{ic,t}$ represents quarterly investment flows of fund i domiciled in country c into Chinese assets, as described in Section 5. The variable $Growthdiff_{c,t}$ is the year over year gross domestic product growth differential between China and the investor's domicile economy. The bilateral exchange rate between the Chinese renminbi and the investor's currency is denoted by $EX_{c,t}$. The variable $Indiff_{c,t}$ measures the interest rate differential between China and the investor's domicile economy. The variable $Retdiff_{c,t}$ captures the stock market return differential between China and the investor's domicile economy, while $Volratio_{c,t}$ denotes the ratio of stock market volatility in China relative to that of the investor's domicile economy. Detailed definitions of all macroeconomic and financial variables are provided in Appendix D.

Table 2: Baseline: media narratives and flows

Dep. Var.:	$Flow_{ic,t}$			
	(1)	(2)	(3)	(4)
$sen_{c,t-1}$	1.042***	1.047***	0.977***	0.955***
	(0.245)	(0.245)	(0.247)	(0.247)
$num_{c,t-1}$	0.210	0.141	0.270	0.216
	(0.258)	(0.259)	(0.257)	(0.258)
$Growthdiff_{c,t-1}$		0.039		0.026
		(0.060)		(0.061)
$EX_{c,t-1}$		-1.535***		-1.735***
		(0.321)		(0.328)
$Intdiff_{c,t-1}$		-0.339		-0.414
		(0.222)		(0.227)
$Retdiff_{c,t-1}$			22.560*	26.051**
			(9.857)	(9.924)
$Volratio_{t-1}$			0.862*	1.345**
			(0.407)	(0.419)
$Constant$	7.405***	19.087***	6.159***	18.845***
	(0.064)	(2.676)	(0.601)	(2.671)
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.055	0.055	0.055	0.055
N	307603	307541	307603	307541

Notes: This table reports results from equation (6) estimated at the fund-quarter level over the period 2007Q1-2022Q1 for a sample of funds domiciled in 16 countries. The dependent variable is the%age change in the flow of institutional investors' investments in China. The main independent variable is the sentiment index, which is standardized for each country. Columns (2) and (4) include a set of macroeconomic controls that may influence cross-border flows: the year-on-year real GDP growth differential between China and the investor's domicile economy, the bilateral exchange rate between the Chinese renminbi and the currency of the investor's domicile country, and the interest rate differential between China and the investor's economy. Columns (3) and (4) include a set of financial controls: the return differential between the Chinese stock market and that of the investor's domicile economy, and the volatility ratio of the Chinese stock market and that of the investor's domicile economy, 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 and quarter 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 3: Robustness checks: media narratives and flows

Panel A: Bag-of-word media narratives and flows				
Dep. Var.:	$Flow_{ic,t}$			
	(1)	(2)	(3)	(4)
$sen^{bag}_{c,t-1}$	0.945***	0.963***	0.913***	0.933***
	(0.260)	(0.260)	(0.261)	(0.261)
$num_{c,t-1}$	0.122	0.065	0.206	0.170
	(0.250)	(0.252)	(0.249)	(0.252)
Macro Controls	No	Yes	No	Yes
Financial Controls	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.055	0.055	0.055	0.055
N	307603	307541	307603	307541
Panel B: Cross-language media narratives and flows				
Dep. Var.:	$Flow_{ic,t}$			
	(5)	(6)	(7)	(8)
$csen_{c,t-1}$	0.027	0.817**	0.803**	0.746**
	(0.216)	(0.250)	(0.252)	(0.251)
$cnum_{c,t-1}$	-0.016	0.141	0.253	0.199
	(0.231)	(0.264)	(0.262)	(0.263)
Macro Controls	No	Yes	No	Yes
Financial Controls	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.055	0.057	0.057	0.057
N	314009	278263	278325	278263
Panel C: Media narrative shocks and flows				
Dep. Var.:	$Flow_{ic,t}$			
	(9)	(10)	(11)	(12)
$senshock_{c,t-1}$	1.574***	1.474***	1.579***	1.470***
	(0.311)	(0.314)	(0.313)	(0.315)
$num_{c,t-1}$	0.008	-0.050	0.092	0.050
	(0.248)	(0.250)	(0.247)	(0.249)
Macro Controls	No	Yes	No	Yes
Financial Controls	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.054	0.054	0.054	0.054
N	306347	306285	306347	306285

Notes: This table reports estimates of equation (6) using fund quarter level data over the period from 2007Q1 to 2022Q1 for a sample of institutional funds domiciled in 16 countries. The dependent variable is the%age change in institutional investors' investment flows into Chinese assets. The main independent variable is the media narrative sentiment measure, constructed using the bag of words method in Panel A as described in Section 5.1, the cross language media sentiment index in Panel B as described in Section 5.2, and media narrative shocks in Panel C as described in Section 5.3. Columns (2), (4), (6), (8), (10), and (12) include a set of macroeconomic controls that may influence cross border investment flows. These controls include the year on year real gross domestic product growth differential between China and the investor's domicile economy, the bilateral exchange rate between the Chinese renminbi and the currency of the investor's domicile country, and the interest rate differential between China and the investor's economy. Columns (3), (4), (7), (8), (11), and (12) additionally include financial controls, namely the stock market return differential between China and the investor's domicile economy and the ratio of stock market volatility in China relative to that of the investor's domicile economy, measured using the volatility of the Shanghai Shenzhen CSI 300 index. All independent variables are lagged by one quarter. All specifications include fund fixed effects and quarter fixed effects. Standard errors are clustered at the fund level and reported in parentheses. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Table 4: Asymmetric and higher-moment effects of media narratives on capital flows

Panel A: Asymmetric effects of media sentiment on flows				
Dep. Var.:	$Flow_{ic,t}$			
	(1)	(2)	(3)	(4)
$pos_{c,t-1}$	0.290	0.346	0.345	0.422
	(0.211)	(0.219)	(0.212)	(0.219)
$neg_{c,t-1}$	-0.775**	-0.770**	-0.712**	-0.694**
	(0.252)	(0.255)	(0.253)	(0.256)
$num_{c,t-1}$	0.133	0.082	0.223	0.195
	(0.250)	(0.253)	(0.250)	(0.253)
Macro Controls	No	Yes	No	Yes
Financial Controls	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.055	0.055	0.055	0.055
N	307603	307541	307603	307541
Panel B: Second-moment (risk) effects of media narratives on flows				
Dep. Var.:	$Flow_{ic,t}$			
	(5)	(6)	(7)	(8)
$risk_{c,t-1}$	-0.817**	-0.667**	-0.825**	-0.659**
	(0.251)	(0.250)	(0.251)	(0.250)
$num_{c,t-1}$	0.194	0.084	0.290	0.192
	(0.262)	(0.261)	(0.261)	(0.261)
Macro Controls	No	Yes	No	Yes
Financial Controls	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Adj. R^2	0.055	0.055	0.055	0.055
N	307603	307541	307603	307541

Notes: This table reports estimates of equation (6) using fund quarter level data over the period from 2007Q1 to 2022Q1 for a sample of institutional funds domiciled in 16 countries. The main independent variables are the positive and negative media sentiment indices in Panel and the media risk index in Panel B, as described in Section 6. The positive index, negative index, and risk index are standardized within each country. Columns (2), (4), (6), and (8) include a set of macroeconomic controls that may affect cross border investment flows. These controls include the year on year real gross domestic product growth differential between China and the investor's domicile economy, the bilateral exchange rate between the Chinese renminbi and the currency of the investor's domicile country, and the interest rate differential between China and the investor's economy. Columns (3), (4), (7), and (8) additionally include financial controls, namely the stock market return differential between China and the investor's domicile economy and the ratio of stock market volatility in China relative to that of the investor's domicile economy, measured using the volatility of the Shanghai Shenzhen CSI 300 index. All independent variables are lagged by one quarter. All specifications include fund fixed effects and quarter fixed effects. Standard errors are clustered at the fund level and reported in parentheses. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Table 5: Media narratives and capital flows following the Arab Spring

Panel A: Stage 1 : Media Narrative Changes following Arab Spring					
(a) Attention Index:					
Dep. Var.:			$num_{c,t}$		
Event Window:	12m	18m	24m	30m	36m
	(1)	(2)	(3)	(4)	(5)
$Post \times HighGeoPolitics$	-0.003	0.003	0.009	0.014	0.012
	(0.006)	(0.005)	(0.007)	(0.011)	(0.010)
Country FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.982	0.978	0.964	0.949	0.943
N	336	504	668	820	971
(b) Sentiment index:					
Dep. Var.:			$sen_{c,t}$		
Event Window:	12m	18m	24m	30m	36m
	(6)	(7)	(8)	(9)	(10)
$Post \times HighGeoPolitics$	-0.037*	-0.047**	-0.040**	-0.034***	-0.034**
	(0.016)	(0.015)	(0.010)	(0.007)	(0.008)
Country FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.757	0.770	0.774	0.764	0.752
N	336	504	668	820	971
Panel B: Stage 2: Fund Flow Changes following Arab Spring					
Dep. Var.:			$Flow_{ic,t}$		
Event Window:	4q	6q	8q	10q	12q
	(11)	(12)	(13)	(14)	(15)
$Post \times HighGeoPolitics$	-6.103***	-5.090***	-4.782***	-3.851***	-4.030***
	(1.589)	(1.330)	(1.209)	(1.154)	(1.113)
Fund FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Macro & Financial Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.074	0.069	0.067	0.069	0.064
N	32434	46084	58694	71042	83492

Notes: This table reports results from an event study analysis that uses the Arab Spring as a global narrative shock, as described in Section 5.4. Panel A examines changes in media attention to China in panel (a) and media sentiment toward China in panel (b) for countries with high geopolitical attention following the Arab Spring event, relative to countries with low geopolitical attention, as specified in equation (7). Panel B examines changes in institutional investment flows for countries with high media sentiment exposure relative to countries with low exposure, as specified in equation (8). Each column corresponds to a different event window before and after the Arab Spring event. Standard errors are clustered at the country level in Panel A and at the fund level in Panel B, and are reported in parentheses. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% 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	
EU	EMU	Financial Times	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 Times	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 30, 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	
UK	U.K.	Financial Times	Jan 01, 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.

Table A2: Media List (Non-English Newspapers)

Region abbr	Region	Source	Date	Langrage	Keyword
DE	Germany	Die Tageszeitung	Aug 5, 2008-May 31, 2022	German	China
DE	Germany	Die Welt	Nov 1, 2009-May 31, 2022	German	China
DE	Germany	Welt am Sonntag	Jan 6, 2008-May 31, 2022	German	China
FR	France	Le Monde	Jan 1, 2007-May 31, 2022	French	Chine
ES	Spain	El Pais	July 28, 2008-May 31, 2022	Spanish	China
CH	Switzerland	Le Temps	Sep 22, 2010-May 31, 2022	French	Chine
AT	Austria	Die Presse	May 28,2011-May 31, 2022	German	China

Notes: This table shows the list of newspapers in each country used to construct all media indices in language other than English.

B Additional Indices

For each media outlet, we conduct a textual analysis to compile the raw data used for the following indices, 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.(6) The total count of risk-related words in each article ($risksum_{im,d}$) using the risk word list in Hassan, Hollander, Van Lent and Tahoun (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.

Bag-of-word Method Sentiment Index. We follow the similar methodology of Flynn and Sastry (2024) and Hassan, Hollander, Van Lent and Tahoun (2019) to construct the sentiment index ($sen^{bag}_{c,t}$) for investors domiciled in country c at quarter t, which serves as one of our key measures of media narratives at the intensive margin. For each article, we first calculate sentiment as the difference between the number of positive words ($possum_{im,d}$) and the number of negative words ($negsum_{im,d}$), scaled by the total number of words in the article ($totalwords_{im,d}$) to control for differences in article length. We then compute the average article sentiment for each media outlet in each month. Finally, the country-level sentiment index is obtained by averaging these media-level sentiment measures across all outlets within each country.

Risk Index. We follow the approach in Hassan, Hollander, Van Lent and Tahoun (2019) to construct the risk index ($risk_{c,t}$) for investors domiciled in country c at month t. For each article, we compute the share of risk-related words by dividing the total number of risk words ($risksum_{im,d}$) by the total word count of the article ($totalwords_{im,d}$), which adjusts for differences in article length. We then take the monthly average of these risk shares within each media outlet. The country-level risk index is constructed by aggregating these outlet-level averages across all newspapers within a country.

C Cross-Language FinBERT Model Selection

This appendix summarizes the model-selection criteria used in our multilingual FinBERT sentiment analysis pipeline. For each language, we review available FinBERT-style transformer models and document the final package adopted in our analysis. We focus on conceptual strengths and limitations of each model without presenting sentence-level comparisons or numerical evaluation results. All selected packages follow the standard three-way polarity structure (`positive`, `neutral`, `negative`), ensuring consistency across languages.

C.1 English

Selected Package: `ProsusAI/finbert`

Among multiple English-language FinBERT variants, we adopt `ProsusAI/finbert` as the primary sentiment engine in our pipeline. The model is fine-tuned on a large corpus of financial documents, allowing it to capture tone in macroeconomic policy discussions, corporate disclosures, and market commentary. Compared with alternative packages, it produces better-calibrated confidence distributions and avoids overly sharp classifications.

A further advantage is its compatibility with multilingual sentiment workflows: its labeling structure aligns closely with FinBERT-style models in other languages. A potential limitation is that its sensitivity to environmental or policy-oriented sentiment can be weaker than that of some non-English domain-specific models, reflecting the narrower scope of its fine-tuning data.

C.2 German

Selected Package: `Scherrmann/GermanFinBERT`

For German financial sentiment classification, we select `Scherrmann/GermanFinBERT`. This model is explicitly trained on German financial disclosures, earnings reports, and economic news, enabling it to accurately detect tone in both firm-level and macroeconomic statements. It distinguishes nuanced sentiment shifts—particularly in ambiguous or mixed-tone contexts—more effectively than general-purpose German sentiment models.

The model's native German labels (`Positiv`, `Neutral`, `Negativ`) map cleanly into the FinBERT framework used across languages. Its primary limitation is conservative treatment of non-financial domains such as political or environmental reporting, for which it sometimes assigns more neutral sentiment than expected.

C.3 French

Selected Package: `bardsai/finance-sentiment-fr-base`

For French-language analysis, we adopt the financial-domain model `bardsai/finance-sentiment-fr-base`. This DistilCamemBERT-based transformer is fine-tuned on labeled French financial sentences, allowing it to reliably classify tone in earnings releases, policy announcements, and macroeconomic commentary. It also generalizes well to adjacent domains relevant for financial research, such as regulatory developments and environmental reporting.

The model retains the standard FinBERT polarity scheme, ensuring comparability with other languages in our pipeline. As a distilled model, it may capture fewer subtle linguistic nuances than a full CamemBERT-based architecture, but its efficiency and stability make it well-suited for large-scale text processing.

C.4 Spanish

Selected Package: `bardsai/finance-sentiment-es-base`

For Spanish financial sentiment classification, we select `bardsai/finance-sentiment-es-base`. Unlike general-purpose Spanish sentiment models, this package is fine-tuned specifically on financial text, yielding greater sensitivity to credit risk language, earnings-related tone, fiscal and monetary policy narratives, and broader macro-financial developments.

The model also performs consistently in political or environmental contexts when such narratives influence financial markets. Its FinBERT-compatible labeling scheme facilitates seamless integration into the multilingual pipeline. A potential limitation is that it may underperform general-purpose models in highly colloquial or conversational text, although such cases are not central to financial analysis.

In summary, the selected models share key advantages: strong financial-domain alignment, well-calibrated sentiment distinctions, and consistent polarity structures across languages. Together, they provide a unified multilingual FinBERT framework for cross-country sentiment analysis in financial research.

D Variable Definitions

Table A3 shows the definitions and source of variables used in equation (6).

Table A3: Variable definitions

Variable	**Def**	**Source**
$Growthdiff_{c,t}$	GDP growth difference between China and invstero domicle country, where GDP is the real quarterly GDP growth on a year-to-year basis	CEIC
$EX_{c,t}$	The exchange rate between the Chinese renminbi and the investor's domicile currency, expressed as the number of renminbi required to purchase one unit of the domicile country's currency.	Bloomberg
$Intdiff_{c,t}$	Interest rate differential between China and the fund domicile country, which is constructed using short-term interest rates from the *OECD*. In cases where a country's short-term interest rates are unavailable, we substitute with the lending interest rate difference from the *IMF*. If both sets of rates are missing, we default to using China's short-term interest rates.	OECD, IMF International Financial Statistics (IFS)
$Retdiff_{c,t}$	The stock market return differential is defined as the difference between China's stock market return and that of the investor's domicile country. China's stock market return is measured as the quarterly average of monthly returns on the Shanghai Shenzhen CSI 300 index. The indices used to calculate stock returns for the investor's domicile countries are listed in Table A4.	Bloomberg
$Volratio_{c,t}$	Stock market volatility ratio is defined as the ratio of China's stock market volatility to that of the investor's domicile country. China's stock market volatility is measured as the quarterly average of the monthly volatility of daily returns on the Shanghai Shenzhen CSI 300 index. For the investor's domicile countries, the stock indices used to calculate volatility are listed in Table A4.	Bloomberg

Notes: This table shows the definitions and source of variables used in equation (6).

Table A4: Variable definitions: Bloomberg tickers

Country Code	Index Name	Bloomberg Ticker	Currency Name	Bloomberg Ticker
AU	S&P/ASX 200	AS51	Australian Dollar	AUDCNY
CA	S&P/TSX Composite Index	SPTSX	Canadian Dollar	CADCNY
UK	FTSE All-Share Index	ASX	British Pound	GBPCNY
HK	Hang Seng Index	HSI	Hong Kong Dollar	HKDCNY
Eurozone	Euro Stoxx 50	SX5E	Euro	EURCNY
IN	Nifty 50	NIFTY	Indian Rupee	INRCNY
KR	KOSPI Composite Index	KOSPI	South Korean Won	KRWCNY
MY	FTSE Bursa Malaysia KLCI	FBMKLCI	Malaysian Ringgit	MYRCNY
NZ	S&P/NZX 50 Index	NZSE50FG	New Zealand Dollar	NZDCNY
PH	PSEi (Philippine Stock Exchange Index)	PCOMP	Philippine Peso	PHPCNY
SG	Straits Times Index (STI)	STI	Singapore Dollar	SGDCNY
TH	SET Index	SET	Thai Baht	THBCNY
TW	TAIEX (Taiwan Capitalization Weighted Index)	TWSE	Taiwan Dollar	TWDCNY
US	S&P 500	SPX	US Dollar	USDCNY
ZA	FTSE/JSE All Share Index	JALSH	South African Rand	ZARCNY

Notes: This table lists the Bloomberg tickers for the variables described in Table A3.

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   GDP, inflation, consumption, investment, unemployment, industrial output,
   macroeconomic performance, stimulus.

3. Financial Markets, Banking \& FX
   Stocks, bonds, currencies, interest rates, central banks, monetary policy,
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   capital flows, banking.

4. Real Estate, Debt \& Financial Stability
   Property markets, mortgages, developers, credit risks, financial fragility.

5. Technology, Innovation \& Industry Policy
   Tech companies, semiconductors, AI, telecom, industrial upgrading, automation,
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   Government policy, regulations, administrative actions, leadership decisions,
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