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Portrayals of Chinese companies in American and British economic news tweets during China's macroeconomic transitions 2007–2023

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This study investigates how Chinese companies are portrayed in American and British economic news tweets, as well as their relationship to Chinese economic fluctuations. The analysis included a corpus of 55,394 tweets (934,155 words) from well-known media outlets between 2007 and 2023. It also incorporated China's quarterly Gross Domestic Product (GDP) and monthly Purchasing Managers' Index (PMI) to contextualise the tweets in terms of their actual economic performance. Using van Dijk's ingroup and outgroup ideologies, this project examined the ideological depiction through sentiments and emotions. RoBERTa-based transformer models were used to analyse sentiments and emotions, whereas Large Language Models (LLMs) were used for evaluative target annotation. Positive and negative sentiments were found to be significantly ($p < 0.01$) correlated with China's macroeconomic indices. The representation of Chinese companies trended between ingroup and outgroup portrayals. Positive sentiment diminished as the economy transitioned from expansion to contraction, while negative sentiment increased. American news tweets were most positive during economic balance and most negative during downturns, while British news tweets were most positive during stability or early recovery and most negative when a downturn was predicted. As the economy shifted from growth to decline, positive sentiment emphasised corporate external opportunities alongside corporate strengths, with both evaluative targets reinforcing ingroup representation. Negative sentiment shifted from corporate weaknesses to contextual threats, both strengthening outgroup representation. Moreover, certain emotions had a significant ($p < 0.0001$) influence on sentiment swings and ideological transitions. These findings emphasise how economic changes and journalistic factors influence the ideological representation of Chinese firms in economic news on social media.

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Introduction

This study examines how the portrayal of China-headquartered companies in economic news tweets varies with changes in China's macroeconomic contexts. Between 2007 and 2023, China's economy experienced rapid growth with intermittent fluctuations. This study investigates how American and British economic news tweets respond to these fluctuations, highlighting the crucial role of Chinese companies in domestic growth and US-UK trade relations. Applying van Dijk's (2018) perspective on the power of sentiments, emotions, and themes in shaping ideologies, this project uses sentiment analysis to identify ideological shifts in the media representation of Chinese firms. Given the growing reliance on social media for news (Hermida and Mellado 2020; Soroka et al. 2018), this project focuses on X (formerly Twitter) that is widely used for economic news dissemination (Strauß et al. 2018).

Sentiments in economic news have been empirically linked to prevailing economic conditions. Because of negative bias, poor domestic economic indicators typically lead to more negative news coverage. However, positive economic trends rarely produce a proportional increase in optimistic news (Fogarty 2005; Lischka 2015; van Dalen et al. 2017). Likewise, Soroka et al. (2018) discerned that increased negative media coverage correlates with higher US unemployment rates. In international economic news, Zhu (2019) found that Chinese stock market indices have a modest but considerable impact on sentiment in news about Chinese companies. This research examines how key Chinese macroeconomic indicators, such as Gross Domestic Product (GDP), influence the sentiment in the social media economic news about Chinese firms. The performance of Chinese companies, which influences the business decisions of public investors, is naturally influenced by the macroeconomic conditions prevailing in China. Consequently, international news media should reflect China's macroeconomic contexts when covering Chinese companies.

In the news on social media, the economic value of news is impacted by user engagement. It encourages interactions between the media and the general audience, thus reinforcing content visibility and web traffic (Degen et al. 2024). To encourage user engagement, journalists typically create emotive or sentiment-driven content to attract different audiences (Al-Rawi 2020; Choi et al. 2021). Therefore, sentiment analysis in the study of news tweets about Chinese firms reveals the tactics used to engage audiences and enhance economic value.

In sum, this study applies sentiment analysis to explore how American and British media portrayed Chinese companies on X during China's economic transitions between 2007 and 2023. Drawing on van Dijk's theoretical framework (1998a, 1998b, 2011, 2018), this project considers that ingroup ideology emphasises positive sentiments and emotions directed at specific evaluative targets (themes) while downplaying negative ones. In contrast, outgroup ideology highlights targeted negative sentiments and emotions while minimising positive ones. By analysing these shifts in targeted sentiments and emotions over time, this study aims to uncover ideological transformations in media representation in response to varying economic conditions, potentially revealing how economic performance and journalistic factors influence the framing of Chinese firms in American and British media discourse. This study is guided by the following research questions:

RQ1. How do positive and negative sentiments correlate with China's GDP and Purchasing Managers' Index (PMI)? How do sentiment variations influence the ideological representation of Chinese firms?

RQ2. How are Chinese companies' strengths, weaknesses, opportunities, and threats evaluated by positive and negative sentiments, and what implications do these targeted sentiments have for their representation?

RQ3. Which emotions have a significant ($p < 0.05$) impact on the change of positive and negative sentiments, and how do they influence the representation of Chinese companies?

The findings of this study can benefit business journalists and researchers by enhancing the production and dissemination of economic news about Chinese companies on social media. The performance of Chinese firms is intricately linked to China's domestic economic conditions. Incorporating China's macroeconomic trends into research on the media representation of Chinese companies can help clarify the impact of China's economic fluctuations on the coverage of these enterprises. These insights can guide the development of more nuanced reporting strategies, thereby enhancing the quality of digital economic journalism concerning the Chinese economy.

American and British media representations of the Chinese economy

Recent studies indicate that American media typically portray China's economy negatively, especially during financial crises and trade tensions. Tang (2018) employed corpus-assisted transitivity analysis to examine how leading newspapers depicted economic activities as unethical during the 2008 crisis. The news implies the necessity of monitoring trade with China. Similarly, Wang et al. (2023a) used sentiment analysis to observe that *The New York Times* expresses doubts about China's financial stability while acknowledging its economic progress. Song et al. (2019) identified a shift in post-crisis coverage, again, with corpus-assisted critical discourse analysis. Framing China's emerging economy as a potential opponent and threat to Western dominance is notable. During heightened trade disputes, American news has used a bellicose tone. War metaphors were applied to depict China as an aggressive player and harmful to American corporate interests (Chen and Wang 2020; Li 2021). Wang et al. (2023b) extended this analysis to the depiction of Chinese businesses with corpus linguistics. Their findings show a negative portrayal of Chinese products, particularly in trade disputes.

Comparatively, Studies on British media have revealed a mixed attitude towards China's economy, combining ethical concerns, risks, and opportunities. Song et al. (2019) identified a dichotomous representation from 2009 to 2017, depicting China as both a market disruptor and a potential economic catalyst. Zhao et al. (2023) observed an equilibrium between risk and opportunity until 2005, after which tariff disputes shifted focus towards risks and human rights issues. Notwithstanding this trend, Apirakvanalee and Zhai (2023b) noted recent favourable depictions of Chinese economic achievements in BBC podcasts covering China's Belt and Road Initiative while also highlighting uncertainties about its global impacts. Their subsequent analysis (2023a) uncovered concerns regarding global trade inequity stemming from this economic project. This nuanced portrayal extends to specific sectors, as shown in Pei and Cheng's (2024) study of "5G" in British news. They found that Chinese tech firms, particularly Huawei, are portrayed negatively as a geopolitical pawn within the Sino-US trade frictions rather than solely as a security concern. This depiction is compounded by the scientific uncertainties surrounding 5G technology.

Previous research on the media representation of the Chinese economy has primarily focused on two distinct areas: China's macroeconomic landscape (e.g., Apirakvanalee and Zhai 2023a; Song et al. 2019; Wang et al. 2023a) and specific Chinese companies in traditional media, notably Huawei (e.g., Dong and Gao 2022; Pei and Cheng 2024). These studies primarily used corpus-assisted discourse analysis. However, the representation of Chinese companies on social media platforms remains underdeveloped. This study bridges the gap by exploring how Chinese companies are represented in the news on the X platform. Methodologically, corpus-assisted discourse analysis is used, particularly sentiment analysis and evaluative target annotation.

Ingroup/outgroup ideologies in sociocognitive approach

This study employs van Dijk's concept of ingroup and outgroup ideologies (1998a, 1998b, 2011, 2018) as its theoretical framework, rooted in the sociocognitive approach to critical discourse analysis. Van Dijk (1998a) posits that individuals categorise others into "us" or "them" based on shared culture, knowledge, attitudes, and ideology. The construction of ingroup ideology involves emphasising positive properties and downplaying negative ones, while outgroup ideology is formed by highlighting negative properties and minimising positive ones (van Dijk 1998b). To explore these ideologies, van Dijk (2011) suggests examining discourse features that convey positive and negative properties. Specifically, van Dijk (2018) emphasises the role of opinion and emotion words, topics, and themes in shaping ingroup and outgroup ideologies. In the context of news discourse, ingroups are primarily portrayed positively, while outgroups are depicted negatively, reflecting the cultural background of the media outlets (van Dijk 2009). This approach has been widely employed in media discourse analysis (e.g., Ye and Thomas 2020; van Dijk 2006; Wang et al. 2023b). Corpus-assisted discourse analysis and NLP-based methods are often applied, such as sentiment analysis (Gao and Feng 2023; Wang et al. 2023a) and topic modelling (Ye and Thomas 2020).

The ingroup and outgroup ideological framework has been widely applied in media discourse analyses of representing China's economy (e.g., Apirakvanalee and Zhai 2023a; Li 2021; Wang et al. 2023b). Such studies are based on the notion that media narratives reflect their producers' ideologies within a sociopolitical environment. They frequently applied corpus-assisted discourse analysis, such as sentiment analysis, topic identification, and semantic prosody examination. Building on the established research, this project extends this framework by investigating the dynamic interplay between macroeconomic conditions and journalistic values and ideologies. Specifically, this research employs sentiment analysis to reveal how national economic fluctuations influence the ingroup and outgroup portrayals of Chinese firms. This analysis is complemented by an examination of journalistic values and ideologies. By analysing how sentiment and emotional expressions are employed to engage audiences and satisfy their information needs, this research seeks to understand the variations in attitudes and ideologies across different economic scenarios.

Methodology

Data collection. A corpus was compiled from thirty-five verified X accounts of 19 prominent US and UK economic news outlets, including *the Financial Times* and *Wall Street Journal* (see Appendix). It encompasses financial, business, and economic news about Chinese companies from each agency's inception to the end of 2023. Twint, a Python-based tool, and 22 seed words about Chinese companies, such as CHINESE FIRM and names of frequently occurring Chinese companies (see Appendix), were used to collect 55,394 tweets (934,155 words) from 08/2007 to 12/2023. This corpus was then split into two sub-corpora. One was compiled with 27,566 tweets (443,352 words) from American media, and another with 27,828 tweets (490,803 words) from British media. As recurring information considerably influences ideology, duplicate tweets were included in the analysis.

This project also sourced China's GDP and PMI from August 2007 to December 2023 via CEIC (CEIC Data 2024b, 2024a). These two indexes are frequently used together to evaluate China's macroeconomic performance (Oppenheimer 2020). GDP measures the total value of all goods and services produced in a country and reflects the current economic performance and growth levels. When monitoring China's economic fluctuations, GDP indicates phases of quarter-on-quarter expansion or contraction (CEIC Data 2024b, 2024a). In addition, the PMI, which was proposed by Oppenheimer (2020) for joint consideration with GDP, provides a comprehensive view of economic conditions. The Composite PMI Output Index was used, which combines the insights of purchasing managers from 31 manufacturing and 42 non-manufacturing sectors to forecast national economic trends. The index uses a critical threshold of 50 to signal economic expansion (above 50), contraction (below 50), or stability (at 50) (CEIC Data 2024a).

Table 1 Economic news tweets in economic conditions.

Economic condition		Examples	Number of news tweets	
Indicators	Explanation		American media	British media
GDP UP/ PMI > 50	Sustained growth	06/2014; 07/2020; 08/2020	12,952	12,866
GDP UP/ PMI = 50	Economic balance	06/2016; 11/2018; 08/2018	587	437
GDP UP/ PMI < 50	Potential decline	12/2018; 05/2019; 09/2019	8096	8228
GDP DOWN/ PMI > 50	Potential growth	03/2019; 01/2021; 03/2021	4004	4112
GDP DOWN/ PMI = 50	Economic stagnation	01/2021	219	415
GDP DOWN/ PMI < 50	Sustained decline	01/2015; 02/2015; 02/2020	1708	1770

In the final stage of data collection, the analysis categorised the tweets into six macroeconomic scenarios reflecting China's deteriorating economy. The date of each tweet was matched with the corresponding economic condition. For example, GDP UP/ PMI > 50 corresponded to tweets posted in certain months, such as June 2014, July, and August 2020. Table 1 shows the distribution of tweets across these economic scenarios.

Analytical procedure. A four-step analysis procedure integrated both quantitative and qualitative analytical approaches.

Step 1. Identifying the probability of sentiments and emotions. Transformer-based neural models were used to analyse the sentiments and emotions in 55,394 tweets. These models, such as RoBERTA-based models, have excellent performance in sentiment analysis (Overbeck et al. 2023). Transformer-based sentiment analysis differs from typical lexicon-based techniques, which use predetermined dictionaries like the NRC lexicon. Instead, transformers can capture long-range dependencies in text. They can then understand the contextual meaning of words and phrases and provide more precise predictions about emotions and sentiments.

Transformers use contextual word embedding to understand the semantic and syntactic context of words in text. Each word is presented by a distinct vector, which is influenced by nearby words. Transformers are then able to use a self-attention mechanism to evaluate the importance of every word relative to other words before performing the prediction. The models should be trained with sentiment-tagged datasets, where, for instance, positive, negative, and neutral expressions were annotated. Once the training has been completed, the models are able to predict sentiment categorisation using probabilities over predefined sentiment categories (Azizah et al. 2023). The predictive model assigns each text a sentiment score ranging from one to zero, which indicates the probability of each category (e.g., the negative score is 0.52). Based on these probabilities, models give sentiment labels (e.g., neutral, negative, or positive) to texts that have the highest probability, as in Tweet 1.

The present project used two RoBERTa-based models to explore sentiments and emotions in tweets due to their apt performance in handling short texts (Barbieri et al. 2020). Specifically, the twitter-roberta-base-sentiment and twitter-roberta-base-emotion-multilabel models developed by Cardiff University[1] were applied. In the model of sentiment, the algorithm was fine-tuned on 124 million tweets to predict the probability of positive, negative, and neutral sentiments. It attained a performance score (F1) of 0.76 from the pre-trained data (Barbieri et al. 2020). In the current study, Python was used to apply the sentiment model to 55,394 tweets. The model assigned probabilities of positivity, negativity, and neutrality to each tweet, along with a sentiment label, as in the following tweets. Consequently, the corpus included 17,074 positive and negative, and 38,320 neutral tweets.

1. Alibaba reports **rapid sales growth** (11/08/2016, Financial Times)[a]	Negativity (0.00); Neutrality (0.05); **Positivity (0.95)**
2. Security Fears **Kill**[b] Huawei Bid in US (7/11/2010, WSJ Asia)[c]	**Negativity (0.82);** Neutrality (0.17); Positivity (0.01)
3. The London Stock Exchange opens an office in Beijing, as it aims to attract listings by Chinese companies. (18/01/2008, BBC Business)[d]	Negativity (0.01); **Neutrality (0.82)**; Positivity (0.08)

[a]https://twitter.com/FinancialTimes/status/763699153612472320.
[b]The bolded are evaluative expressions, sentiment and emotional labels. The use is applied consistently throughout this paper.
[c]https://twitter.com/WSJAsia/status/944757404606465.
[d]https://twitter.com/BBCBusiness/status/613006832.

Tweet 1 above uses "rapid sales growth" for Alibaba to imply the company's success, resulting in a high positive probability. Tweet 2 generates a high negative probability because of the phrase "Security Fears Kill". The phrase is linked to the negative associations of fear and cancellation. Tweet 3 is primarily neutral, as it states a fact without expressing strong positive or negative sentiments.

The emotion model was trained on 154 million tweets published up to 2022 and refined for classification into eleven emotions. The emotions are anger, anticipation, disgust, fear, joy, love, optimism, pessimism, sadness, surprise, and trust. It has achieved an F1 of 0.72 on the pre-trained data (https://huggingface.co/cardiffnlp/twitter-roberta-base-emotion-multilabel-latest). In this project, the model was also applied via Python to the corpus of 55,394 tweets. It calculated the probability of each of the 11 emotions for each tweet and assigned the most likely emotion label, as in (4). The following section provides more details on the emotion analysis.

4. Alibaba is actually pretty **scary**. Here are three reasons why: (18/09/2014, Bloomberg Opinion)[e]	Anger (0.18); Anticipation (0.06); Disgust (0.28); **Fear (0.98);** Joy (0.00); Love (0.01); Optimism (0.03) Pessimism (0.13); Sadness (0.15); Surprise (0.03); Trust (0.01)

[e]https://twitter.com/opinion/status/512447290536386560.

In Tweet 4 above, the modifier "scary" explicitly describes the fear associated with Alibaba by conveying the potential threats the company poses to the audience. As such, the model identifies fear as the primary emotion.

The two RoBERTA models, fine-tuned on extensive text datasets, can capture sarcasm and irony, understanding disagreements between journalists and quotations. Their ability to analyse the meaning of each word and phrase in discourse enables accurate calculation of sentiments and emotions in every tweet.

Step 2. Developing an annotation scheme to identify evaluative targets in positive and negative tweets. The second step is developing an annotation scheme to discern evaluative targets in 17,074 news tweets. In this project, they are defined as subjects or entities being evaluated through their ideational meanings (Su and Hunston 2019). The analytical unit is a tweet as it focuses on one factor of Chinese firms. Hence, the targets are the themes presented in the tweets.

The theme of the tweets was classified into four main areas: strengths, weaknesses, opportunities, and threats. This is consistent with Hayes' (2014) observation that economic news about enterprises often covers companies' internal performance (strengths and weaknesses) and the external factors (opportunities and challenges) that influence them. Similarly, Müller (2023) also emphasised that internal and external company factors are essential themes in the various genres of economic coverage, such as business and financial news. In business news, journalists frequently report on the internal factors of corporate financial performance and market position. Building on these insights, a compelling rationale was constructed for investigating how positive and negative sentiments were used to evaluate the strengths, weaknesses, opportunities, and threats of Chinese firms.

The annotation scheme contained four evaluative targets. Strengths encompass attributes of Chinese companies that foster their growth, such as solid financial results ("Huawei's net **rose** 30% last year.") and strong brand reputations ("Chinese brands poised for **success**."). Weaknesses pertain to internal issues that restrict growth. Typical examples contain financial disappointments ("Alibaba, Yahoo slump after Alibaba's holiday-quarter revenue **falls short**.") and legal infractions ("JD.com leader Liu temporarily **detained in the US for alleged misconduct**."). Opportunities include sociopolitical elements that have the potential to advance Chinese businesses. Typical examples are favourable policies ("**Ant Group's IPO might receive approval**") and surging market trust ("Tencent Music's **IPO secures over $1 billion**."). Threats encompass external challenges that could hinder growth, such as adverse legislative actions ("The FCC designated Chinese manufacturers **as national security threats**") and declining market confidence ("Baidu stock **plummets**").

Step 3. Annotating evaluative targets in positive and negative tweets. This step involved annotating the evaluative targets in 17,074 positive and negative tweets. Evaluative targets are specific themes evaluated through their ideational meanings (Su and Hunston 2019). The annotation was assisted by large language models (LLMs). ChatGPT-4 was primarily used because of its popularity (Curry et al. 2024) and accuracy in annotation (Yu et al. 2023). A two-stage annotation process focused on corporate strengths and weaknesses, as well as opportunities and threats to Chinese companies.

The first stage involved prompt optimisation, which is essential for refining user interaction with the language model (Curry et al. 2024). Yu et al. (2023) recommend multiple trials for effective prompt engineering. In line with this, this research tested various prompts on 100 tweets using zero-shot prompting, where the model generates results from a single task description (Yu et al. 2023). The prompt used in this project, detailed in the Appendix, included task instructions, the annotation scheme, identifiers for Chinese companies, economic condition cues (e.g., GDP UP/ PMI < 50), and annotated examples. In addition, the prompt emphasised clarity, succinctness, and grammatical correctness, exemplified by "Annotate each tweet with /S/ for strengths… related to Chinese companies ".

The examples for the prompts were selected based on recurring errors found while testing ChatGPT-4. To make it easier for the model to understand, each example was labelled with an explanatory caption. The prompt began with the lead sentence, "Enhancement efforts show strengths or weaknesses", followed by an illustrative tweet. The final prompt included four examples that addressed ChatGPT-4's most common weaknesses.

In the second stage, the prompt was applied to 17,074 positive and negative tweets. Three aspects were considered when evaluating ChatGPT-4's performance in annotating evaluation targets. First, ChatGPT-4 was used to annotate the tweets, with 30% manually reviewed. The result is an intercoder agreement rate of 75.6%. Second, Claude 3 and Microsoft Copilot were consulted for a third opinion in cases of disagreement. The same prompt as ChatGPT-4 was used when annotations were required. A different prompt was used for explanations (e.g., "Why does the tweet show a weakness rather than a threat to the Chinese company when the GDP is UP/PMI > 50?").

Disagreements often occurred when tweets contained strengths and opportunities or weaknesses and threats (5). Annotations depended on whether they were caused by internal (strengths or weaknesses) or external factors (opportunities or threats). Finally, the sample tweets and the entire dataset were reviewed to ensure the consistency of this distinction.

5. **China's freeze on videogame approvals** is said to have **cost** companies such as Tencent and NetEase **roughly $1.4 billion in lost revenue**. (25/10/2018, WSJ Business News)[2] [Negativity: 0.76]

In Tweet 5, the negative sentiment is caused by the regulatory changes in China that affect Tencent and NetEase and thus pose a threat. The subsequent phrase "1.4 billion dollar revenue loss" indicates poor financial performance and weakness. However, as this loss is because of government regulations, the sentiment indicates a threat to the companies.

Step 4. Performing statistical analyses. Statistical analyses of 55,394 tweets were performed with SPSS 29, using Spearman correlation and multiple linear regression. The Spearman method analyses the intensity and direction of the relationship between two continuous or ordinal variables. It is ideal for non-normally distributed data. The correlation results range from −1 to 1, with a p-value below 0.05 indicating significance (Brezina 2018). After checking the normality of Chinese GDP, PMI, and sentiment probabilities, Spearman analyses were used to correlate the indices with the probability of positive and negative sentiments.

Multiple linear regression analyses were performed to investigate the influence of emotions on sentiment changes in news tweets. This model examines how multiple continuous independent variables predict a single continuous dependent variable. Following the guidelines of Field (2018), the analysis included four main aspects. R-squared was used to examine the fit of the model. Variance inflation factors (VIFs) were applied to identify multicollinearity, with values greater than five suggesting exclusions. The 95% confidence intervals for B were examined to determine the reliability of the predictors. Intervals including zero or larger than the estimated coefficients revealed the unreliability of the predictors. These predictors were excluded from the analysis. Finally, the significance of the B coefficient was evaluated, where $p < 0.05$ indicated significant predictors. For the dependent variable, positive B values indicated significant ($p < 0.05$) positive predictors, while negative values indicated significant ($p < 0.05$) negative predictors. This framework was applied in four separate analyses to examine which emotions influence positivity and negativity in the news tweets from both countries.

Findings

This section presents the statistical and qualitative analysis results, revealing links between sentiment valence, economic indicators, evaluative targets, and emotional impacts on news sentiment shifts.

Associations between sentiment valence and the Chinese macroeconomy. The Spearman correlation analysis revealed significant ($p < 0.01$) correlations between the sentiments in American and British news tweets about Chinese companies ($N = 55{,}394$) and the macroeconomic indicators. Figure 1 below illustrates how the probabilities of positive and negative sentiments shifted across six economic conditions.

The above figure shows a shift from positive to negative sentiment in American news tweets that correlates with China's economic performance. The median probability of positive sentiment peaked when the economy was balanced (GDP UP/ PMI = 50). In times of continuous economic decline (GDP DOWN/PMI < 50) or potential downturn (GDP UP/PMI < 50), a sharp decrease in positive sentiment was observed. Conversely, the mean probability of negative sentiment peaked during a prolonged economic downturn (GDP DOWN/PMI < 50). Amid a balanced economy (GDP UP/PMI = 50), a sharp decrease in negative sentiment was observed.

Following van Dijk's theory about ingroup and outgroup ideologies (1998a, 1998b, 2011, 2018), the portrayal of Chinese firms in American economic news tweets shifted from the ingroup to the outgroup representation as China's macroeconomy worsened. This shift was evident in the changing probabilities of positive and negative sentiments across various economic scenarios (see Fig. 2 below). When China's economy was growing and stable (GDP UP/PMI = 50), the trend towards the ingroup representation of Chinese firms was most prominent (cf. van Dalen et al. 2017). This was characterised by a high median probability of positivity (0.12) and a low median probability of negativity (0.02). As economic indicators declined, a gradual shift towards the outgroup representation of Chinese firms became apparent, with decreasing positivity and increasing negativity. This trend was particularly evident during prolonged economic downturns (GDP DOWN/PMI < 50), where negativity peaked at 0.14 and positivity dropped to 0.05.

British news tweets showed a slight decrease in positivity and an increase in negative sentiment (see Fig. 1 above). This change occurred as China's economy moved from sustained expansion to contraction. The mean probability of positive sentiment increased when China's economy showed stability (GDP UP/PMI = 50) or potential growth (GDP Down/PMI > 50). However, it decreased when economic contraction was expected (GDP UP/PMI < 50). In contrast, negative sentiment peaked when an economic contraction was expected (GDP UP /PMI < 50). This agrees with van Dalen et al. (2017), who argued that economic news frequently emphasises negativity before a confirmed economic slump. Furthermore, negative sentiment declined when China's economy was sustainable (GDP UP/PMI > 50) or showed growth potential (GDP DOWN/PMI > 50).

Similar to American news tweets, British economic news tweets also shifted from the ingroup to the outgroup representation of Chinese firms as China's economic situation deteriorated (see Fig. 3 below). When China's economy showed signs of stability or

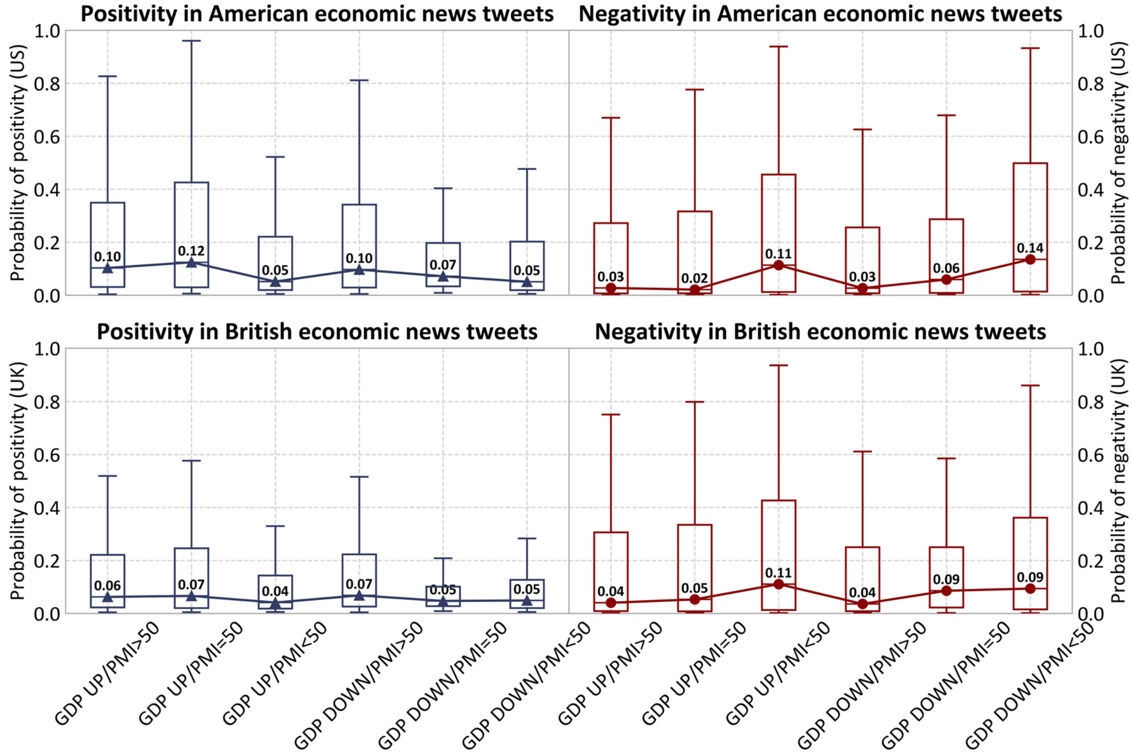

Fig. 1 Media sentiments and China's economic fluctuations. Due to its presentation in a non-normative distribution, the median probability represents the variation in sentiment.

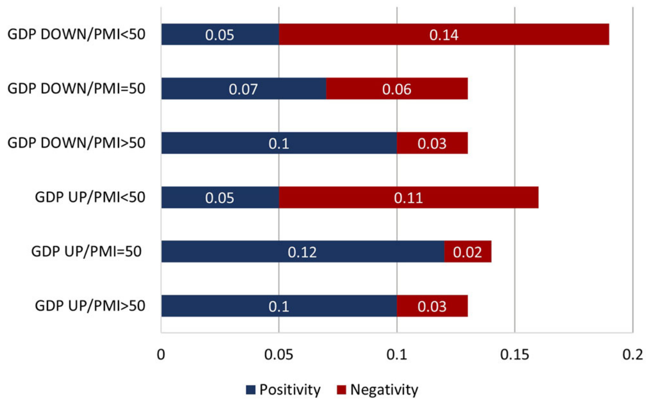

Fig. 2 Positivity/negativity in American economic news tweets. The numbers represent the median probabilities of positive and negative sentiments.

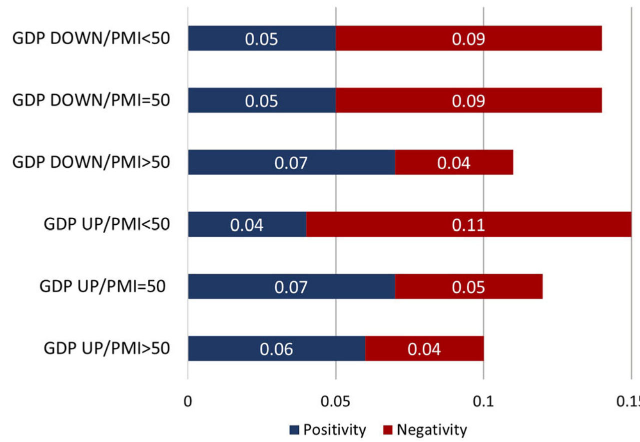

Fig. 3 Positivity/negativity in British economic news tweets.

potential recovery (e.g., GDP UP/PMI = 50), the ingroup representation of Chinese firms was most prominent, characterised by high positivity and low negativity. As economic indicators worsened, a gradual shift towards the outgroup representation of Chinese companies became marked. This trend was most pronounced when the Chinese economy indicated potential contraction (GDP UP/PMI < 50), with negativity peaking at 0.11 and positivity dropping to 0.04.

Evaluative targets in positive and negative tweets. Analysing positive and negative tweets ($N = 17{,}074$) revealed key evaluative targets. Positive tweets focused on strengths and opportunities, while negative ones underscored weaknesses and threats.

American media: key evaluative targets in positive/negative tweets. Figure 4 below shows a slight reduction in the emphasis on the strengths of Chinese companies when the Chinese economy moved from full growth to decline. The percentage of corporate strengths was highest at economic equilibrium (GDP UP/PMI = 50) but lowest when an economic downturn was expected (GDP UP/PMI < 50). The ingroup representation of Chinese companies' competitive advantages was more pronounced when the economy was stable but decreased when a downturn was anticipated. In contrast, opportunities increased when the economy deteriorated. They were particularly emphasised during potential economic downturns (GDP UP/PMI < 50) but reached their lowest point when the economic climate appeared balanced (GDP UP/PMI = 50). The ingroup representation of companies' opportunities changed during the course.

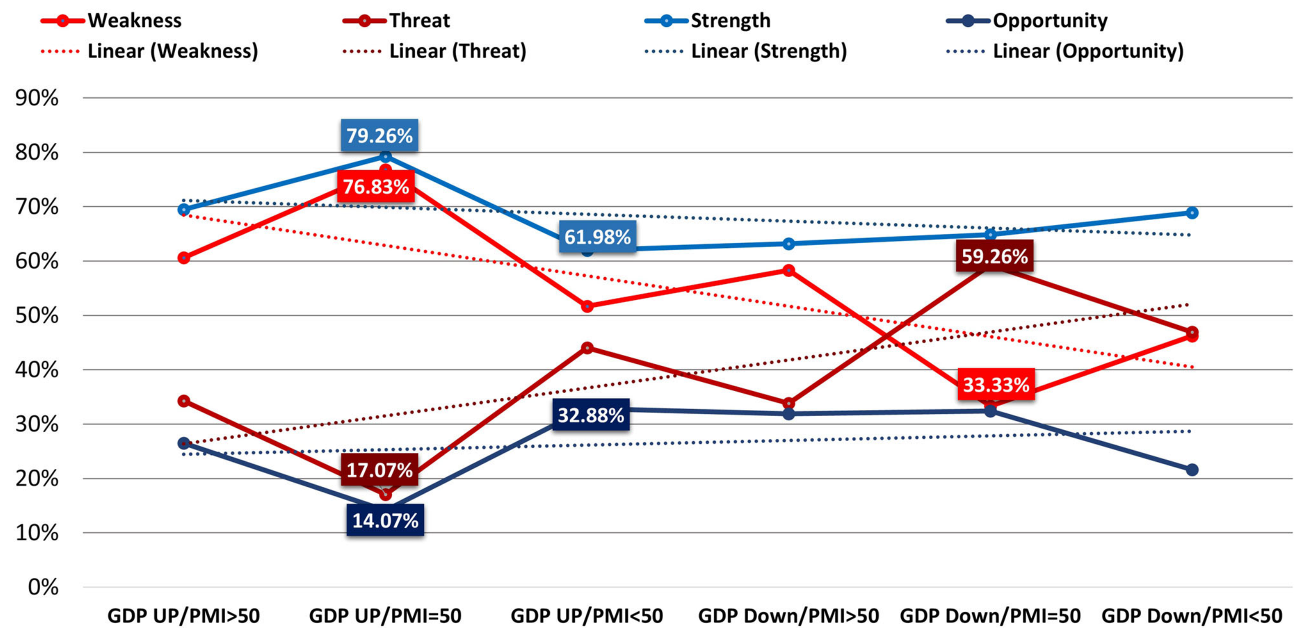

Fig. 4 Key evaluative targets in American news tweets. A percentage = the frequency of a target/ the total number of positive or negative tweets within a specific economic condition.

Positive tweets targeted the vitality of high-tech companies, including robust smartphone sales, the development of AI and autonomous vehicle technologies, and commitment to 5G innovations, as described in (6). 85% of 3123 positive tweets targeting corporate strengths addressed these technological advancements. This emphasis on China's technological capabilities agrees with the focus observed in US economic news (Chen and Wang 2020; Li 2021). In addition, external opportunities contained the growth potential of companies, manifested in activities such as large IPOs, investment inflows, and favourable regulatory changes, as shown in (7). 90% out of 1372 positive tweets targeting opportunities covered these themes.

6. Baidu has **unveiled AI** that **can translate languages in real time**. (12/11/2018, CNBC)[3] [Positivity: 0.63]

7. Chinese Often Send Money to Each Other Over the Lunar New Year. That Was a **Big Opportunity** for Alibaba and Tencent. (19/01/2020, Barron's)[4] [Positivity: 0.76]

Tweet 6 portrays Baidu in a favourable manner by highlighting the economic prospects of their artificial intelligence technology. Tweet 7 highlights China's pro-business policies, which present enterprises in a positive light due to their crucial role in the home market.

Figure 4 above also shows that negative tweets targeting corporate weaknesses decreased with the economic downturn. The percentage was highest during economic equilibrium (GDP UP/PMI = 50). This implies that the media want to moderate the public's interest in investments and thus fulfil a watchdog function. In contrast, the percentage of threats exceeded the focus on weaknesses during an economic decline. The rate peaked during stagnation (GDP DOWN/PMI = 50) and bottomed during stability (GDP UP/PMI = 50). The outgroup representation of corporate external threats became more pronounced when the Chinese (non-)manufacturing sectors neither expanded nor contracted.

Negative tweets about Chinese companies often focused on their legal and financial difficulties and competitive challenges, painting an illicit and incompetent picture. In 2870 negative tweets targeting corporate weaknesses, 68% addressed these evaluative targets. They not only emphasise the companies' market disruption (cf. Chen and Wang 2020), but also their performance problems, as in (8). Furthermore, 2031 threat-targeted negative tweets highlighted external threats, such as increasing trade tensions between China and the US, security concerns, and market barriers abroad. Such evaluative targets reinforce a prudent view of the companies (9), which confirms a cautious attitude towards China's economy (Chen and Wang 2020; Song et al. 2019).

8. Xiaomi may **struggle to** reach some of the loftier goals its founder Lei Jun has set (02/07/2015, Forbes)[5] [Negativity: 0.64]

9. US tells UK using Huawei 5G gear would be **'nothing short of madness**,' report says (14/01/2020, CNBC)[6] [Negativity: 0.57]

Tweet 8 uses the metaphor "struggle" to describe Xiaomi's difficulty in achieving its goals, portraying the company as incapable. Tweet 9 underscores an outgroup depiction of Huawei by quoting the US government's denunciations of its 5G technology.

British media: key evaluative targets in positive/negative tweets. Figure 5 shows a notable decrease in the percentage of strengths and a simultaneous increase in opportunities during economic downturns. The percentage of positivity centred on strengths peaked during balanced economic conditions (GDP UP/PMI = 50) and bottomed during stagnation (GDP DOWN/PMI = 50). The ingroup representation of Chinese companies through strengths was emphasised during economic stability. In contrast, the emphasis on opportunities peaked when the economy started to recover (GDP DOWN/PMI > 50). When economic growth is expected in China, British media often emphasised the ingroup representation of the potential opportunities for Chinese companies, reflecting market confidence. These prospects could direct public investors towards business opportunities with Chinese firms.

Positive tweets emphasised corporate successes, including product appeal, meeting market demands, and financial health. 75% out of 2189 corporate strength-targeted positive tweets addressed these evaluative targets, which portrayed the group companies as having a strong market position (cf. Apirakvanalee and Zhai 2023b), as in (10). In addition, positive tweets also emphasised opportunities for these companies, such as successful IPOs, share price increases (see Tweet 11), regulatory support,

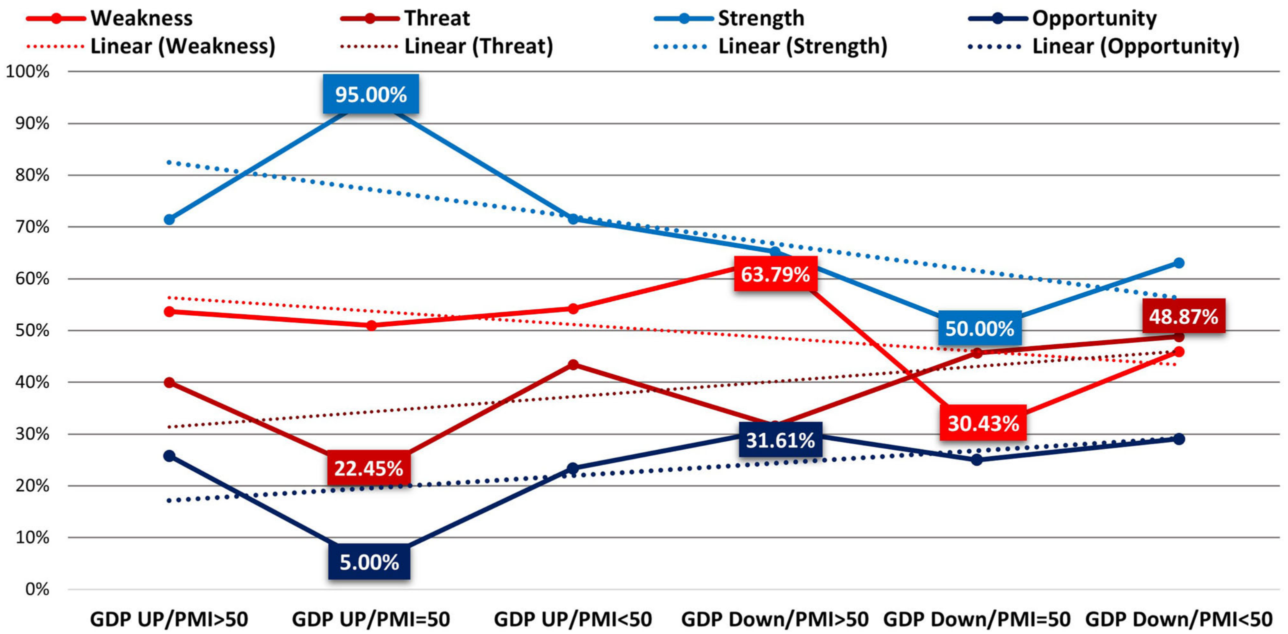

Fig. 5 Key evaluative targets in British news tweets.

and access to European fundraising opportunities. They reflect the commitment of the global market to Chinese companies, with a particular focus on the European market.

10. Huawei: **'No doubt'** that **we will meet German 5G security standards** (24/06/2019, Reuters)[7] [Positivity: 0.63]

11. UPDATE: **JD.com shares hit record high** on report of US entry by end of 2018, last up 5 percent. (27/01/2018, Reuters Business)[8] [Positivity: 0.52]

Tweet 10 presents an ingroup portrayal by emphasising Huawei's confidence in becoming a reliable 5G provider in Germany. Tweet 11 expresses a positive depiction of market confidence in JD.com, thus reflecting the optimistic outlook for its future.

Figure 5 above also shows that the emphasis on weakness-targeted negativity in British news tweets decreased as the economy deteriorated. The percentage was highest during China's economic recovery (GDP DOWN/PMI > 50) and lowest during stagnation (GDP DOWN/PMI = 50). This result suggested that the outgroup representation of corporate weaknesses increased as China's (non-)manufacturing sectors grew. In contrast, the focus on threats increased when the economy declined. They peaked during protracted recessions (GDP DOWN/PMI < 50) and bottomed when economic metrics showed a return to stability (GDP UP/PMI = 50). During a period of great economic trouble in China, British news intensified the outgroup representation of corporate external threats. This approach allows journalists to provide audiences with a deeper understanding of the external factors that can affect the performance of Chinese firms.

British news tweets criticised Chinese firms for their financial shortcomings, safety failings, labour issues, and mismanagement. In 2,652 weakness-targeted negative tweets, 65% addressed these themes. Notably, tweets covering an unhealthy workplace culture (Tweet 12) and personal scandals in Chinese companies contribute to their unethical portrayal and satisfy the online audience's desire for soft news. This type of information appears to be more attractive to the public because of its compelling nature to invoke emotion (Hermida and Mellado, 2020). In addition, negative tweets also emphasised external threats, such as regulatory actions and bans (Tweet 13), antitrust fines and investigations, and the threat of delisting. This rhetoric reflects the thematic framing of the threat in American news tweets, which consistently paint a negative picture of Chinese companies.

12. Chinese software developers launched the **'996 ICU'** awareness campaign, which says that if you work 9 am to 9 pm, six days a week, **you'll end up in intensive care**. In two years, **they have crowdsourced allegations of mistreatment at 200 Chinese companies**. (10/06/2021, Financial Times)[9] [Negativity: 0.69]

13. Alibaba faces **growing regulatory threat** as **China's economy falters**. (14/01/2019, Financial Times)[10] [Negativity: 0.65]

In Tweet 12, the "996 ICU" campaign highlights systematic labour issues in Chinese firms, uncovering an exploitative working environment. Tweet 13 uses "regulatory threats" and economic downturns to shadow Alibaba's future.

Emotional dynamics in shaping positivity and negativity. Findings from linear regression analyses showed that nine emotions significantly ($p < 0.0001$) impacted positive and negative sentiment variance in news tweets ($N = 55{,}394$). The coefficient of determination (R-squared) was more significant than 0.53 in the four analyses. The statistical model accounted for over 53% of the variance observed in the data. Details are shown in Table 2.

American media: impacts of joy, trust, and surprise on positivity. The emotions of joy, trust, and surprise had a significant ($p < 0.0001$) effect on the positive sentiment. Table 2 above illustrates that a one-unit increase in the probability of joy would increase the probability of positive sentiment by 0.605. A one-unit increase in trust would increase the probability by 0.186. In contrast, a one-unit increase in the probability of surprise would lead to a 0.42 decrease in positive sentiment. These findings align with van Dijk's (2009, 2018) concept of ingroup ideology, which posits that positive emotions and sentiments reinforce ingroup representation. The positive effects of joy and trust suggested a tendency to portray Chinese companies positively, increasing their characteristics as an ingroup. However, the negative impact of surprise indicated that unexpected information disrupted the

Table 2 The influence of emotions on the sentiment change.

Sentiment	Influential emotion	B	Sig.	VIF	95.0% Confidence Interval for B	
Positivity (US)	Joy	0.605	****	2.486	0.596	0.615
	Trust	0.186	****	2.546	0.149	0.222
	Surprise	−0.42	****	1.142	−0.445	−0.395
Negativity (US)	Fear	0.202	****	1.244	0.193	0.210
	Anticipation	−0.614	****	1.244	−0.623	−0.605
Positivity (UK)	Love	1.51	****	2.47	1.416	1.603
	Joy	0.523	****	3.793	0.513	0.534
Negativity (UK)	Fear	0.185	****	1.286	0.177	0.193
	Anticipation	−0.615	****	1.286	−0.624	−0.605

The results come from four multiple linear regression analyses. The current project used sentiment probability as a dependent variable. It also used eleven types of emotions as independent variables. The analysis excluded variables with multicollinearity or confidence intervals, including zero or larger than their B values.
****$p < 0.0001$.

favourable narrative, potentially undermining the movement towards a positive portrayal.

Further analysis revealed that the expressions of joy described the companies' own robust financial figures. Phrases such as "the most valuable maker…" and "revenue jumped…" celebrated corporate achievements (Tweet 14). Trust was often placed on Chinese high-tech growth and conveyed through language that evinced great certainty. The expressions "be set to" and "will" alongside cognitive verbs "believe", "vow", and "make sure" were evident (Tweet 15). Hayes (2014) noted that economic news serves as a vital tool for investors in strategic development. For investors evaluating the growth possibilities of Chinese companies in a thriving economy, confident tweets play a crucial role. These tweets can influence their perceptions and decisions regarding the companies' future performance. In addition to confidence, surprise was also observed, especially when evaluating technological advances and market reactions. The emotions emphasised the potency and potential of these companies (Tweet 16).

14. **Alibaba's revenue beats expectations** after its core **e-commerce arm returned to growth, a big step for a national icon** trying to revive its business in a volatile economy. (10/08/2023, Bloomberg)[11] [Joy: 0.94]

15. Alibaba has a few new tricks up its sleeve to **make sure** the 10th annual Singles Day shopathon is a success. (10/11/2018, WSJ)[12] [Trust: 0.96]

16. Huawei recently released the Mate 60 Pro smartphone, with capabilities that **shocked** the world in terms of its performance. How China pulled it off despite efforts to contain its chip industry. (7/12/2023, Bloomberg Markets)[13] [Surprise: 0.79]

In Tweet 14, the phrases about corporate success and resilience invoke the joy of the organisation and reinforce the image of a resilient leader within the group. In Tweet 15, Alibaba's commitment to success with "make sure" suggests a competent image. In addition, the use of "shocked" in Tweet 16 emphasises Huawei's influence with its innovative smartphone and highlights its innovation.

American media: impacts of fear and anticipation on negativity. Fear and anticipation were significantly ($p < 0.0001$) correlated with the negative shifts in tweets corresponding with economic changes in China. This suggests that changes in the Chinese economy have a considerable impact on the emotional tone of American news, particularly in terms of fear and anticipation (Strauß et al. 2018). A one-unit increase in the probability of fear would increase the probability of negativity by 0.202. In contrast, a one-unit increase in the probability of anticipation would decrease the probability of negativity by 0.614 (see Table 2). These findings align with van Dijk's (2009, 2018) concept of outgroup ideology, which posits that negative emotions can reinforce outgroup representations. Increased expressions of fear strengthened the trend towards portraying Chinese companies negatively, reinforcing characteristics associated with outgroup representation. In contrast, increased anticipation mitigated this tendency.

The emotion of fear underscored threats to Chinese high-tech firms, such as American regulatory scrutiny and market trust (Tweet 17). It reveals that the firms are intertwined in the Sino-US technological rivalry (Li 2021). Anticipation was mainly used to evaluate corporate strategic and operational weaknesses, including issues with new business strategies (Tweet 18) and obstacles in international expansion (e.g., Huawei's 5G equipment concerns).

17. This likely will be a week of reconciliation as the market digests the **horrible** performance of tech stocks in October, specifically Apple and Alibaba. (06/11/2018, Fortune)[14] [Fear: 0.52]

18. Xiaomi **predicted** it would sell 100 million phones in 2015 and it fell almost 30 million shorts. (25/06/2016, Fortune)[15] [Anticipation: 0.64]

Tweet 17 labels Alibaba's stock drop as "horrible", which suggests a negative future outlook for the firm. Tweet 18 uses the word "predicted" to question Xiaomi's inability to meet a sales goal, portraying it as incapable.

British media: impact of love and joy on positivity. The emotions of love and joy significantly ($p < 0.0001$) influenced positive sentiment in British news tweets. Table 2 illustrates that a unit increase in the probability of love would elevate the probability of positive expressions by 0.587. A unit increase in joy would elevate the probability by 0.267. The increasing presence of the two emotions amplified the probability of a positive portrayal of Chinese companies. This pattern suggested that, similar to their American counterparts, British news emphasised corporate activities that invoked positive emotional responses.

The analysis revealed a frequent use of love to evaluate the appeal of offerings. Modifiers such as "popular" and "the best", as well as mental verbs like "love" and "like", resonate with the consumer's affection for products and services (Tweet 19). Joy was mainly used to appraise corporate healthy financial performance, which contained revenue growth and sales performance, as in (20). When financial accomplishments were characterised, they typically invoked happiness from the company's perspective (cf. joy in American news).

19. Despite US charges against Huawei, Europe's top telecom carriers have at least 20 billion reasons to **love** the Chinese company (01/02/2019, Reuters Business)[16] [Love: 0.7]

20. Tencent, the world's largest video game company, **posted an 11% rise in revenue, beating analyst expectations**. (18/05/2023, Reuters Business)[17] [Joy: 0.98]

In Tweet 19, the verb "love" presents Huawei's strong ability to maintain its value to European partners, which reveals a competent ingroup image. Tweet 20 celebrates Tencent's revenue growth exceeding forecasts and portrays a capable and successful image.

British media: impact of fear and anticipation on negativity. The emotions of anticipation and fear exerted a significant ($p < 0.0001$) impact on negative sentiment. An increase of one unit in the probability of fear would increase the probability of negativity by 0.185. In contrast, a unit increase in the probability of anticipation would decrease the probability of negative expressions by 0.615 (see Table 2). These findings, similar to those in American media, suggested that heightened fear expressions amplified the trend towards the negative portrayal of Chinese companies. Specifically, this shifted the narrative towards a more outgroup representation. Conversely, increased anticipation mitigated this trend by mitigating the negative tone of the tweets.

Fear expressions were linked to perceived corporate deficits, where operational and financial performances were observable when eliciting negative responses (Tweet 21). Anticipation was often associated with financial, investment, and operational challenges. The main focus of anticipation was on areas of corporate weaknesses (Tweet 22). Overall, weakness-targeted fear and anticipation play a role in balancing investor awareness of economic risks with market interest in Chinese firms.

21. Tencent has had a **horrid** year even by tech industry standards. Here are five things ahead of the company's third-quarter earnings to watch out for. (13/11/2018, Financial Times)[18] [Fear: 0.98]

22. Breakingviews - Tencent WeChat Pay rejig **would** have 1 bln problems (18/03/2022, Reuters Business)[19] [Anticipation: 0.53]

Tweet 21 uses the emotive adjective "horrid" to characterise Tencent's unsatisfactory financial performance, which casts the company as ineffective. In Tweet 22, the verb "would" evaluates potential operational problems. This portrays an incompetent corporate image.

Discussion and conclusions

This study investigated how quantifiable sentiments in US and UK economic news tweets about Chinese companies correlate with China's economic indicators. This shows that economic fluctuations influence media ideological bias. Grounded in ingroup and outgroup ideologies (van Dijk 1998a, 1998b, 2011, 2018), it combined NLP techniques and LLM-assisted annotation to analyse this relationship from three analytical angles. The results and implications are synthesised below.

The present project identified the correlation between sentiments, evaluation targets, and emotions in news tweets about Chinese companies and China's economic performance. These findings revealed that the representation of Chinese firms shifted with economic fluctuations.

First, it revealed a significant ($p < 0.01$) correlation between positivity and negativity in the tweets and Chinese economic indicators (GDP and PMI). Positive sentiment decreased from sustained growth to downturns, while negative sentiment increased during these declines. As China's economic indicators worsened, the representation of Chinese firms in tweets became increasingly negative, which reinforced a trend towards portraying these firms as an outgroup.

Second, as the Chinese economy transitioned from growth to decline, positive sentiment emphasising corporate strengths declined but still surpassed emerging positive sentiment targeting external opportunities. Negative sentiment shifted from corporate weaknesses to contextual threats. Correspondingly, the ingroup representation of environmental opportunities strengthened, while the positive portrayal of corporate strengths weakened. Meanwhile, the outgroup portrayal of internal corporate weaknesses decreased, whereas the negative representation of external threats increased.

Third, joy and trust had a significant ($p < 0.0001$) positive impact on positive sentiment in American news tweets, while surprise had a negative influence. Joy and trust were associated with an increased trend towards the ingroup portrayal of Chinese firms, whereas surprise was linked to a decrease in this tendency. In British news tweets, love and joy considerably boosted positive sentiment, leading to a reinforcement of trends towards the ingroup portrayal of Chinese firms. Conversely, fear had a positive impact on negative sentiment in both American and British news tweets, while anticipation had a significant ($p < 0.0001$) negative influence. The increase in fear and decrease in anticipation strengthened trends towards the outgroup representation of these companies.

Theoretical and practical implications. First, this study broadens the understanding of the relationship between sentiment in economic news discourse and the prevailing economic climate. Fogarty (2005) and van Dalen et al. (2017) claimed that business journalists often downplay positive sentiment during economic growth. In contrast, the results showed increased positivity associated with China's economic expansion. The trend was notable when the economy appeared stable (GDP UP/PMI = 50) and when a potential economic expansion was expected (GDP DOWN/PMI > 50). This discrepancy may be attributed to the unique ability of social media to disseminate economic news. Soroka et al. (2018) argued that economic news on X has a bias towards positivity compared to traditional media because it is designed to encourage audience engagement. Therefore, the amplification of positivity in tweets about Chinese companies highlighted investment prospects and business opportunities to the audience when economic conditions were favourable. Such a strategy is likely to attract the interest of public investors, leading to an increased distribution and response to these tweets.

Previous studies have shown that economic news emphasises negativity during economic downturns (Fogarty 2005; Lischka 2015). The news responds to shifts in forward-looking indicators rather than the current state of the economy (Soroka 2014; van Dalen et al. 2017; Zhu 2019). Results in the present study confirm that British news tweets about Chinese companies amplified negative sentiment when a slowdown in China's economy was expected (GDP UP/PMI < 50), as in Fig. 1. Nevertheless, American news showed an increase in negativity in response to the prolonged economic downturn (GDP DOWN/PMI < 50). This disparity can alert public investors during critical economic fluctuations. Given the large trade volume between China and America, this communication aims to uphold investor vigilance without excessively disrupting established trading patterns. This practice could maintain the existing supply chain to the US while serving a watchdog function.

Second, this study contributes to the existing literature on media representation of the Chinese economy by providing a more nuanced understanding of the portrayal of Chinese companies on social media. Previous research has indicated a predominantly negative imagery of China's economy during its period of rapid growth (e.g., Chen and Wang 2020; Li 2021; Song et al. 2019), often depicting Chinese businesses as an outgroup. This project extends this perspective by demonstrating that such negative representations intensify during periods of economic decline. Specifically, despite China's overall economic boom, the analysis revealed a further shift towards the outgroup representation of Chinese companies during economic downturns. This study observed the intensification of negative tones and a reduction of positive sentiments in tweets about Chinese firms as economic indicators worsened. This trend potentially reflects media efforts to caution audiences about potential risks associated with China's economic challenges, even within the context of the country's long-term economic rise.

This project identified that Chinese companies' strengths and opportunities as an ingroup were emphasised in specific macroeconomic scenarios. American and British news tweets highlighted corporate strength when the economy was balanced (GDP UP/PMI = 50). American tweets notably featured Chinese technological achievements, addressing US market interest in Chinese high-tech companies during favourable economic conditions (cf. Li 2021; Pei and Cheng 2024). Furthermore, the news tweets highlighted Chinese firms' opportunities during economic uncertainties. American media showcased new business possibilities during anticipated downturns (GDP UP/PMI < 50). In this context, the tweets could serve to remind investors that asset relocation could be a viable strategy in the face of potential economic declines. Similarly, British media spotlighted opportunities during sustained economic distress (GDP DOWN/PMI < 50), possibly to bolster market confidence. Given the significance of China-UK trade, British journalists likely aim to direct attention to Chinese firms' prospects without disrupting existing trade relations.

Extending the existing literature that associates the negative portrayal of Chinese business pertaining to threats (e.g., Pei and Cheng 2024; Song et al. 2019; Zhao et al. 2023), immorality (e.g., Apirakvanalee and Zhai 2023a; Tang 2018) and illegality (e.g., Wang et al. 2023b), the current study offers a nuanced perspective. Figure 4 shows that American news tweets emphasised the outgroup representation of the weaknesses of Chinese companies in times of economic stability (GDP UP/PMI = 50). This focus on the corporate legal and financial challenges serves to dampen the enthusiasm of public investors. When stagnation happened (GDP DOWN/PMI = 50), tweets shifted to emphasise contextual threats, often related to Sino-US trade relations. The emphasis could provide audiences with a strategic view of how trade tensions have affected China's companies. Meanwhile, it could construe the negative impact of the disputes on China's economy.

In contrast, during the early stages of recovery (GDP DOWN/PMI > 50), the British media focused on financial irregularities and unethical behaviours. 65% of negative tweets targeting corporate weaknesses addressed these themes. They used soft news and risk portrayal to appeal to audiences and potentially cool down the passion to collaborate with the firms. As economic challenges intensified (GDP DOWN/PMI < 50), British news focused on Sino-US trade tensions and Chinese regulatory changes. These evaluative targets could make audiences aware of the global business changes of companies and shift blame to protect Sino-British business relationships (cf. Pei and Cheng 2024).

Third, this study illuminates the interplay between economic dynamics and ideological shifts in news tweets. While ideology is shaped by discourse (van Dijk 2000) and sociopolitical contexts (van Dijk 2018), the findings suggest that economic pressures also substantially influence ideological change. Notably, strength-targeted joy played a crucial role in the trend towards an ingroup portrayal of Chinese companies, a trend that waned as China's economic situation deteriorated. This emotion, known to enhance audience engagement on social media (Al-Rawi 2020; Choi et al. 2021), likely stimulates investor discussions about Chinese companies' financial successes. Additionally, strength-targeted surprise negatively influenced this trend in American news tweets. This emotion, which boosts digital news engagement (Choi et al. 2021), potentially amplifies investor attention to technological progress and market confidence, especially during economic downturns.

Choi et al. (2021) noted that fear can increase audience engagement with international news. Building on this insight, the current project indeed identified that fear was applied to draw public investors' attention to shifting the portrayal of Chinese firms to an outgroup. It was specifically found that fear was a factor that correlated positively with a tendency towards the outgroup representation of Chinese companies, especially during China's economic downturns. American news invoked fear by emphasising threats and linking China's economic situation to the US's domestic problems. British news used weakness-targeted fear to caution investors about financial challenges in Chinese companies. Overall, using fear can help investors gain a nuanced understanding of the risks associated with Chinese companies and develop mitigation strategies.

Limitations and future studies. The present project has two major limitations. First, it only analysed the impact of Chinese GDP and PMI on economic news about Chinese companies, although these are crucial indicators of the Chinese macroeconomy (Oppenheimer 2020). Second, it focused only on economic news from US/UK media, which, while having a considerable global audience and influence on business practices, may not represent all international media. Future studies could address these limitations by including additional macroeconomic indices and expanding the scope to include economic news from other regions.

Data availability

The dataset and code employed in this study are available on Open Science Framework: https://doi.org/10.17605/OSF.IO/6FA7M

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Notes

1 The two models are accessible via https://cardiffnlp.github.io/.
2 https://twitter.com/WSJbusiness/status/1055252613577482240.
3 https://twitter.com/CNBC/status/1061696581093769216.
4 https://twitter.com/barronsonline/status/1218921772273278978.
5 https://twitter.com/Forbes/status/616611283908063232.
6 https://twitter.com/CNBC/status/1217026378261987329.
7 https://twitter.com/ReutersWorld/status/1143179814154768386.
8 https://twitter.com/ReutersBiz/status/956944939996385280.
9 https://twitter.com/FinancialTimes/status/1402811221611401216.
10 https://twitter.com/FT/status/1084827959104622592.
11 https://twitter.com/business/status/1689591082198138880.
12 https://twitter.com/WSJ/status/1061211935767752704.
13 https://twitter.com/markets/status/1732686775405936797.
14 https://twitter.com/FortuneMagazine/status/1059475473426718722.
15 https://twitter.com/FortuneMagazine/status/746418875529592832.
16 https://twitter.com/ReutersBiz/status/1091158583121768448.
17 https://twitter.com/ReutersBiz/status/1658925354965409810.
18 https://twitter.com/FinancialTimes/status/1062117605316673536.
19 https://twitter.com/ReutersBiz/status/1504759589841129504.

References

Al-Rawi A (2020) Networked emotional news on social media. J Pr 14(9):1125–1141. https://doi.org/10.1080/17512786.2019.1685902

Apirakvanalee L, Zhai Y (2023a) An ideological square analysis of the podcast discourse in "Chinese Dreams" of the BBC World Service. Crit Discourse Stud. 20(4):379–395. https://doi.org/10.1080/17405904.2022.2087702

Apirakvanalee L, Zhai Y (2023b) Telling stories from the New Silk Road: a news discourse analysis of BBC's podcast episodes on the Belt and Road Initiative. Journalism 24(11):2551–2569. https://doi.org/10.1177/14648849221107223

Azizah SFN, Cahyono HD, Sihwi SW, Widiarto W (2023) Performance analysis of transformer based models (BERT, ALBERT and RoBERTa) in fake news detection. arXiv. https://doi.org/10.48550/arXiv.2308.04950

Barbieri F, Camacho-Collados J, Anke LE, Neves L (2020) TweetEval: unified benchmark and comparative evaluation for tweet classification. arXiv. https://doi.org/10.48550/arXiv.2010.12421

Brezina V (2018) Statistics in corpus linguistics. Cambridge University Press, Cambridge

CEIC Data (2024a) China: purchasing managers' index, CEIC Data Company. https://www.ceicdata.com/en. Accessed 4 March 2024
CEIC Data (2024b). China: quarterly GDP. CEIC Data Company. https://www.ceicdata.com/en/. Accessed 4 March 2024
Chen F, Wang G (2020) A war or merely friction? Examining news reports on the current Sino-U.S. trade dispute in The New York Times and China Daily. Criti Discourse Stud 1–18. https://doi.org/10.1080/17405904.2020.1844252
Choi J, Lee SY, Ji SW (2021) Engagement in emotional news on social media: intensity and type of emotions. J Mass Commun Q 98(4):1017–1040. https://doi.org/10.1177/1077699020959718
Curry N, Baker P, Brookes G (2024) Generative AI for corpus approaches to discourse studies: a critical evaluation of ChatGPT. Appl Corpus Linguist 4(1):100082. https://doi.org/10.1016/j.acorp.2023.100082
Degen M, Olgemöller M, Zabe C (2024) Quality journalism in social media – what we know and where we need to dig deeper. Journal Stud. 25(4):399–420. https://doi.org/10.1080/1461670X.2024.2314204
Dong M, Gao MF (2022) Appraisal as co-selection and media performativity: 5G technology imaged in German news discourse. Text. Talk. 42(2):177–208. https://doi.org/10.1515/text-2020-0012
Field AP (2018) Discovering statistics using IBM SPSS statistics, 5th ed. Sage, London
Fogarty BJ (2005) Determining economic news coverage. Int J. Public Opin. Res 17(2):149–172. https://doi.org/10.1093/ijpor/edh051
Gao Q, Feng D (2023) Alignment and antagonism in flux: a diachronic sentiment analysis of attitudes towards the Chinese mainland in the Hong Kong press. Journalism. https://doi.org/10.1177/14648849231211884
Hayes K (2014) Business journalism: how to report on business and economics. Apress, New York City
Hermida A, Mellado C (2020) Dimensions of social media logics: mapping forms of journalistic norms and practices on Twitter and Instagram. Digit J 8(7):864–884. https://doi.org/10.1080/21670811.2020.1805779
Li J (2021) US-China trade negotiation discourses in the press. J Lang Polit 20(6):932–953. https://doi.org/10.1075/jlp.20062.li
Lischka JA (2015) What follows what? Relations between economic indicators, economic expectations of the public, and news on the general economy and unemployment in Germany, 2002–2011. J Mass Commun Q 92(2):374–398. https://doi.org/10.1177/1077699015574098
Müller H (2023) Challenging economic journalism. Springer International Publishing, Heidelberg. https://doi.org/10.1007/978-3-031-31030-0
Oppenheimer PC (2020) The long good buy: analysing cycles in markets. John Wiley & Sons, New Jersey
Overbeck M, Baden C, Aharoni T, Amit-Danhi E, Tenenboim-Weinblatt K (2023) Beyond sentiment: an algorithmic strategy for identifying evaluations within large text corpora. Commun Methods Meas 1–22, https://doi.org/10.1080/19312458.2023.2285783
Pei J, Cheng L (2024) Representations of 5G in the Chinese and British press: a corpus-assisted critical discourse analysis. Humanit Soc Sci Commun 11(1):400. https://doi.org/10.1057/s41599-024-02896-8
Song Y, Lee C-C, Huang Z (2019) The news prism of nationalism versus globalism: How does the US, UK and Chinese elite press cover 'China's rise'? Journalism 22(8):2071–2090. https://doi.org/10.1177/1464884919847143
Soroka S, Daku M, Hiaeshutter-Rice D, Guggenheim L, Pasek J (2018) Negativity and positivity biases in economic news coverage: traditional versus social media. Commun Res 45(7):1078–1098. https://doi.org/10.1177/0093650217725870
Soroka SN (2014) Negativity in democratic politics. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9781107477971
Strauß N, Vliegenthart R, Verhoeven P (2018) Intraday news trading: the reciprocal relationships between the stock market and economic news. Commun Res 45(7):1054–1077. https://doi.org/10.1177/0093650217705528
Su H, Hunston S (2019) Language patterns and attitude revisited. Funct Lang 26(3):343–371. https://doi.org/10.1075/fol.16030.su
Tang L (2018) Transitive representations of China's image in the US mainstream newspapers: a corpus-based critical discourse analysis. Journalism 22(3):804–820. https://doi.org/10.1177/1464884918801116
van Dalen A, de Vreese C, Albæk E (2017) Economic news through the magnifying glass. J Stud 18(7):890–909. https://doi.org/10.1080/1461670X.2015.1089183
van Dijk TA (1998a) Ideology: a multidisciplinary approach. Thousand Oaks, California
van Dijk TA (1998b) Opinions and ideologies in the press. In: Bell A, Garrett P (eds) Approaches to media discourse, Blackwell Publishing Ltd, Oxford, pp 21–63
van Dijk TA (2000) Ideology and discourse: a multidisciplinary introduction. Pompeu Fabra University, Barcelona
van Dijk TA (2006) Ideology and discourse analysis. J Polit Ideol 11(2):115–140. https://doi.org/10.1080/13569310600687908
van Dijk TA (2009) News, discourse and ideology. In: Wahl-Jorgensen K, Hjanitzsch T (eds) The handbook of journalism studies, Routledge, London, pp 191-204
van Dijk TA (2011) Discourse and ideology. In: Van Dijk TA (ed) Discourse studies: A multidisciplinary introduction, Sage Publication Ltd, London, pp 497–531
van Dijk TA (2018) Sociocognitive discourse studies. In Richardson J, Flowerdew J (eds) Handbook of discourse analysis, Routledge, London, pp 26–42
Wang G, Liu Y, Tu S (2023a) Discursive use of stability in *New York Times'* coverage of China: a sentiment analysis approach. Humanit Soc Sci Commun 10(1):666. https://doi.org/10.1057/s41599-023-02165-0
Wang Y, Coler M, Redeker G (2023b) A contrastive study on the representation of "Made in China" in Chinese and U.S. newspapers. Front Commun 8. https://doi.org/10.3389/fcomm.2023.1129376
Ye M, Thomas P (2020) Paternalism in China Daily's coverage of Chinese Muslims (2001–2015). Discourse Commun. 14(3):314–331. https://doi.org/10.1177/1750481319893770
Yu D, Li L, Su H, Fuoli M (2023) Assessing the potential of AI-assisted pragmatic annotation: the case of apologies. ARXIV. https://doi.org/10.48550/arXiv.2305.08339
Zhao X, De Swert K, Boukes M, Vliegenthart R (2023) Framing EU–China trade relations: a content analysis of UK newspaper coverage (2001–2021). Journal Stud 24(15):1918–1936. https://doi.org/10.1080/1461670X.2023.2260497
Zhu Y (2019) Determining economic news about China in global news feed: evidence from global database of events, language and tone. Glob Media China 4(2):272–285. https://doi.org/10.1177/2059436419848827

Author contributions

Meng Ye conceptualised the project, conducted data collection and analysis, and drafted the manuscript. Eric Friginal contributed to data analysis and supervised the project implementation.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

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Additional information

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