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From Shanghai to Wall Street: The Influence of Chinese News Sentiment on US Stocks

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ABSTRACT
This study explores the influence of Chinese news sentiment on US stocks, focusing on the potential policy shift granting Chinese retail traders direct access to US markets. Analyzing the flow of information between Chinese news sentiment and global news sentiment using transfer entropy, the findings reveal a significant influence of Chinese news sentiment on global news sentiment. Moreover, the study identifies a predominant unidirectional flow of information from news sentiment to stock returns, with Chinese news sentiment having a more substantial impact on future returns of US stocks compared to global news sentiment. This suggests that if the proposed policy changes succeed, Chinese retail traders may rely on Chinese news sentiment, potentially leading to increased volatility in the US market. Policymakers and market participants should be aware of these implications to prepare for changes in the US stock market dynamics. Further research can provide deeper insights into the interplay between news sentiment, investor behavior, and market volatility.

KEYWORDS
Behavioral finance; investor sentiment; retail investors; textual analysis; information flow

1. Introduction

If Chinese traders enter US markets, they may bring volatility with them.[1]

In 2021, there was news that China was considering a policy shift that would allow its population of over 170 million retail traders direct access to overseas stock markets, including US exchanges (Xu Klein 2021). The potential implementation of this policy could empower each retail trader to invest as much as US$50,000 annually in US stocks, marking a significant milestone in the dynamics of international stock markets. Some analysts have stated that if permitted, this change has the potential to increase the volatility of US markets (Xu Klein 2021). Motivated by these suggested policy changes, this study aims to investigate the effect of firm-level Chinese news sentiment on US stock returns, given the documented fact that the Chinese investors predominantly consist of retail traders (Nyakurukwa and Seetharam 2023a; Titman, Wei, and Zhao 2022).

To understand the potential impact of Chinese news sentiment (sentiment extracted from Chinese news media) on US stock markets, we quantify the flow of information between Chinese news sentiment and constituents of the Dow Jones Industrial Average (DJIA). We choose DJIA constituents because of their size and their increased potential of being mentioned on news platforms daily. For comparison purposes, we also use global news sentiment (news sentiment gathered from various sources irrespective of the country of origin) to understand whether it is dynamically associated with US stock returns. We also attempt to understand whether there is a causal relationship between Chinese news sentiment and global news sentiment.

The proposed policy change, granting millions of Chinese retail traders direct access to foreign stocks, introduces an unprecedented volume of new investors with unique characteristics into the US markets. Substantial empirical evidence has shown that Chinese retail traders make investment decisions based on personal circumstances and emotions (e.g. Dong et al. 2022). Their bounded rationality (Selten 1990) constrains their ability to process vast amounts of information, leading to cognitive and temporal limitations. As a result, retail traders often resort to heuristic decision-making to simplify the complex task of choosing among thousands of potential stock purchases. One such heuristic involves limiting the choice set to stocks that have recently captured the investor's attention (Barber and Odean 2008). Stocks featured in

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recent news or those experiencing market-moving events act as anchors for investment decisions. This attention-based heuristic allows investors to narrow down their choices and allocate their resources more efficiently, mitigating the effects of information overload (Barber and Odean 2008).

In the context of Chinese retail traders potentially entering US markets, the impact of firm-level Chinese news sentiment becomes even more pertinent. If Chinese retail traders are exposed to specific news events or sentiments related to certain US stocks, these stocks may attract their attention and become the focus of their investment decisions. Understanding how firm-level Chinese news sentiment influences the attention and subsequent investment choices of investors in US exchanges provides valuable insights into market dynamics. If Chinese retail traders concentrate their investments on specific stocks influenced by Chinese news sentiment, this behavior could lead to concentrated buying or selling activities, affecting the stock returns of those companies and potentially amplifying market volatility. The collective impact of Chinese retail traders' actions could significantly influence overall market sentiment and contribute to increased volatility in the USA market. We, therefore, examine whether news sentiment originating from Chinese media can potentially impact US stocks.

According to Barber and Odean (2008), an attention-grabbing event is likely to be reported in the news. Events such as corporate announcements, earnings reports, mergers, acquisitions, or major economic developments are often deemed newsworthy and become the focus of media discussions and financial news outlets. While news stories serve as significant attention anchors for investors, it is essential to recognize that not all news stories are created equal. News reports can vary in their impact on investor behavior, depending on the perceived significance and relevance of the event. Some news stories may have a profound and lasting impact on investor sentiment, prompting heightened activity in the market, while others may be viewed as less consequential and receive minimal attention.

The significance of firm-level Chinese news sentiment directed at US stocks lies in its potential to shape investors' perceptions and influence their investment decisions. A news story highlighting positive developments or prospects for a particular company could attract positive attention from investors, potentially leading to increased buying activity and a surge in stock prices. Conversely, negative news coverage, such as controversies or financial woes, could drive pessimism among investors, triggering selling pressure and causing stock prices to plummet (Nyakurukwa and Seetharam 2023b). Moreover, the context and timing of news reports can play a crucial role in determining their impact on investor attention. In times of heightened market volatility or uncertainty, investors may be more receptive to news stories that confirm their preexisting beliefs or fears, leading to emotional reactions and further amplification of market fluctuations.

We proceed as follows; Section 2 looks at the data and methods, Section 3 presents the results, Section 4 discusses the results and Section 5 concludes.

2. Data and methods

2.1. Data

We use all (30)[2] stocks that are constituents of the Dow Jones Industrial Average (DJIA) because they are some of the largest stocks in the USA and are frequently mentioned on various news platforms, and hence likely to have good quality news sentiment scores. We get our news sentiment scores and stock returns from Bloomberg. The sample period starts from 9 September 2021 to 24 April 2023, together constituting 423 daily observations. Our selection of the sample period is guided by the availability of data. Chinese news sentiment scores only started being incorporated on Bloomberg platforms recently (in 2021). We use two measures of news sentiment, Chinese news sentiment and global news sentiment. Chinese news sentiment is sentiment directed at DJIA stocks and is extracted from Chinese news media while global news sentiment is sentiment directed at DJIA stocks irrespective of the origin of the news.

The process of computing the daily average news sentiment scores employed by Bloomberg Inc. begins with a manual analysis of extensive news datasets by human experts. Labels are then assigned to each news article and sorted into positive, negative or neutral categories based on the question:

> *"Considering an investor with a long position in the mentioned security reads this tweet, would their stance be bullish, bearish, or neutral on their holdings?"*

These manually categorized inputs are then fed into machine learning models, which are trained to mimic language experts in analyzing text messages. The finalized machine learning models are subsequently utilized to assess new articles associated with tickers and assign a sentiment score at the story level, ranging from −1 to +1, in real time. The daily average news sentiment for a firm is then derived from the weighted average of story-level sentiment scores from the past 24 h collected from various news media sources. This average news sentiment is updated every day, 10 min before the opening of stock markets. Average news sentiment ranges from −1, the most negative sentiment to +1, the most positive sentiment. This means that an average sentiment score of 0 denotes neutral sentiment. Firm-level stock returns are computed as log returns.

2.2. Methods

2.2.1. Granger causality

The Granger causality test (Granger, 1980) is a classical model for testing causality between time series that has been extensively used in economics and finance. To establish if a variable X causes another variable Y, the Granger causality concept predicts Y using its own history, its history plus the history of the variable X, and finally evaluating the difference between the two to find if the added variable has some effect on the predictions of the targeted variable. To this end, two $VAR(p)$ (Vector auto-regressive) models are formally considered where the first uses the precedent values of Y and the second uses both past values of X and Y to predict Y as follows:

$$Model\ 1\ \ Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + u_t \qquad [1]$$

$$Model\ 2\ \ Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + u_t \qquad [2]$$

where p is the lag parameter, $[\alpha_0, \ldots, \alpha_p]$ *and* $[\beta_0, \ldots, \beta_p]$ are the parameters of the models and u is a white noise error term. To quantify the causality, we evaluate the variances of the errors of Model 1 and Model 2 resulting in a Granger causality index (GCI) which is formulated as follows;

$$GCI = \log\left(\frac{\sigma_1^2}{\sigma_2^2}\right) \qquad [3]$$

where σ_1^2 and σ_2^2 are the variances of the errors of Model 1 and Model 2 respectively. To compute the statistical significance of the difference between these variances, the Fisher test is utilized;

$$F = \frac{(RSS_1 - RSS_2)/p}{RSS_2/(n-2p-1)} \qquad [4]$$

where RSS_1 and RSS_2 are the residual sum of squares related to models 1 and 2 respectively and n is the size of the lagged variables. The following hypotheses are considered:

$$\begin{aligned} &H_0: \forall i \in \{1, \ldots, p\},\ \ \beta_i = 0 \\ &H_1: \exists i \in \{1, \ldots, p\},\ \ \beta_i \neq 0 \end{aligned} \qquad [5]$$

where H_0 is the hypothesis that X does not cause Y and where H_0 follows the Fisher distribution with $(p,\ n-2p-1)$ as degrees of freedom. To determine the dominant flow of information between the two variables, we utilize the GCI. We conclude that information flows dominantly from Chinese news (Global media) to Global news (Chinese news) if the GCI for *Chinese news* → *Global news* is greater than the GCI for *Global news* → *Chinese news* for each sampled firm. In evaluating the dominant flow of information between Chinese news and global news for all the sampled companies, we only consider the GCI values if one or both of *Chinese news* → *Global news* and *Global news* → *Chinese news* are statistically significant at the 5% level. We use the same approach to establish the flow of information between Chinese (Global) news sentiment and stock returns.

2.2.2. Transfer entropy

Entropy-based approaches have gained popularity in the fields of economics and finance since they were first introduced by Schreiber (2000). In this study, transfer entropy was chosen as the foundation due to its robustness when compared to traditional Granger causality tests, particularly in capturing extreme events within return distributions (Nyakurukwa 2021). A distinctive feature of transfer entropy is its freedom from model constraints, allowing it to gauge the directed flow of information between random variables over time. This characteristic offers an asymmetrical approach to measuring information transfer (Yao 2020).

Transfer entropy serves as a non-parametric measure designed to assess the directed and asymmetric transfer of information between two time series processes. Notably, it operates without making any assumptions specific to the underlying stochastic processes. In a context where "log" symbolizes the base-2 logarithm, the concept of Shannon entropy (Shannon 1948) posits that for a discrete random variable J, characterized by a probability distribution $p(j)$ where "j" signifies the distinct potential outcomes of J, the average number of bits required for optimal encoding of independent samples drawn from J's distribution can be computed using the following equation:

$$H_J = -\sum p(j)\ .\ \log(p(j)) \qquad [6]$$

In essence, Equation [6] quantifies the level of uncertainty, which increases as the required bits for optimal encoding of a sequence of J's realizations grow. The measurement of information flow between two time series processes involves a fusion of the concepts of Shannon entropy and Kullback-Liebler distance. This fusion is applied while assuming that the underlying process evolves temporally through a Markov process (Schreiber 2000). Denoting two discrete random variables as I and J, with marginal probability distributions $p(i)$ and $p(j)$ respectively, along with a joint distribution $p(i,j)$ whose dynamic structures correspond to stationary Markov processes of order k and j, the Markov property yields the conditional probability of observing I in state i at time $t+1$, given the previous k observations:

$$p(i_{t+1}|i_t,\ldots,i_{t-k+1}) = p(i_{t+1}|i_t,\ldots,i_{t-k}) \quad [7]$$

The average number of bits needed to encode the observation at time $t+1$, given knowledge of the preceding k values, is expressed as:

$$h_1(k) = -\sum p\left(i_{t+1}, i_t^{(k)}\right) \, . \, \log(p\left(i_{t+1}|i_t^{(k)}\right) \quad [8]$$

where $(\mathrm{i}_\mathrm{t}^{(\mathrm{k})} = (\mathrm{i}_\mathrm{t},\ldots,\mathrm{i}_{\mathrm{t}-k+1}))$. A similar derivation applies to $(h_j(l))$ for process J. In a bivariate scenario, quantifying the information flow from process J to process I involves a departure from the generalized Markov property $\left(p\left(i_{t+1}|i_t^{(k)}\right) = p\left(i_{t+1}|i_t^{(k)}, j_t^{(l)}\right)\right)$ using Kullback-Leibler distance (Schreiber 2000). The Shannon transfer entropy is quantified as follows:

$$T_{J\to I}(k,l) = \sum\nolimits_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) \cdot \log\left(\frac{p\left(i_{t+1}|i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1}|i_t^{(k)}\right)}\right) \quad [9]$$

Here, $(T_{J\to I})$ quantifies the flow of information from process J to process I, while a parallel derivation can determine $(T_{I\to J})$, representing information flow from I to J.

The transfer entropy represented by Equation [9] may yield biased results due to the influence of limited sample size effects. To address this issue, the

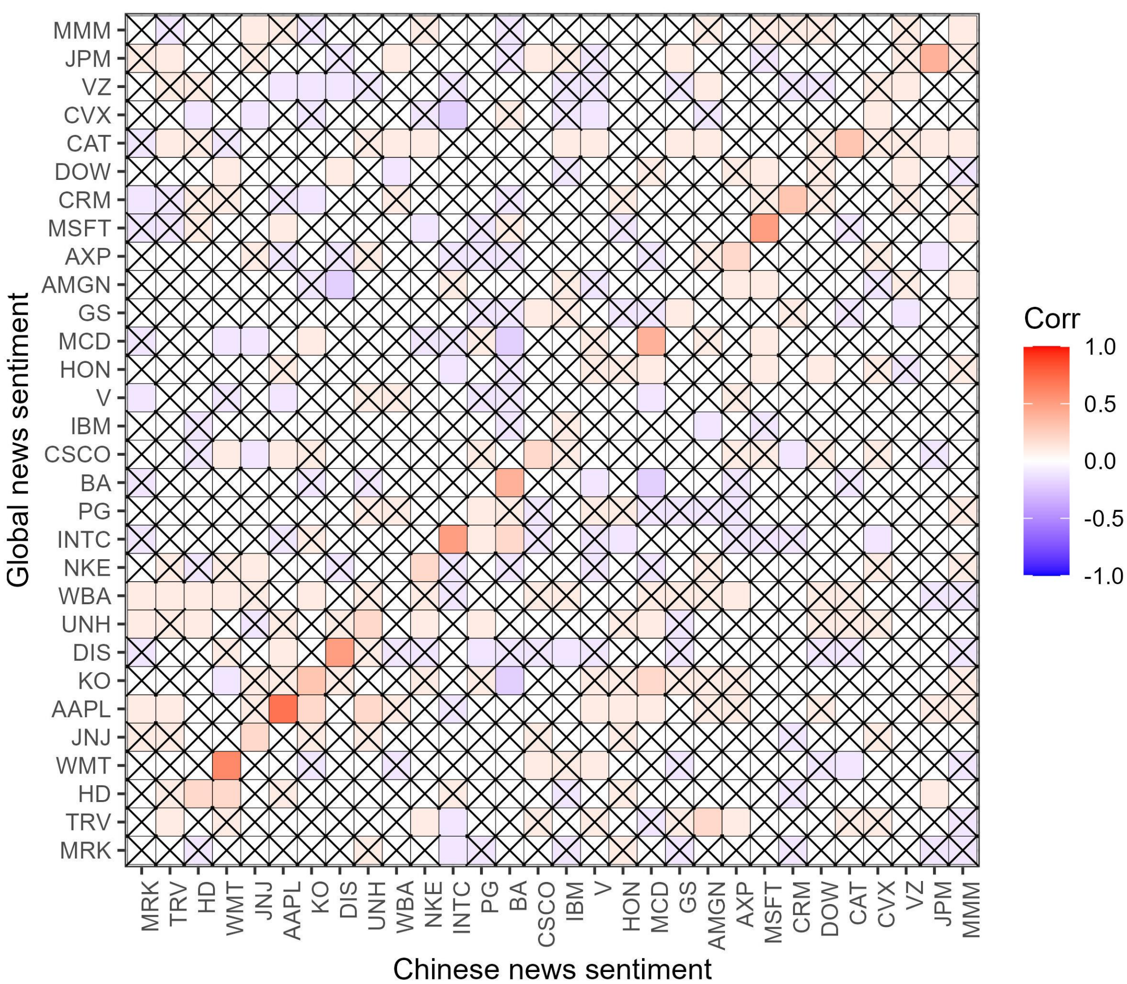

Figure 1. Correlations between Chinese news media and global news media scores.

effective transfer entropy (ETE) method introduced by Marschinski and Kantz (2002) 2002 is utilized. The computation of effective transfer entropy, as outlined in the subsequent Equation [10], involves subtracting the transfer entropy calculated using a shuffled version of the J time series:

$$ET_{J\to I}(k,l) = T_{J\to I} - T_{Jshuffled\to I}(k,l) \qquad [10]$$

Here, $\mathrm{T}_{\mathrm{Jshuffled}\to\mathrm{I}}(\mathrm{k},\mathrm{l})$ is obtained by applying shuffling to the time series of *J*. This shuffling process involves randomly rearranging values from *J's* time series to create a new sequence. The purpose of shuffling is to eliminate the temporal dependencies within *J's* time series and the statistical associations between *I* and *J*. As a consequence, the value of $(\mathrm{T}_{\mathrm{Jshuffled}\to\mathrm{I}}(\mathrm{k},\mathrm{l}))$ tends to approach zero as the sample size increases. Any non-zero value indicates the presence of small sample effects. To ensure reliable estimation, the shuffling process is repeated multiple times, and the resulting transfer entropy values are averaged. This average is then subtracted from the Shannon transfer entropy estimates, yielding corrected effective transfer entropy values that are unbiased.

The statistical significance of the transfer entropy estimates is determined using the Markov block bootstrap method (Dimpfl and Peter 2013). Unlike the shuffling process described earlier, the Markov block bootstrap method maintains the temporal dependencies within the time series data. This method generates a distribution of transfer entropy estimates under the null hypothesis of no information flow. Subsequently, the Shannonian transfer entropy is computed using simulated time series data. This procedure is repeated, generating a distribution of entropy transfer estimates under the null hypothesis. The *p*value associated with the null hypothesis of no information transfer is calculated as $(1 - \mathrm{q}_{\mathrm{TE}})$, where $(\mathrm{q}_{\mathrm{TE}})$ represents the quantile of the simulated distribution that corresponds to the original transfer entropy estimate.

It's important to highlight that the computation of Shannonian relies on discrete data. However, since this study deals with continuous data, the data is discretized using symbolic coding. This involves dividing the data into discrete bins based on the quantiles of the empirical data distribution. Assuming the bounds specified for the n bins are represented by $q_{1,}\, q_2, \ldots, q_n$

Table 1. Results from Granger causality.

	Chinese news media sentiment and global news sentiment					Chinese news media sentiment and stock returns				
	Chinese news → Global news		Global news → Chinese news			Chinese news → Returns		Returns → Chinese news		
Ticker	Ftest	GCI	Ftest	GCI	Diff	Ftest	GCI	Ftest	GCI	Diff
AAPL	18.4519***	0.0432	11.7016***	0.0276	0.0156	2.9043*	0.0069	1.4921	0.0036	0.0034
AMGN	1.0242	0.0024	0.0054	0.0000	0.0024	4.1767**	0.0099	0.3143	0.0008	0.0092
AXP	13.6258***	0.0321	0.3378	0.0008	0.0313	22.5503***	0.0525	0.0094	0.0000	0.0525
BA	103.2363***	0.2207	1.7793	0.0042	0.2165	56.9665***	0.1278	1.5353	0.0037	0.1241
CAT	19.3340***	0.0452	0.0867	0.0002	0.0450	27.3465***	0.0634	0.6315	0.0015	0.0619
CRM	33.2061***	0.0764	0.0737	0.0002	0.0763	18.8897***	0.0442	0.2388	0.0006	0.0436
CSCO	17.5563***	0.0411	0.3285	0.0008	0.0404	17.6275***	0.0413	0.5136	0.0012	0.0401
CVX	19.3499***	0.0453	0.0232	0.0001	0.0452	11.9421***	0.0282	1.6104	0.0038	0.0243
DIS	18.4781***	0.0433	9.8233***	0.0232	0.0200	6.9566***	0.0165	1.8178	0.0043	0.0122
DOW	0.2051	0.0005	1.3620	0.0033	−0.0028	0.4885	0.0012	4.3172**	0.0103	−0.0091
GS	3.2294*	0.0077	0.5937	0.0014	0.0063	1.8151	0.0043	4.7899**	0.0114	−0.0071
HD	6.2635**	0.0149	0.4353	0.0010	0.0138	9.7598***	0.0231	2.1929	0.0052	0.0178
HON	8.4073***	0.0199	0.0117	0.0000	0.0199	11.8029***	0.0278	2.6494	0.0063	0.0215
IBM	6.5687**	0.0156	0.2597	0.0006	0.0150	56.7099***	0.1272	1.1856	0.0028	0.1244
INTC	4.8672**	0.0116	0.0037	0.0000	0.0116	15.4526***	0.0363	0.4239	0.0010	0.0353
JNJ	2.9806*	0.0071	0.0796	0.0002	0.0069	11.1067***	0.0262	1.9492	0.0047	0.0216
JPM	1.3295	0.0032	1.5385	0.0037	−0.0005	1.8444	0.0044	1.3165	0.0031	0.0013
KO	3.1343*	0.0075	0.5263	0.0013	0.0062	4.8348**	0.0115	0.1795	0.0004	0.0111
MCD	4.4954**	0.0107	0.2180	0.0005	0.0102	6.3467**	0.0151	2.1025	0.0050	0.0101
MMM	0.6762	0.0016	0.2965	0.0007	0.0009	1.9615	0.0047	0.5593	0.0013	0.0033
MRK	0.2688	0.0006	1.5508	0.0037	−0.0031	1.7968	0.0043	0.1627	0.0004	0.0039
MSFT	21.5932***	0.0504	8.2431***	0.0195	0.0308	10.9250***	0.0258	0.9789	0.0023	0.0235
NKE	25.5517***	0.0593	0.3849	0.0009	0.0584	15.6212***	0.0367	1.8270	0.0044	0.0323
PG	6.9402***	0.0165	2.1544	0.0051	0.0113	5.1996**	0.0124	2.7489*	0.0066	0.0058
TRV	1.8922	0.0045	0.0387	0.0001	0.0044	11.6993***	0.0276	3.5516*	0.0085	0.0191
UNH	6.5483**	0.0155	0.0004	0.0000	0.0155	8.9784***	0.0213	0.0388	0.0001	0.0212
V	10.0559***	0.0238	4.7001**	0.0112	0.0126	2.3141	0.0055	3.2109*	0.0077	−0.0021
VZ	2.4710	0.0059	0.0454	0.0001	0.0058	6.7170***	0.0159	5.2349**	0.0124	0.0035
WBA	1.6992	0.0041	2.0438	0.0049	−0.0008	3.6633*	0.0087	1.9268	0.0046	0.0041
WMT	77.3506***	0.1698	0.2013	0.0005	0.1693	44.3908***	0.1009	0.1313	0.0003	0.1006

Notes: In Table 1, Ftest shows the F-statistic, GCI represents the Granger Causality Index, and Diff shows the differences in the GCIs in both directions. Statistical significance at the 1%, 5% and 10% level is represented by three, two and one astericks respectively.

where $q_1 < q_2 ... < q_n$, and assuming that a time series is denoted by y_t, the data is recoded by:

$$\begin{cases} 1 & for y_t \leq q_1 \\ 2 & for q_1 < y_t \leq q_2 \\ \vdots & \vdots \\ n-1 & for q_{n-1} < y_t \leq q_2 \\ n & for y_t \geq q_n \end{cases}$$

Each value in the time series y_t is replaced with an integer $(1, 2, ..., n)$ according to how S_t relates to the interval specified by the lower and upper bounds $q_1 q_n$. The choice of bins is justified by the empirical distribution of the data. For both Granger causality and transfer entropy, we primarily use a lag length of one. This is motivated by literature that reports that financial time series can be appropriately modeled with Markov chains of order one (McQueen and Thorley 1991; Turner, Startz, and Nelson 1989). However, for robustness, we also use a lag length that minimizes the BIC from a bivariate VAR framework consisting of the variables of interest.

3. Results

3.1. Summary statistics

Tables A1 and A2 (in the Appendix) show the summary statistics for the firm-level news sentiment using Chinese news sentiment and global news sentiment respectively. Some interesting characteristics of the variables can be observed. First, looking at the mean of the firm-level sentiment scores, there seems to be consistency between the Chinese news sentiment and global news sentiment as, for most stocks (70% of the stocks), the mean scores have the same sign (both positive or both negative). This means that on average, the news sentiment carried by Chinese news media is consistent with the news sentiment carried by the global news media. An interesting phenomenon can also be observed where MCD (McDonald's Corp) has the same mean score (0.04) for Chinese news sentiment and global news sentiment. There is also evidence that all series do not follow a Gaussian distribution (Jarque and Bera 1980), are stationary (Elliott, Rothenberg, and Stock 1996) and exhibit autocorrelation and ARCH/GARCH errors (Fisher and Gallagher 2012). The summary statistics motivate modeling the interdependence of the variables using models that are robust in the presence of these characteristics. In Figure 1, we show correlations between firm-level Chinese news sentiment scores and firm-level global news sentiment scores. Correlations range from -1 to +1 with blue representing the lowest correlation (-1), white representing a correlation of 0 and red representing the highest correlation coefficient (+1). Correlations that are checked are not significant at the 5% level of significance.

Figure 1 shows that the correlation between Chinese news sentiment for one stock and the global news sentiment for another stock is generally statistically insignificant (Most of the correlations are checked out, showing statistical insignificance at the 5% level). For the few stocks that have significant correlations between Chinese news sentiment and global news sentiment (e.g. the correlation between MRK and AAPL), the correlations are mostly positive. This generally shows that the Chinese and global news media sentiment generally moves in the same direction, even for different companies. An interesting pattern can be observed in the bottom left to upper right diagonal where the correlations are positive and stronger (as shown by the brighter colours). In the diagonal, 23 (76.67%) of the correlations are statistically significant at the 5% level of significance. This diagonal represents the correlations between Chinese news sentiment and global news sentiment for the same stock. Thus, the diagonal shows that generally, an increase in Chinese news sentiment is associated with an increase

Table 2. Global news sentiment and USA stock returns.

	Global news → Returns		Returns → global news		
Ticker	Ftest	GCI	Ftest	GCI	Diff
AAPL	0.0232	0.0001	0.0028	0.0000	0.0000
AMGN	1.3499	0.0032	2.6945	0.0064	−0.0032
AXP	0.1558	0.0004	0.0401	0.0001	0.0003
BA	5.4987**	0.0131	0.0137	0.0000	0.0130
CAT	1.1716	0.0028	0.1379	0.0003	0.0025
CRM	18.7450***	0.0439	0.2389	0.0006	0.0433
CSCO	3.0108*	0.0072	0.3931	0.0009	0.0062
CVX	0.9902	0.0024	0.3093	0.0007	0.0016
DIS	8.3522***	0.0198	7.1131***	0.0169	0.0029
DOW	1.9057	0.0045	3.0496	0.0073	−0.0027
GS	0.5093	0.0012	0.5459	0.0013	−0.0001
HD	0.0975	0.0002	2.7904*	0.0067	−0.0064
HON	0.2142	0.0005	2.4628	0.0059	−0.0054
IBM	1.7996	0.0043	0.3748	0.0009	0.0034
INTC	1.8508	0.0044	3.1639*	0.0075	−0.0031
JNJ	0.1013	0.0002	3.0775*	0.0073	−0.0071
JPM	1.4805	0.0035	1.6617	0.0040	−0.0004
KO	0.3631	0.0009	0.6604	0.0016	−0.0007
MCD	4.5945**	0.0109	4.2139**	0.0100	0.0009
MMM	0.0202	0.0000	0.6040	0.0014	−0.0014
MRK	0.0029	0.0000	1.5313	0.0037	−0.0036
MSFT	13.7533***	0.0324	5.7352**	0.0136	0.0187
NKE	12.6649***	0.0298	6.0551**	0.0144	0.0155
PG	5.4120**	0.0129	0.8815	0.0021	0.0108
TRV	3.2715*	0.0078	0.1112	0.0003	0.0075
UNH	0.4169	0.0010	0.7166	0.0017	−0.0007
V	0.4372	0.0010	0.0031	0.0000	0.0010
VZ	0.1420	0.0003	0.0229	0.0001	0.0003
WBA	0.9987	0.0024	0.3428	0.0008	0.0016
WMT	14.1483***	0.0333	0.0005	0.0000	0.0333

Notes: In Table 2, Ftest shows the F-statistic, GCI represents the Granger Causality Index, and Diff shows the differences in the GCIs in both directions. Statistical significance at the 1%, 5% and 10% level is represented by three, two and one astericks respectively.

Table 3. Flow of information between Chinese and global news sentiment.

	Chinese sentiment → Global sentiment			Global sentiment → Chinese sentiment			
TICKER	TE	ETE	SE	TE	ETE	SE	Diff
AAPL	0.0763	0.0605***	0.0068	0.0098	0.0000	0.0053	0.0605
AMGN	0.0093	0.0000	0.0074	0.0078	0.0000	0.0056	0.0000
AXP	0.0196	0.0068	0.0065	0.0207	0.0054*	0.0056	0.0014
BA	0.0632	0.0513***	0.0062	0.0090	0.0000	0.0063	0.0513
CAT	0.0282	0.0137**	0.0068	0.0173	0.0019	0.0053	0.0118
CRM	0.0669	0.0539***	0.0060	0.0103	0.0000	0.0048	0.0539
CSCO	0.0437	0.0294***	0.0055	0.0122	0.0000	0.0064	0.0294
CVX	0.0476	0.0319***	0.0066	0.0227	0.0083*	0.0061	0.0236
DIS	0.0605	0.0432***	0.0061	0.0283	0.0121**	0.0062	0.0312
DOW	0.0136	0.0000	0.0060	0.0194	0.0058*	0.0052	−0.0058
GS	0.0228	0.0095*	0.0060	0.0138	0.0023	0.0057	0.0072
HD	0.0098	0.0000	0.0062	0.0277	0.0114*	0.0066	−0.0114
HON	0.0178	0.0023	0.0063	0.0140	0.0015	0.0053	0.0009
IBM	0.0109	0.0000	0.0069	0.0102	0.0000	0.0060	0.0000
INTC	0.0620	0.0477***	0.0054	0.0095	0.0000	0.0063	0.0477
JNJ	0.0145	0.0000	0.0065	0.0233	0.0081*	0.0063	−0.0081
JPM	0.0281	0.0152***	0.0051	0.0255	0.0121**	0.0048	0.0030
KO	0.0346	0.0207***	0.0057	0.0101	0.0000	0.0054	0.0207
MCD	0.0265	0.0158**	0.0053	0.0225	0.0083	0.0064	0.0075
MMM	0.0208	0.0068*	0.0063	0.0127	0.0000	0.0046	0.0068
MRK	0.0056	0.0000	0.0064	0.0139	0.0000	0.0063	0.0000
MSFT	0.0427	0.0284***	0.0059	0.0169	0.0000	0.0068	0.0284
NKE	0.0469	0.0331***	0.0056	0.0300	0.0171**	0.0058	0.0160
PG	0.0212	0.0060	0.0067	0.0064	0.0000	0.0057	0.0060
TRV	0.0091	0.0000	0.0068	0.0204	0.0065*	0.0058	−0.0065
UNH	0.0179	0.0018	0.0068	0.0074	0.0000	0.0047	0.0018
V	0.0425	0.0313***	0.0051	0.0152	0.0047*	0.0034	0.0266
VZ	0.0196	0.0076*	0.0056	0.0135	0.0031	0.0052	0.0045
WBA	0.0079	0.0000	0.0049	0.0060	0.0000	0.0036	0.0000
WMT	0.0240	0.0091**	0.0053	0.0206	0.0048	0.0064	0.0044

Notes: Observations are discretised based on the 5%- and 95%-quantiles estimates. Inference is based on 300 bootstrapped transfer entropies for each stock. TE, ETE and SE represent Transfer Entropy, Effective Transfer Entropy and standard errors respectively.
***, **, * shows statistical significance at the 1%, 5% and 10% respectively.

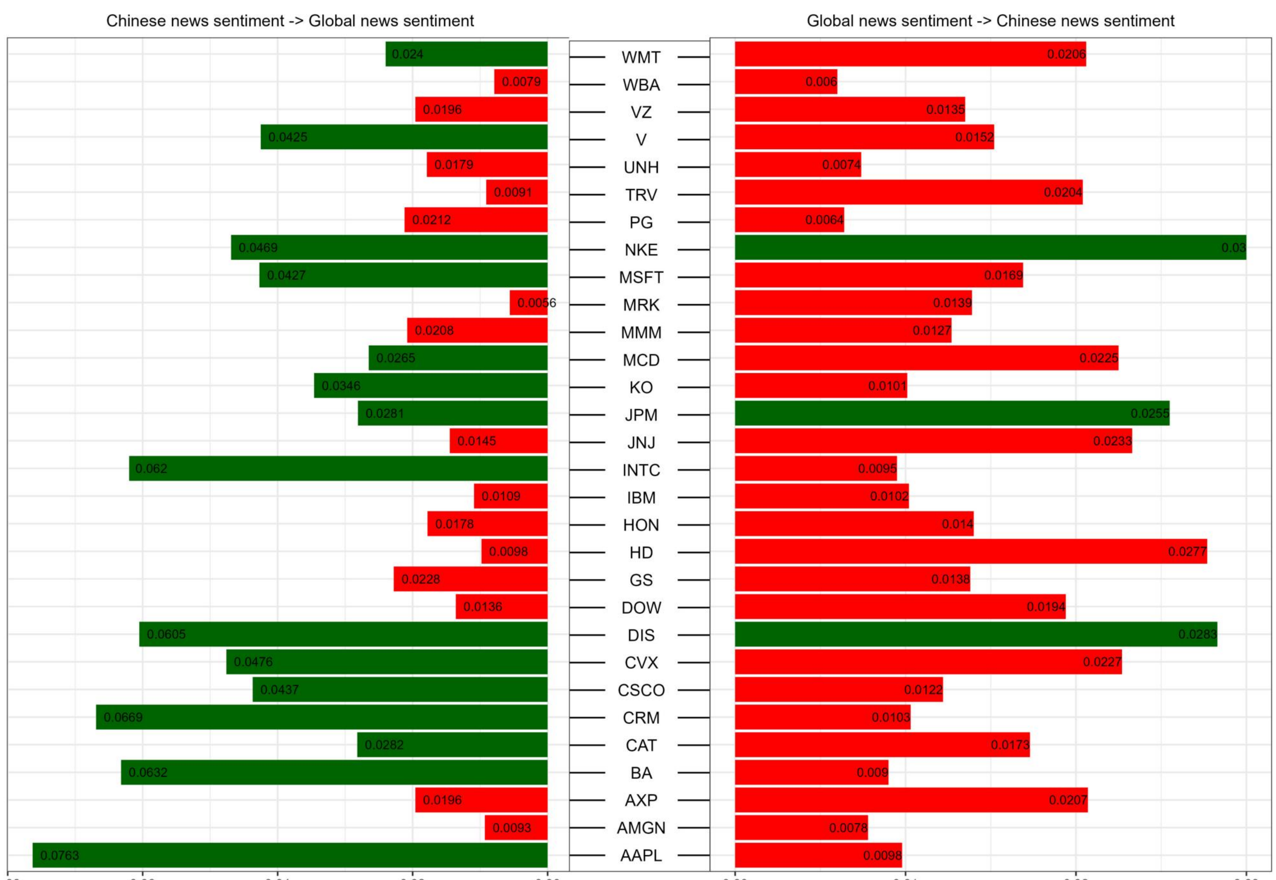

Figure 2. Visualizing the flow of information between Chinese and global news sentiment.

in global news sentiment for the same stock. It, therefore, becomes important to understand whether there is a lead-lag relationship between Chinese news sentiment and global news sentiment using a more robust method. We report this in the next sections.

3.2. Granger causality

We first report results on the dominant flow of information between Chinese news sentiment and global news sentiment using Granger causality in Table 1. Though Granger causality has some weaknesses emanating from the stringent assumptions, it is essential to report the findings and compare them with the results obtained from a more robust method, transfer entropy in the next section. Starting with the causal relationship between Chinese news sentiment and global news sentiment, we observe that the former Granger causes the latter in 19 (63.33%) of the 30 stocks while 11 stocks exhibit a non-significant causal relationship at the 5% level of significance. Shifting to the reverse causal relationship, only 4 stocks exhibit a significant causal relationship from global news sentiment to Chinese news sentiment. Turning to our variables of interest, Table 1 shows that Chinese news sentiment has a significant effect on USA stock returns in 22 (73.33%) stocks while the reverse relationship shows significant causality from USA stock returns to Chinese news sentiment in only 3 (10%) stocks. Looking at the relationship between the global news sentiment and stock returns (Table 2), we, however, observe deviations from the results reported for Chinese news sentiment and USA stock returns (Table 1). Table 2 shows that only 8 (26.67%) of the stocks exhibit a significant causality from global news sentiment to stock returns while only 4 (13.33%) of stocks exhibit a significant reverse causal relationship. In the next section, we present results from transfer entropy, which is robust to the assumptions inherent in traditional Granger causality.

3.3. Transfer entropy

In this section, we report the findings from the transfer entropy empirical specifications explained in the methodology section. We first report results on the flow of information between Chinese news sentiment and global news sentiment in Table 3. TE, ETE and SE respectively represent Transfer Entropy, Effective Transfer Entropy and Standard Errors. The significant flow of information at 1%, 5% and 10% is correspondingly represented by

Table 4. Flow of information from sentiment to stock returns.

	Chinese sentiment → Returns			Global sentiment → Stock returns			
TICKER	TE	ETE	SE	TE	ETE	SE	Diff
AAPL	0.0270	0.0152**	0.0053	0.0132	0.0024	0.0054	0.0128
AMGN	0.0055	0.0000	0.0067	0.0157	0.0025	0.0062	−0.0025
AXP	0.0279	0.0117**	0.0069	0.0126	0.0000	0.0064	0.0117
BA	0.0925	0.0780***	0.0073	0.0452	0.0294***	0.0072	0.0486
CAT	0.0250	0.0121**	0.0056	0.0116	0.0000	0.0065	0.0121
CRM	0.0447	0.0328***	0.0055	0.0104	0.0000	0.0057	0.0328
CSCO	0.0315	0.0165**	0.0063	0.0256	0.0107*	0.0068	0.0058
CVX	0.0412	0.0267***	0.0069	0.0105	0.0000	0.0059	0.0267
DIS	0.0309	0.0171***	0.0067	0.0273	0.0126**	0.0066	0.0045
DOW	0.0196	0.0038	0.0058	0.0052	0.0000	0.0062	0.0038
GS	0.0101	0.0000	0.0057	0.0120	0.0000	0.0067	0.0000
HD	0.0273	0.0159**	0.0065	0.0237	0.0118**	0.0056	0.0041
HON	0.0425	0.0267***	0.0064	0.0112	0.0000	0.0064	0.0267
IBM	0.0539	0.0395***	0.0066	0.0131	0.0000	0.0066	0.0395
INTC	0.0581	0.0504***	0.0040	0.0348	0.0263***	0.0048	0.0241
JNJ	0.0268	0.0137**	0.0058	0.0088	0.0000	0.0059	0.0137
JPM	0.0236	0.0104**	0.0057	0.0416	0.0298***	0.0053	−0.0194
KO	0.0149	0.0000	0.0066	0.0128	0.0000	0.0063	0.0000
MCD	0.0217	0.0102*	0.0056	0.0226	0.0109**	0.0058	−0.0007
MMM	0.0138	0.0000	0.0061	0.0143	0.0000	0.0061	0.0000
MRK	0.0231	0.0125**	0.0055	0.0103	0.0000	0.0053	0.0125
MSFT	0.0342	0.0230***	0.0061	0.0201	0.0090*	0.0058	0.0140
NKE	0.0414	0.0290***	0.0059	0.0348	0.0234***	0.0057	0.0056
PG	0.0279	0.0144**	0.0062	0.0117	0.0000	0.0065	0.0144
TRV	0.0412	0.0253***	0.0066	0.0439	0.0301***	0.0068	−0.0048
UNH	0.0241	0.0105*	0.0061	0.0216	0.0084*	0.0063	0.0021
V	0.0141	0.0015	0.0052	0.0474	0.0336***	0.0069	−0.0321
VZ	0.0136	0.0027	0.0054	0.0107	0.0000	0.0066	0.0027
WBA	0.0065	0.0000	0.0046	0.0143	0.0000	0.0066	0.0000
WMT	0.0550	0.0416***	0.0061	0.0586	0.0449***	0.0061	−0.0033

Notes: Observations are Discretized based on the 5%- and 95%-quantiles estimates. Inference is based on 300 bootstrapped transfer entropies for each stock. TE, ETE and SE represent Transfer Entropy, Effective Transfer Entropy and standard errors respectively.
***, **, * shows statistical significance at the 1%, 5% and 10% respectively.

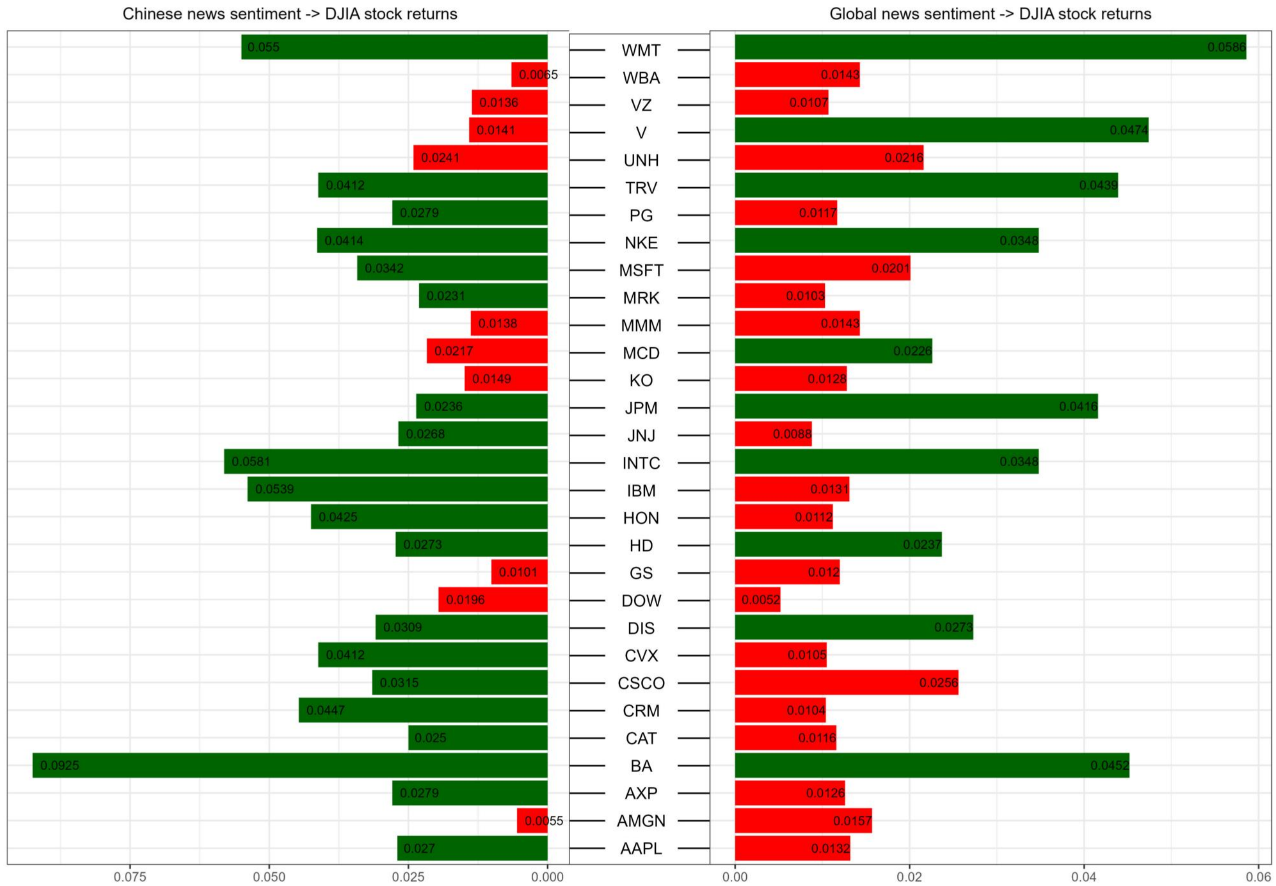

Figure 3. Visualizing the flow of information from sentiment to stock returns.

three, two and one asterisks. Columns 2 to 4 quantify the flow of information from Chinese news sentiment to global news sentiment. This information is also visualized in Figure 2 for clarity. Figure 2 shows the TE values for all the sampled stocks, with significant values at the 5% level of significance shown in the green color while the red color shows TE values which are not statistically significant at any of the conventional levels of significance. In the left panel of Figure 2, green-coloured TE values amount to 15 (constituting 50% of the stocks). This shows that in half of the DJIA stocks, information dominantly flows from Chinese news sentiment to global news sentiment. This shows that in these stocks, knowledge of Chinese news sentiment today may help in predicting the future global news sentiment directed at the same stocks.

When we look at the reverse flow of information between the Chinese news sentiment and global news sentiment, a different picture emerges. Quantification of the flow of information from global news sentiment to Chinese news sentiment is now only significant in 3 of the 30 stocks (only 10% of the stocks). For these stocks, if we calculate the difference between the flow of information from Chinese sentiment to global sentiment vis-à-vis the flow of information from global sentiment to Chinese sentiment (column labeled Diff in Table 3), we find that the differences are all positive. This shows the dominance of Chinese sentiment over global sentiment in terms of the flow of information between these sources of sentiment.

In Table 4, we portray how Chinese and global news sentiments directed at the DJIA stocks are related to their respective stock returns. As before, we also visualize the firm-level relationships for clarity in Figure 3. The statistically significant flow of information at the 5% level of significance is represented by the green color while relationships shown by the red color show statical insignificance at any of the conventional levels of significance.

The information in Table 4 and Figure 3 show that information significantly flows from Chinese news sentiment to stock returns for 20 (66.67%) stocks while only 10 (33.33%) exhibit an insignificant flow of information from Chinese news sentiment to stock returns. When it comes to the flow of information from global news sentiment to stock returns, most of the stocks (66.67%) exhibit an insignificant flow of information while only one-third of the stocks show a significant flow of information at the 5% level of significance. It is interesting to note that there are stocks in which

Table 5. Flow of information from stock returns to news sentiment.

	Returns → Chinese sentiment			Returns → Global sentiment			
TICKER	TE	ETE	SE	TE	ETE	SE	Diff
AAPL	0.0098	0.0000	0.0050	0.0241	0.0086*	0.0064	−0.0086
AMGN	0.0089	0.0000	0.0052	0.0093	0.0000	0.0066	0.0000
AXP	0.0101	0.0000	0.0062	0.0148	0.0033	0.0059	−0.0033
BA	0.0194	0.0059	0.0060	0.0107	0.0000	0.0058	0.0059
CAT	0.0163	0.0014	0.0053	0.0163	0.0015	0.0066	−0.0001
CRM	0.0191	0.0057*	0.0052	0.0210	0.0082	0.0063	−0.0025
CSCO	0.0182	0.0025	0.0064	0.0162	0.0019	0.0055	0.0007
CVX	0.0177	0.0034	0.0062	0.0179	0.0012	0.0065	0.0022
DIS	0.0189	0.0027	0.0066	0.0178	0.0028	0.0070	−0.0002
DOW	0.0141	0.0023	0.0050	0.0187	0.0053	0.0065	−0.0030
GS	0.0118	0.0000	0.0069	0.0111	0.0000	0.0056	0.0000
HD	0.0253	0.0098*	0.0063	0.0191	0.0058	0.0061	0.0040
HON	0.0201	0.0074*	0.0054	0.0050	0.0000	0.0066	0.0074
IBM	0.0142	0.0000	0.0059	0.0113	0.0000	0.0064	0.0000
INTC	0.0240	0.0078*	0.0063	0.0112	0.0000	0.0063	0.0078
JNJ	0.0264	0.0113*	0.0065	0.0146	0.0000	0.0065	0.0113
JPM	0.0159	0.0024	0.0051	0.0178	0.0049	0.0045	−0.0025
KO	0.0101	0.0000	0.0051	0.0144	0.0004	0.0055	−0.0004
MCD	0.0098	0.0000	0.0067	0.0255	0.0140**	0.0050	−0.0140
MMM	0.0130	0.0000	0.0054	0.0097	0.0000	0.0061	0.0000
MRK	0.0194	0.0048	0.0058	0.0381	0.0225***	0.0062	−0.0177
MSFT	0.0146	0.0000	0.0067	0.0112	0.0000	0.0060	0.0000
NKE	0.0144	0.0009	0.0054	0.0245	0.0101*	0.0060	−0.0092
PG	0.0183	0.0029	0.0056	0.0097	0.0000	0.0064	0.0029
TRV	0.0150	0.0013	0.0060	0.0184	0.0035	0.0062	−0.0022
UNH	0.0091	0.0000	0.0062	0.0135	0.0000	0.0068	0.0000
V	0.0194	0.0099**	0.0043	0.0136	0.0010	0.0059	0.0089
VZ	0.0082	0.0000	0.0045	0.0137	0.0000	0.0064	0.0000
WBA	0.0024	0.0000	0.0033	0.0178	0.0017	0.0075	−0.0017
WMT	0.0418	0.0258***	0.0063	0.0147	0.0000	0.0058	0.0258

Notes: Observations are discretized based on the 5%- and 95%-quantiles estimates. Inference is based on 300 bootstrapped transfer entropies for each stock. TE, ETE and SE represent Transfer Entropy, Effective Transfer Entropy and standard errors respectively. ***, **, * shows statistical significance at the 1%, 5% and 10% respectively.

information significantly flows from global news sentiment to stock returns but for the same stocks no significant flow of information from Chinese news sentiment to stock returns is observed (these stocks V and MCD). Finally, we would like to establish whether the information between news sentiment and stock returns is bidirectional. Table 5 and Figure 4 quantify the flow of information from Chinese news sentiment and global news sentiment to stock returns.

As shown in Figure 4, there is a significant flow of information from both news sentiment proxies to stock returns in only 2 stocks respectively (constituting only 6.67% of the stocks). This is in stark contrast to the findings reported for the flow of information from news sentiment to stock returns. This shows that the flow of information is generally unidirectional from news sentiment to stock returns.

3.4. Robustness

To check the robustness of our results and to ensure that the results are not driven by specific model specifications, we institute a raft of robustness measures. In the results reported above, the lag length used for both Granger causality and transfer entropy was one. For robustness, we choose a lag length for both methods using the minimum Bayesian information criterion (BIC) obtained from a commonly used bivariate VAR framework that includes the variables of interest. The results (which are not reported for brevity but are available upon request) show that the lag length chosen was invariably 1, except for a single stock (TRV). The results do not qualitatively change from the results reported earlier, showing that the results are robust to the lag length. Second, in contrast to utilizing Discretization relying on the 5% and 95% quantiles in the transfer entropy method, we adopt the approach proposed by Behrendt and Prange (2021) to incorporate Discretization based on the 10% and 90% quantiles. The results show that information dominantly flows from Chinese news sentiment to USA stock returns (global news sentiment) for most of the stocks.

4. Discussion

The results reported in the previous section show that information significantly flows mostly from Chinese news sentiment to global news sentiment. This shows the importance of Chinese news media in financial markets' narratives globally. When it comes to the

Figure 4. Visualizing the flow of information from returns to news sentiment.

causal relationship between news sentiment and stock returns, the findings of the study generally reveal that Chinese news sentiment affects future returns of DJIA stocks compared to global news sentiment. This means if the proposed policy changes in China that will allow direct investment in foreign stocks succeed, there are chances that Chinese investors could use news sentiment to simplify the complex task of choosing among various choices of potential investments (Barber and Odean 2008). Given that Chinese news sentiment is a significant predictor of stock returns for most of the sampled stocks, this may result in increased volatility in the US stocks, at least in the short run. As a result of language barriers, a sizable number of Chinese investors is likely to depend on sentiment expressed in Chinese media than sentiment expressed in foreign media for the same stocks. There is elementary evidence that the proposed changes may have an impact on the market dynamics of US markets.

5. Conclusion

This study examines the influence of Chinese news sentiment on US stocks, considering the potential policy shift that would grant Chinese retail traders direct access to US markets. The findings reveal a significant flow of information from Chinese news sentiment to global news sentiment, suggesting that sentiment expressed in Chinese media can influence overall market sentiment. Moreover, the study identifies a predominant unidirectional flow of information from news sentiment to stock returns, with Chinese news sentiment having a more substantial impact on the future returns of DJIA stocks compared to global news sentiment. The proposed policy change, if implemented, could introduce millions of new Chinese retail investors into the US markets. These investors, known for making decisions based on emotions and limited information processing capabilities, may rely heavily on attention-based heuristics, leading them to concentrate their investments on specific stocks influenced by Chinese news sentiment. This behavior could potentially lead to concentrated buying or selling activities, affecting the stock returns of those companies and contributing to increased market volatility. Policymakers, investors, and market participants need to be aware of these potential implications to better prepare for the changes that may occur in the US stock market if Chinese traders gain direct access. Additionally, further research in this area could provide deeper insights into the interplay between news sentiment, investor behavior, and market volatility in the context of increasing global interconnectedness.

Notes

1. https://www.scmp.com/news/china/money-wealth/article/3126504/if-chinese-traders-enter-us-markets-they-may-bring
2. A full list of the stocks is included as Table A3 in the Appendix.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1. Summary statistics for the firm-level Chinese news sentiment scores.

	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS	Q(20)	$Q^2(20)$
AAPL	−0.002	0.003	−1.886***	62.346***	68759.915***	−7.659***	59.196***	3.724
AMGN	0.006	0.114	0.236**	1.930***	69.591***	−4.403***	433.584***	360.012***
AXP	−0.019	0.068	−0.510***	4.442***	366.079***	−7.262***	60.850***	60.971***
BA	−0.013	0.007	−1.869***	28.299***	14360.916***	−8.608***	30.235***	5.395
CAT	0.022	0.189	0.013	−0.025	0.024	−6.981***	263.060***	191.162***
CRM	−0.025	0.123	−0.107	1.817***	59.012***	−7.29***	76.638***	80.364***
CSCO	0.015	0.067	0.551***	4.685***	408.179***	−6.914***	46.830***	76.250***
CVX	0.09	0.063	1.245***	3.016***	269.545***	−6.347***	41.524***	36.664***
DIS	−0.02	0.047	−0.077	8.539***	1285.586***	−6.383***	109.939***	44.551***
DOW	0.107	0.166	−0.18	−0.482**	6.383**	−4.225***	1132.478***	466.639***
GS	−0.006	0.001	0.794***	19.436***	6702.466***	−2.756***	11.502	10.12
HD	0.001	0.146	0.175	0.932***	17.467***	−7.495***	83.994***	129.272***
HON	−0.005	0.01	−2.661***	25.498***	11957.918***	−8.78***	26.215***	28.755***
IBM	0.009	0.009	3.149***	40.382***	29440.864***	−8.728***	56.168***	11.503
INTC	−0.006	0.002	−12.418***	193.610***	671542.855***	−7.939***	16.064*	0.412
JNJ	0.009	0.052	−0.495***	7.328***	963.735***	−8.724***	30.249***	36.376***
JPM	−0.003	0.001	−2.195***	17.695***	5858.282***	−8.038***	35.495***	17.923**
KO	0.062	0.036	3.108***	9.163***	2160.942***	−7.511***	118.725***	137.113***
MCD	0.004	0.001	9.082***	101.865***	188700.497***	−8.376***	29.263***	2.261
MMM	−0.142	0.1	−1.052***	0.793***	89.051***	−6.43***	148.869***	183.489***
MRK	0.054	0.033	1.754***	6.488***	958.701***	−7.717***	82.920***	73.466***
MSFT	−0.006	0.006	−5.425***	46.866***	40786.925***	−8.336***	95.955***	86.924***
NKE	−0.051	0.091	−0.459***	2.826***	155.595***	−7.506***	58.063***	41.588***
PG	0.007	0.022	1.975***	18.283***	6166.234***	−7.496***	47.748***	49.919***
TRV	0.193	0.259	−0.518***	−1.066***	38.967***	−3.823***	1108.091***	954.392***
UNH	0.066	0.138	−0.568***	0.607**	29.236***	−2.689***	370.584***	352.968***
V	0.011	0.086	0.265**	1.747***	58.704***	−5.902***	353.837***	194.267***
VZ	−0.018	0.072	−0.870***	3.272***	241.998***	−6.326***	275.985***	214.776***
WBA	−0.102	0.176	−0.224*	−0.718***	12.616***	−3.965***	1431.651***	1286.511***
WMT	0.003	0.014	−0.263**	26.873***	12733.271***	−7.498***	132.037***	83.682***

Notes: Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott, Rothenberg, and Stock (1996) unit-root test; *Q*(20) and $Q^2(20)$: Fisher and Gallagher (2012) weighted portmanteau tests

Table A2. Summary statistics for the firm-level Chinese news sentiment scores.

	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS	Q(20)	$Q^2(20)$
AAPL	−0.011	0.002	−2.016***	27.433***	13550.925***	−7.375***	13.698	2.832
AMGN	−0.073	0.314	0.152	−0.857***	14.590***	−7.532***	37.181***	93.349***
AXP	−0.001	0.022	0.487***	7.104***	906.112***	−7.625***	17.805**	11.603
BA	−0.03	0.014	−3.247***	18.506***	6778.932***	−4.08***	21.889***	12.374
CAT	0.068	0.157	0.012	0.203	0.736	−9.055***	33.674***	29.766***
CRM	−0.009	0.021	−0.680***	8.602***	1336.589***	−8.549***	23.378***	5.107
CSCO	0.013	0.043	0.977***	7.006***	932.581***	−3.227***	43.930***	45.488***
CVX	0.021	0.063	−0.073	1.203***	25.872***	−9.592***	8.476	37.274***
DIS	−0.003	0.002	−1.587***	41.381***	30357.842***	−7.976***	59.651***	53.168***
DOW	−0.019	0.114	0.02	1.522***	40.854***	−6.694***	26.620***	19.475**
GS	−0.03	0.018	−2.623***	18.695***	6645.212***	−8.068***	12.521	5
HD	0.02	0.065	0.098	3.258***	187.752***	−7.755***	13.71	12.146
HON	−0.013	0.032	−0.480***	3.150***	191.118***	−11.239***	27.628***	151.192***
IBM	−0.11	0.201	0.184	−0.28	3.783	−8.035***	10.16	49.603***
INTC	−0.015	0.006	−2.599***	20.870***	8153.135***	−7.528***	29.388***	9.506
JNJ	−0.035	0.04	−0.715***	6.412***	760.708***	−6.945***	41.818***	52.133***
JPM	−0.022	0.007	−5.581***	41.933***	33186.940***	−7.171***	126.632***	48.147***
KO	0.032	0.052	0.147	4.014***	285.450***	−7.657***	62.523***	58.553***
MCD	0.004	0.014	0.699***	23.182***	9506.131***	−8.676***	16.283*	3.52
MMM	−0.122	0.133	−0.300**	−0.053	6.378**	−6.756***	25.372***	82.635***
MRK	0.019	0.051	0.054	5.182***	473.412***	−8.878***	13.925	40.912***
MSFT	0.000	0.001	1.308***	39.431***	27524.628***	−8.484***	43.661***	58.569***
NKE	−0.004	0.042	0.346***	5.747***	590.535***	−6.433***	27.207***	25.721***
PG	−0.001	0.19	−0.178	−0.202	2.947	−3.719***	17.671**	113.990***
TRV	−0.032	0.248	−0.037	−0.830***	12.249***	−8.213***	35.108***	32.445***
UNH	0.037	0.119	−0.246**	1.332***	35.519***	−7.078***	25.978***	32.941***
V	−0.001	0.02	0.119	12.170***	2611.384***	−7.952***	25.222***	13.855
VZ	−0.026	0.021	−1.642***	13.824***	3558.000***	−8.725***	12.371	5.177
WBA	−0.071	0.225	−0.046	−0.367*	2.526	−8.009***	19.204**	58.797***
WMT	−0.01	0.01	−3.587***	37.291***	25416.802***	−8.326***	72.859***	29.968***

Notes: Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott, Rothenberg, and Stock (1996) unit-root test; *Q*(20) and $Q^2(20)$: Fisher and Gallagher (2012) weighted portmanteau test

Table A3. Sampled companies.

	SYMBOL	COMPANY	SECTOR
1	AAPL	Apple Inc.	Technology
2	AMGN	Amgen Inc.	Healthcare
3	AXP	American Express Company	Financials
4	BA	Boeing Company	Industrials
5	CAT	Caterpillar Inc.	Industrials
6	CRM	Salesforce Inc.	Technology
7	CSCO	Cisco Systems Inc.	Technology
8	CVX	Chevron Corporation	Energy
9	DIS	Walt Disney Company	Communication Services
10	DOW	Dow Inc.	Chemicals
11	GS	Goldman Sachs Group Inc.	Financials
12	HD	Home Depot Inc.	Consumer Discretionary
13	HON	Honeywell International Inc.	Industrials
14	IBM	International Business Machines	Technology
15	INTC	Intel Corporation	Technology
16	JNJ	Johnson & Johnson	Healthcare
17	JPM	JPMorgan Chase & Co	Financials
18	KO	Coca-Cola Company	Consumer Staples
19	MCD	McDonald's Corporation	Consumer Discretionary
20	MMM	3M Company	Industrials
21	MRK	Merck & Co. Inc.	Healthcare
22	MSFT	Microsoft Corporation	Technology
23	NKE	NIKE Inc. Class B	Consumer Discretionary
24	PG	Procter & Gamble Company	Consumer Staples
25	TRV	Travelers Companies Inc.	Financials
26	UNH	UnitedHealth Group Incorporated	Healthcare
27	V	Visa Inc. Class A	Financials
28	VZ	Verizon Communications Inc.	Communication Services
29	WBA	Walgreens Boots Alliance Inc.	Healthcare
30	WMT	Walmart Inc.	Consumer Staples