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Words matter: Market responses to changes in U.S. and Chinese trade-related internet search frequency under different U. S. administrations

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ABSTRACT

This paper employs internet search frequency data as a proxy for investor interest in innovations in stock market volatility surrounding the U.S./China trade relationship. The study documents a positive correlation between U.S. and China trade-related investor attention and market-wide share-price volatility in both nations—especially during the Trump administration. In addition, the study confirms previously established volatility spillover effects between U.S. and Chinese markets, which, again, are strongest during the Trump presidency. Overall, the results of the study support the validity of using publicly-available internet search data as a proxy for investor attention.

1. Introduction

Although Richard Nixon famously visited China in 1972, and Jimmy Carter recognized the existence of "one China" in 1979, trade between the United States and China was not officially normalized until the passage of the U.S.-China Relations Act of 2000—the act that paved the way for China to join the World Trade Organization (WTO) in 2001. Despite an often-uneven political environment that continues to this day,[1] since that time trade between the two nations has exploded, rising over 10% per year from $121 billion in 2001 to $655 billion in 2018 (the trade peak).[2] Not surprisingly, the U.S. trade deficit with China rose in tandem, with China supplanting Japan to become the largest U.S. creditor nation in 2008, and today holds over $1.3 trillion of U.S. treasury debt.[3]

It is precisely because of the joint economic and strategic importance of the U.S.-China relationship to the welfare and security of both nations (to say nothing of the rest of the world) that investors so keenly focus on developments involving trade and tension. Indeed, despite representing just over 20% of the world's population, together the U.S. and China account for *over half* of total corporate equity valuations and military spending.[4]

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[1] Almost as if on cue, in April 2001 a U.S. reconnaissance plane collided with a Chinese fighter near Hainan Island in the South China Sea and was forced to make an emergency landing on Chinese territory. Chinese authorities' detention of the twenty-four-member U.S. crew ended 12 days later with what became known as "the letter of the two sorries." See, e.g. https://en.wikipedia.org/wiki/Hainan_Island_incident.

[2] See, e.g. https://www.census.gov/foreign-trade/balance/c5700.html.

[3] As of April 2021, Mainland China holds $1.1 trillion; Hong Kong $216 billion (https://ticdata.treasury.gov/Publish/mfh.txt)

[4] See, e.g. https://www.statista.com/statistics/262742/countries-with-the-highest-military-spending/

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Perhaps not surprisingly, the increase in real goods trading between the U.S. and China has led to significant connections between the two nations' financial markets, as well. Two related areas of study—the linkage between U.S. economic fundamentals and Chinese stock market returns and so-called volatility "spillovers" between U.S. and Chinese equity markets—have received attention in the literature. For example, in work supportive of the integration of emerging and mature financial markets,[5] Goh, Jiang, Tu, and Wang (2013) demonstrated that following China's admittance to the WTO, reports on select U.S. economic fundamentals led to changes in Chinese equity returns, while Chen, Jiang, Li, and Xu (2016) found that U.S. Consumer Price Index (CPI) announcements had significant short-term impacts on the level, liquidity, and volatility of Chinese stock futures markets. Dutta (2018) finds evidence of long-run transmission of stock market uncertainty from the U.S. to China and Smales (2022) documents the spread of U.S. market uncertainty to other nations, including China. Similarly, Wang and Wang (2010) and Zhou, Zhang, and Zhang (2012) find that a "spillover" of volatility between U.S. and Chinese equities markets not only exists, *but that it runs in both directions*. Higher volatility in the securities market not only means higher risks and financing costs but also pushes up market interest rates (Arestis, Demetriades, & Luintel, 2001), which increases the degree of information asymmetry between investors and fund-raisers, as well as between investors themselves (Illeditsch, 2011), and interferes with the effective allocation of resources (Uppal & Mangla, 2006).

The present study extends this literature by examining if investor "attention" (proxied by search frequency data obtained from Alphabet, Inc.'s, Google Trends SVI search engine) to trade news is in any way associated with perturbations in the volatility of the broader U.S. and Chinese equity markets. Additionally, the results of the study seek to ascertain if differences in volatility responses to these searches were observed under three different U.S. administrations.

Just what *is* the impact of U.S./Chinese trade attention on securities markets? Is investor "attention" statistically correlated with changes in observable market metrics? Have changes in the U.S./Chinese political climate over time been associated with differing market responses to trade attention? More specifically, was the more contentious and confrontational U.S./Chinese relationship during the Trump administration associated with more pronounced market responses than observed previously? The answers to these and related questions are likely to prove of significant interest to a number of constituencies, ranging from corporate managers, investors, and portfolio managers, to academic researchers. They are the questions to which the remainder of this study is specifically addressed.

2. Previous results

Da, Engelberg, and Gao (2011) were the first scholars to employ Google search frequency data (known as Google Trends) as a metric of "investor attention." Since Google searches are voluntary actions undertaken by individuals seeking information on specific topics, the utility of the frequency of such searches as a proxy for individual attention on any given topic of interest is straightforward. Although the literature suggests that search frequency data largely reduces the informational asymmetries facing so-called "retail" investors, it seems reasonable to conclude that the correlation between Google Trends results involving arcane financial data and professional, price-setting investors must also be quite high.

Subsequent research by authors such as Joseph, Wintoki, and Zhang (2011), Vlastakis and Markellos (2012), and Ding and Hou (2015) follow Da et al. (2011) in extending the use of Google Trends results to studies of domestic (U.S.) online stock ticker searchers, information demand and supply at the firm and market level, and stock liquidity, respectively. In all of these studies, Google Trends metrics were shown to be statistically correlated with the selected dependent variables.

In the international realm, Bank, Larch, and Peter (2011) confirm the domestic findings of Ding and Hou (2015) in the context of German equities, and note that an increase in search queries is associated with a rise in trading activity and stock liquidity, while Takeda and Wakao (2014) document virtually identical results in the context of the Japanese equities market. Later work by Gao, Ren, and Zhang (2019) extends the use of Google Trends data to a sample of the consumer sentiment of 38 countries around the time of major sporting results and suggests that such search sentiment may be a contrarian predictor of country-level market returns.

In the context of China (one of the two countries addressed in the present paper), Chen, Liu, Lu, and Tang (2016) employ a different metric of investor attention—the Baidu Search Index.[6] The authors find that events with larger search index scores (i.e., greater investor attention) are associated with greater short-term price impacts and volatility as measured by the Chinese Stock Index (CSI) 300 futures index. Unlike the present paper, however, Chen et al. (2016) restricted to *regularly scheduled* macroeconomic announcements rather than the more ad hoc news associated with US-China trade relations.

Tsai (2014) studies the spillover effects of five major stock markets and finds that Germany and the United States are the main stock markets that convey information to other international markets. Lei and Song (2022) find that economic policy uncertainty drives stock price crash risk for Chinese firms and note that uncertainty increased during the U.S/China trade war.

3. Data

Aggregated website search/click-through data on US and China trade was obtained via Google Trends for the period from January 2004 (the date of first availability) to June 2018 (the final month in the sample period). Rather than employ obviously biased search terms such as "US China trade war," or "US China trade tensions," the more neutral (and general) search term "US China trade" was used to assess changes in search frequency over the time period under study. Since Google Trends reports aggregated statistics for no

[5] See, e.g., Bekaert & Harvey, 1995, and Bekaert, Harvey, Lundblad, & Siegel, 2011.

[6] Baidu, founded in 2000, is the second largest internet search engine in the world and is used almost exclusively by Chinese citizens and nationals.

more than 90 days for each reported search query, the employed daily time series of US/China trade search data was computed over longer time intervals using the procedures developed by and discussed in Risteski and Davcev (2014). Fig. 1 illustrates these temporal patterns graphically. As shown in the figure, it is clear that internet searches on the U.S./China trade relationship were higher in the earlier time period (2004 to 2010) and dramatically higher in the 2016–2018 interval. These results are, of course, consistent with the general geopolitical climate of the times, and will play a crucial role in the analysis to follow.

The volatilities of the Shanghai Stock Exchange 50 (SSE 50) and the Standard and Poor's 500 (S&P 500) are calculated using a Garch (1,1) model from daily price change data of the SSE 50 index and the S&P 500 drawn from the RESSET database. Calculation is necessary since the iVIX—the SSE's publicly-traded volatility index—was not introduced until March 17, 2015. Formally, the Garch model is calculated for each index as follows:

$$\mathrm{r_t} = \sqrt{\mathrm{h_t}}\mathrm{e_t}$$

$$\mathrm{h_t} = a_0 + a_1 r_{t-1}^2 + b_1 h_{t-1}$$

$$\mathrm{e_t} \sim \mathrm{iid}N(0,1),$$

where h_t and h_{t-1} are the conditional variance of current and last day, respectively.

Given the lengthy time-series nature of the present analysis, a number of control variables are employed to mitigate the return and volatility influence of non-trade-related attention. First, as noted in prior literature (e.g., Bernanke & Kuttner, 2005; Cooley & Quadrini, 2006; Jiang, Konstantinidi, & Skiadopoulos, 2012, etc.), changes in monetary policies can dramatically influence the volatility of asset prices. Accordingly, U.S. Federal Reserve Bank Federal Open Market Committee (FOMC) meeting statements and China's base interest rate adjustments from the People's Bank of China were collected, and the first categorized with dummy variables (1 = date with announcement; 0 = no announcement) and subsequently defined as the actual changes in the base rate for demand deposits. During the time period under study, there were a total of 143 announcement dates (118 FOMC meeting statement dates and 25 China base interest rate adjustment dates).

Second, macroeconomic factors such as the level of bilateral import dependence—a metric indicative of the overall level of real goods market integration—have also been shown to influence asset prices and volatility (see, e.g., Bracker, Docking, & Koch, 1999). Specifically, bilateral import dependence in year *t* is measured by the total quantity of imports from each counterpart country (the U.S. or China) divided by the total level of imports for each country over the same calendar year. In all cases, yearly total and bilateral trade data for the U.S. and China were obtained from the United Nations Commodity Trade Statistics database.[7]

Finally, pre-period changes in the volatility of both U.S. and China stock markets, SVI search volume index, and a number of dummy variables and dummy interaction terms (particularly those involving different U.S. presidential administrations) are also included in an effort to ascertain if the overall pricing mechanisms differed by the U.S. political climate. These latter variables are particularly relevant given the widespread belief that the U.S./China trade relationship was unusually fraught during the years of the Trump administration.

4. Empirical methodology

The basic empirical methodology employed to assess the association between trade-related Google Trend searches (*SVI*) and changes in the volatility of U.S. and Chinese stock markets is linear multivariate regression. In order to better isolate the relationship between investor interest (as proxied by the SVI metric) and volatility, a number of different independent variables are included in the regression models. Of particular interest are leading variables capturing pre-period market volatility metrics in an effort to assess the presence and magnitude (if any) of the so-called market "spillover effects."

For example, in regressions of the daily volatility changes in the Shanghai Stock Exchange 50 (SSE 50), the change in the volatility of the S&P 500 one, two, and three days prior are included in the regression. The exact leading metrics employed differs across the various models, but were identified using the Akaike information criterion and the Schwarz criterion, both of which are standardized tools drawn from the time-series literature. Statistical significance of these variables would indicate that the S&P 500 led the Shanghai index (or vice versa)—at least with respect to trade attention over the time period under study.

Regardless of the model or specific methodology employed, the ultimate objective of the analysis is to ascertain the influence of trade-related information on equity market volatility metrics (if any) and, in so doing, add further evidence to the literature on the potential geopolitical influences of changes in stock market volatility. The following section discusses the results of each of these tests in turn.

5. Empirical results

Panels A and B of Table 1 present baseline multivariate regression tests of daily *changes* in the volatility of the Shanghai Stock Exchange's 50 (SSE 50) index (Panel A) and the Standard and Poor's 500 (S&P 500) index (Panel B) over the time period from January 1st, 2004 to June 30th, 2018 under three different empirical specifications. The independent variables employed in both panels

[7] https://comtrade.un.org/

Fig. 1. Monthly search volume index for U.S. and China trade terms.
This figure shows the monthly search volume index (SVI) from Google Trends with the query string "U.S. China trade" ranging from Jan 2004 to Jun 2018.

Table 1
Baseline multivariate regressions on volatility changes.

Panel A: Regressions on daily volatility changes of Shanghai Stock Exchange 50 (SSE 50) Index

	Change of SSE 50 Volatility (t)		
C	1.0E-04	−6.6E-04	−6.2E-04
	[0.061]	[−0.380]	[−0.350]
Change of SVI (t-1)	0.004**	0.005***	0.005***
	[2.332]	[2.691]	[2.611]
Change of S&P 500 Volatility (t-1)		0.060***	0.059***
		[2.904]	[2.793]
Change of S&P 500 Volatility (t-2)		0.071***	0.069***
		[3.431]	[3.291]
Change of S&P 500 Volatility (t-3)			0.017
			[0.820]
n	3459	3345	3233
Adjusted R^2	0.001	0.007	0.006
F-Statistics	5.437	8.655	6.172

Panel B: Regressions on the daily volatility changes of S&P 500 Index

	Change of S&P 500 Volatility (t)		
C	4.7E-04	8.3E-04	7.6E-04
	[0.335]	[0.579]	[0.531]
Change of SVI (t-1)	0.0041***	0.003**	0.003**
	[2.898]	[2.062]	[2.090]
Change of SSE 50 Volatility (t)		0.024*	0.024*
		[1.707]	[1.658]
Change of SSE 50 Volatility (t-1)		0.004	0.006
		[0.270]	[0.409]
Change of SSE 50 Volatility (t-2)			0.026*
			[1.886]
N	3535	3441	3421
Adjusted R^2	0.002	0.001	0.002
F-Statistics	8.397	2.468	2.707

This table reports the results from multivariate regressions on the daily changes of volatility for both stock markets Indices. The sample period is Jan 1st, 2004-June 30th, 2018. The dependent variable equals the change of index volatility multiplied by 100. *SVI,* the search volume index from Google Trends with "U.S. China trade" as the search query string, is scaled by its standard deviation. Spillover effects are also tested with lagged volatility changes from the counterpart market with different lengths. The coefficient estimates, t-statistics (in brackets), adjusted R^2 and F-statistic are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

include the daily change in the Google Trends SVI search index (under the query "U.S. China trade"), the SVI index and two-day lag changes in the volatility of the S&P 500 index (or SSE 50), and the SVI index and three-day lag changes in S&P 500 (or SSE 50) volatility in columns one, two, and three, respectively.[8] As noted above, both the Akaike information criterion and the Schwarz criterion were employed in establishing the regression specifications.

In a new finding previously undocumented in the literature, the volatilities of *both* the SSE 50 *and* the S&P 500 were positively associated with changes in SVI search queries on U.S./China trade. This result (significant at the 5% level or less in all six regressions in the table) holds even when controlled for lagged volatility variables of the S&P 500 (in the case of the SSE 50) and the SSE 50 (in the case of the S&P 500). The fact that SVI is so highly correlated with changes in the overall volatility of such broad-based equity market indexes is clear evidence of the level of attention given by investors to the state of trade relations between the two nations. Unfortunately, the *direction of causality* between the two variables—i.e., does investor attention lead to greater volatility, or do increases in volatility lead to greater investor attention, or possibly both at different times—cannot be determined.

Finally, the fact that the first two of the three lagged S&P 500 volatility change variables (Panel A) are significant at the 1% level provides additional empirical evidence for volatility "spillovers" from the U.S. to Chinese equity markets.[9] As reproduced in Panel B, although there are limited indications (with significance at the 10% level) that volatility changes in the SSE 50 led to increases in the volatility of the S&P 500, the overall regression *F*-statistics are not significant, indicating that the combined results from both panels strongly suggest that the general direction of volatility changes ran—at least in the case of trade-related news over the time period under study here—*from the U.S. to China* and not vice versa.

Table 2 presents some of the most interesting and original results presented in the paper. Indeed, by replacing lagged volatility metrics with U.S. presidential dummy variables[10] and SVI index/presidential administration interaction terms, information concerning the impact of the U.S. political environment and investor interest in trade-related searches on changes in U.S./China equity market volatility may be directly addressed. These tests are particularly important given the clear changes in SVI search volumes on the query "U.S. China Trade" observed over time (see Fig. 1).

Panel A of Table 2 shows the results of five multivariate regressions of changes in SSE 50 volatility using various combinations of explanatory variables. The base case (reproduced from Panel A of Table 1) shows that the change in SVI index (query: "U.S. China trade") is positively correlated with changes in SSE 50 volatility. Columns two, three, and four, on the other hand, add presidential administration dummy variables and SVI/administration interaction terms for the administrations of U.S. presidents George W. Bush (represented in the sample from January 2004 to January 2009), Barack Obama (from January 2009 to January 2017), and Donald Trump (from January 2017 to June 2018—the last date in the sample). By construction, each presidential dummy and interaction term shows the influence of that administration relative to the other two.

The results when focusing on changes in SSE 50 volatility depend on the specification. That is, whereas the changes in search volume (SVI) were negatively correlated with changes in SSE 50 volatility during the Bush administration in column two, the exact opposite was true during the first years of the Trump administration in column four. Neither the Obama administration nor the Obama/SVI interaction terms are significant at conventional levels in column three. However, in column five which includes the interaction terms for both the Obama and Trump administrations, the Obama/SVI interaction is positive and significant while the Trump/SVI interaction is insignificant.

Panel B of Table 2 repeats the tests discussed above in Panel A, employing changes in the volatility of the S&P 500 as the dependent variable—in other words, for the case of investors in U.S. equities. All of the *F*-statistics of the conducted regressions are significant at the 5% level or less. Interestingly, only the results for the two Republican administrations were statistically significant, and these entered with opposite signs. That is, whereas the changes in search volume (SVI) were negatively correlated with changes in S&P volatility during the Bush administration—implying that SVI searches at that time were associated with a "calming" of market jitters—the exact opposite was true during the first years of the Trump administration, when belligerent statements regarding China and U.S./Chinese trade seemed almost staple of daily news reports. Obviously, traders of U.S. equities interpreted trade-related news under President Bush (who was generally perceived as a champion of free trade[11]) very differently from that under President Trump. Neither the Obama administration nor the Obama/SVI interaction terms are significant at conventional levels in column three, underscoring the generally perceived notion that Mr. Obama—who immediately assumed a softer posture in his dealings with China[12]—was viewed as less aggressive than President Bush and far less confrontational than President Trump. Combined, the results presented in Table 2 suggest that although investors in both U.S. and Chinese stocks clearly paid attention to innovations in the U.S./China trade environment over these years, U.S. equity market participants found trade news during the Bush administration decidedly more "soothing"—and news during the Trump administration considerably more concerning—than their Chinese counterparts.

The five columns shown in Table 3 report the results of tests of the prevalence of equity market volatility spillovers by presidential

[8] Careful readers may notice that the lagged variables in the regression for the change in volatility of the S&P 500 (*t*-1, *t*-2, and *t*-3) in Panel A differ those of the changes in volatility of the SSE 50 (*t*, *t*-1, and *t*-2) in Panel B. This is because of the 13-h time difference between Shanghai and New York.

[9] See, e.g., Zhang, et al. (2021) for very support of this phenomenon.

[10] Pun not intended.

[11] Mere days after Trump's surprising 2016 election victory, George W. Bush gave a Dallas speech in which he urged Americans "not to give up on free trade." See https://qz.com/838012/former-us-president-george-w-bush-is-urging-americans-not-to-give-up-on-free-trade-or-nafta/

[12] The Obama administration changed the tone of relationship between the U.S. and China from President George W. Bush's "strategic competition" to one of "strategic partnership." See, e.g., https://factsanddetails.com/china/cat8/sub52/item1714.html.

Table 2
Regressions on investors' attention controlling for different presidencies.

Panel A: Regressions on daily volatility changes of Shanghai Stock Exchange 50 (SSE 50)

	Change of SSE 50 Volatility (t)				
C	−0.001	−0.001	0.000	−0.001	−3.6E-05
	[−0.350]	[−0.391]	[0.153]	[−0.485]	[−0.012]
Change of SVI (t-1)	0.005***	0.013***	0.004**	0.003	0.002
	[2.611]	[3.502]	[2.297]	[1.427]	[1.026]
Bush		0.001			
		[0.222]			
Obama			−0.002		−0.001
			[−0.514]		[−0.364]
Trump				0.003	0.003
				[0.563]	[0.392]
Change of SVI (t-1)*Bush		−0.011***			
		[−2.551]			
Change of SVI (t-1)*Obama			0.004		0.014***
			[0.629]		[2.681]
Change of SVI (t-1)*Trump				0.013**	0.006
				[2.575]	[0.977]
Change of S&P 500 Volatility (t-1)	0.059***	0.060***	0.059***	0.060***	0.060***
	[2.793]	[2.820]	[2.783]	[2.822]	[2.817]
Change of S&P 500 Volatility (t-2)	0.069***	0.072***	0.069***	0.073***	0.073***
	[3.291]	[3.412]	[3.271]	[3.457]	[3.446]
Change of S&P 500 Volatility (t-3)	0.017	0.017	0.017	0.017	0.017
	[0.820]	[0.800]	[0.809]	[0.799]	[0.789]
N	3233	3233	3233	3233	3233
Adjusted R^2	0.006	0.008	0.006	0.008	0.008
F-Statistics	6.172	5.215	4.224	5.265	4.084

Panel B: Regressions on the daily volatility changes of S&P 500 Index

	Change of S&P 500 Volatility (t)				
C	0.001	0.000	0.002	0.000	0.002
	[0.531]	[0.115]	[1.096]	[0.241]	[0.712]
Change of SVI (t-1)	0.003**	0.014***	0.004**	0.000	0.000
	[2.090]	[4.309]	[2.336]	[−0.021]	[0.127]
Bush		0.002			
		[0.505]			
Obama			−0.003		−0.002
			[−0.986]		[−0.715]
Trump				0.005	0.003
				[0.925]	[0.612]
Change of SVI (t-1)*Bush		−0.014***			
		[−3.767]			
Change of SVI (t-1)*Obama			−0.006		−0.002
			[−1.118]		[−0.440]
Change of SVI (t-1)*Trump				0.027***	0.026***
				[5.789]	[5.694]
Change of SSE 50 Volatility (t)	0.024*	0.022	0.024*	0.022	0.022
	[1.658]	[1.570]	[1.665]	[1.574]	[1.575]
Change of SSE 50 Volatility (t-1)	0.006	0.007	0.005	0.007	0.007
	[0.409]	[0.485]	[0.386]	[0.512]	[0.499]
Change of SSE 50 Volatility (t-2)	0.026*	0.028**	0.026*	0.029**	0.029**
	[1.886]	[1.970]	[1.884]	[2.069]	[2.066]
N	3421	3421	3421	3421	3421
Adjusted	0.002	0.006	0.002	0.011	0.011
F-Statistics	2.707	4.219	2.177	7.541	5.742

This table reports the results from multivariate regressions on the daily changes of volatility for S&P 500 and SSE 50 indices, with investor attention measured by the search volume index (SVI) as the key explanatory variable and controls for different presidencies. The sample period is Jan 1st, 2004-June 30th, 2018. The dependent variable equals the change of index volatility multiplied by 100. The change of search volume index (SVI) is scaled in by its standard deviation. *Bush/Obama/Trump* are indicator variables based on the president at the time of the observation. The coefficient estimates, t-statistics (in brackets), adjusted R^2 and F-statistic are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

administration for the SSE 50 (Panel A) and S&P 500 (Panel B). As before, the first column reports the base case scenario of changes in volatility, controlling only for the change in SVI search index volume (query: "U.S. China trade").

As shown in columns two, three, and four of Panel A, the only evidence of pronounced volatility spillovers from the S&P 500 to the SSE 50 occurred during the Trump administration. As such, it seems clear that Mr. Trump's consistently harsher, more confrontational

Table 3
Regressions on spillover effects controlling for different presidencies.

Panel A: Regressions on daily volatility changes of Shanghai Stock Exchange 50 (SSE 50)

	Change of SSE 50 Volatility (t)				
C	−0.001	−0.001	0.001	−0.001	0.000
	[−0.297]	[−0.317]	[0.211]	[−0.508]	[−0.059]
Change of SVI (t-1)	0.005**	0.005**	0.005**	0.005**	0.005**
	[2.529]	[2.523]	[2.538]	[2.550]	[2.547]
Change of S&P 500 Volatility (t-1)	0.062***	0.001	−0.002	0.004	3.806
	[3.040]	[0.139]	[−0.555]	[0.666]	[1.175]
Bush		0.077***			
		[2.958]			
Obama			0.070**		−0.001
			[2.643]		[−0.324]
Trump				0.044*	0.003
				[1.944]	[0.504]
Change of S&P 500 Volatility (t-1)*Bush		−0.039			
		[−0.946]			
Change of S&P 500 Volatility (t-1)*Obama			−0.021		0.011
			[−0.507]		[0.251]
Change of S&P 500 Volatility (t-1)*Trump				0.093*	0.099*
				[1.787]	[1.736]
N	3459	3459	3459	3459	3459
Adjusted R^2	0.004	0.004	0.003	0.004	0.004
F-Statistics	7.685	4.069	3.984	4.784	3.216

Panel B: Regressions on the daily volatility changes of S&P 500 Index

	Change of S&P 500 Volatility (t)				
C	0.001	0.000	0.002	0.000	0.002
	[0.524]	[0.118]	[1.058]	[0.272]	[0.744]
Change of SVI (t-1)	0.004***	0.004***	0.004***	0.004**	0.004***
	[2.633]	[2.622]	[2.661]	[2.569]	[2.582]
Change of SSE 50 Volatility (t)		0.002			
		[0.531]			
Bush			−0.003		−0.002
			[−0.939]		[−0.722]
Obama				0.003	0.002
				[0.702]	[0.391]
Trump	0.025*	0.044**	0.012	0.021	0.002
	[1.790]	[2.321]	[0.619]	[1.453]	[0.091]
Change of SSE 50 Volatility (t)*Bush		−0.042			
		[−1.485]			
Change of SSE 50 Volatility (t)*Obama			0.027		0.074
			[0.952]		[1.297]
Change of SSE 50 Volatility (t)*Trump				0.054	0.037
				[0.993]	[1.267]
n	3535	3460	3460	3460	3460
Adjusted R^2	0.002	0.003	0.002	0.002	0.002
F-Statistics	5.262	3.252	3.077	3.013	2.363

This table reports the results from multivariate regressions on the daily changes of volatility for both stock markets Indices. The sample period is Jan 1st, 2004-June 30th, 2018. The dependent variable equals the change of index volatility multiplied 100. *SVI,* the search volume index from Google Trends with "U.S. China trade" as the search query string, is scaled by its standard deviation. *Bush/Obama/Trump* is a dummy variable, which equals 1 if it is in his presidency. Spillover effects are also tested using the cross term of lagged volatility changes from the counterpart market and different presidencies. The coefficient estimates, t-statistics (in brackets), adjusted R^2 and F-statistic are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

rhetoric (he often specifically referred to China as "our enemy"[13]) had a rather profound impact on the volatility of the SSE 50. There is no evidence of spillover from China to the U.S. in Panel B. Combined, these results suggest Mr. Trump's unusually aggressive trade statements were taken seriously by Chinese investors, but essentially ignored by U.S. investors as mere political bluster.

Table 4 significantly expands the breadth of the analysis of the influences of volatility changes on the SSE 50 (Panel A) and the S&P 500 (Panel B) by including controls for changes in important monetary policies and import dependence. Among the variables included in these regressions are changes in SVI search frequencies, presidential dummies, changes in SVI search frequency/presidential

[13] Mr. Trump wrote "There are people who wish I wouldn't refer to China as our enemy. But that's exactly what they are," in his manifesto, *Great Again: How to Fix Our Crippled America* (2016).

Table 4
Regressions on investors' attention controlling for monetary policies and import dependence.

Panel A: Regressions on daily volatility changes of Shanghai Stock Exchange 50 (SSE 50) Index					
	Change of SSE 50 Volatility (t)				
C	0.001	0.000	0.002	0.000	0.001
	[0.270]	[0.116]	[0.504]	[0.200]	[0.416]
Change of SVI (t-1)	0.005***	0.013***	0.004**	0.003	0.002
	[2.623]	[3.508]	[2.313]	[1.430]	[1.035]
Bush		0.001			
		[0.275]			
Obama			−0.002		−0.002
			[−0.434]		[−0.378]
Trump				0.001	0.001
				[0.206]	[0.115]
Change of SVI (t-1)*Bush		−0.011**			
		[−2.551]			
Change of SVI (t-1)*Obama			0.004		0.006
			[0.606]		[0.955]
Change of SVI (t-1)*Trump				0.013***	0.014***
				[2.587]	[2.685]
Change of S&P 500 Volatility (t-1)	0.058***	0.059***	0.058***	0.059***	0.059***
	[2.751]	[2.774]	[2.741]	[2.784]	[2.777]
Change of S&P 500 Volatility (t-2)	0.068***	0.071***	0.068***	0.072***	0.072***
	[3.238]	[3.354]	[3.218]	[3.411]	[3.397]
Change of S&P 500 Volatility (t-3)	0.016	0.016	0.016	0.016	0.016
	[0.778]	[0.756]	[0.769]	[0.763]	[0.753]
China Base Rate Adjustment	0.018	0.016	0.017	0.018	0.017
	[0.353]	[0.320]	[0.338]	[0.344]	[0.324]
Change in Import Dependence of China	−0.107	−0.071	0.036	−0.107	0.006
	[−0.234]	[−0.143]	[0.065]	[−0.221]	[0.011]
FOMC Meeting	−0.005	−0.004	−0.005	−0.005	−0.005
	[−0.520]	[−0.464]	[−0.487]	[−0.524]	[−0.483]
Change in Import Dependence of US	−0.169	−0.183	−0.166	−0.167	−0.169
	[−0.945]	[−1.012]	[−0.928]	[−0.891]	[−0.903]
N	3765	3687	3687	3687	3687
Adjusted R^2	0.006	0.007	0.005	0.007	0.007
F-Statistic	3.250	3.264	2.655	3.276	2.817

Panel B: Regressions on the daily volatility changes of S&P 500 Index					
	Change of S&P 500 Volatility (t)				
C	0.003	0.002	0.004*	0.002	0.004
	[1.486]	[0.889]	[1.667]	[1.240]	[1.446]
Change of SVI (t-1)	0.003**	0.014***	0.004**	0.000	0.000
	[2.101]	[4.287]	[2.361]	[−0.013]	[0.151]
Bush		0.002			
		[0.647]			
Obama			−0.003		−0.003
			[−0.892]		[−0.829]
Trump				0.002	0.001
				[0.334]	[0.141]
Change of SVI (t-1)*Bush		−0.014***			
		[−3.737]			
Change of SVI (t-1)*Obama			−0.006		−0.003
			[−1.170]		[−0.491]
Change of SVI (t-1)*Trump				0.027***	0.026***
				[5.790]	[5.687]
Change of SSE 50 Volatility (t)	0.023	0.022	0.023	0.022	0.022
	[1.621]	[1.531]	[1.629]	[1.544]	[1.542]
Change of SSE 50 Volatility (t-1)	0.005	0.006	0.005	0.007	0.007
	[0.377]	[0.446]	[0.355]	[0.486]	[0.469]
Change of SSE 50 Volatility (t-2)	0.026	0.027	0.026	0.028	0.028
	[1.831]	[1.914]	[1.828]	[2.020]	[2.014]
China Base Rate Adjustment	0.059	0.055	0.058	0.058	0.057
	[1.155]	[1.082]	[1.145]	[1.134]	[1.114]
Change in Import Dependence of China	−0.118	−0.022	0.117	−0.084	0.113
	[−0.319]	[−0.053]	[0.258]	[−0.215]	[0.248]
FOMC Meeting	−0.003	−0.003	−0.004	−0.003	−0.003
	[−0.425]	[−0.333]	[−0.437]	[−0.426]	[−0.420]

(*continued on next page*)

Table 4 (*continued*)

Panel B: Regressions on the daily volatility changes of S&P 500 Index					
	Change of S&P 500 Volatility (t)				
Change in Import Dependence of US	−0.274*	−0.285*	−0.270*	−0.264*	−0.267*
	[−1.901]	[−1.963]	[−1.872]	[−1.757]	[−1.780]
N	3421	3421	3421	3421	3421
Adjusted R^2	0.002	0.006	0.002	0.012	0.011
F-Statistic	2.010	3.054	1.825	4.986	4.231

This table reports the results from multivariate regressions on the daily changes of volatility for both stock markets Indices. The sample period is Jan 1st, 2004-June 30th, 2018. The dependent variable equals the change of index volatility multiplied by 100. *SVI,* the search volume index from Google Trends with "U.S. China trade" as the search query string, is scaled by its standard deviation. *Bush/Obama/Trump* is a dummy variable, which equals 1 if it is in his presidency. *China Base Rate Adjustment* equals the change of the base rate for demand deposits set by the People's Bank of China on the announcement day, with the percentage sign omitted. *FOMC Meeting* is a dummy variable, which equals 1 when it is on the day the FOMC meeting is closed, and 0 otherwise. *Change in Import Dependence* equals *Import Dependence* in year *t* minus import dependence in year *t-1*. *Import Dependence of China (US)* equals the import from U.S. (China) in year t divided by its total import in year t. The coefficient estimates, t-statistics (in brackets), adjusted R^2 and F-statistic criterion are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

interaction terms, changes in import dependence, spillover effects, and dummy variables for the dates of U.S. FOMC and China national base interest rate adjustments.

As shown in Panel A, the change in search frequency/administration interaction variables are significant for the Bush (negative coefficient) and Trump (positive coefficient) presidencies. As before, the results indicate that U.S./China trade searches during the Trump administration were associated with an increase in the overall volatility of the SSE 50 index. Interestingly, in no regression were the variables for China base rate adjustment, import dependence, or daily monetary policy dummies statistically significant.

In Panel B changes in SVI search volume/administration interaction variables during the Bush and Trump presidencies enter with opposite signs (negative for Bush, positive for Trump consistent with Table 2) with *t*-values of −3.737 and 5.790, respectively. Thus, even when controlled for Chinese interest rate movements, FOMC meeting dates, and changes in import dependence, the influence of the Trump presidency on changes in the daily volatility of the S&P 500 remains pronounced. It is clear that once controlled for other factors known to influence equity volatility metrics, the influence of Mr. Trump's more aggressive approach to U.S./China trade relations is evident, and that the direction of that influence is positive (implying that increases in SVI search volumes during the Trump administration were associated with higher S&P 500 volatility).

Table 5 presents an expanded analysis of volatility spillovers from the S&P 500 to the SSE 50 first reported in Panel A of Table 3 above, this time controlling for U.S./China import dependence, changes in Chinese interest rates, and U.S. FOMC meetings. As before, increases in the daily volatility of the S&P 500 during the Trump administration led to increases in the volatility of the SSE 50. A separate analysis of volatility spillovers from the SSE 50 to the S&P 500 in Panel B shows no statistically significant relationship associated with the Trump administration (either as a separate variable or as an interaction term).

6. Conclusion

This study has presented the first analysis of volatility changes in both U.S. and Chinese equity market indexes to trade-related news under differing U.S. presidential administrations. Using innovations in Google Trends' Search Volume Index (SVI) for the query "U.S. China trade" as the primary independent variable in a series of multivariate regressions, the study documented that daily changes in search volume—a clear proxy for investor interest in U.S./China trade news—were associated with contemporaneous changes in the volatility of the Shanghai Stock Exchange (SSE 50) and the Standard and Poor's 500 (S&P 500) market indexes. Regressions employing lagged volatility changes across the two markets show that, in general, volatility changes run from the S&P 500 to the SSE 50, with little evidence of spillovers from the SSE 50 to the S&P 500.

Interaction terms between changes in SVI search volume and U.S. presidential indicator variables for the George W. Bush, Barack Obama, and Donald Trump administrations show striking differences between the three presidencies, with Bush, Obama, and Trump associated statistically significant *decreases,* no statistical relationship, and statistically significant *increases* in the daily volatility of both indexes, respectively. These results are consistent with the hypothesis that the decidedly more belligerent tone of Mr. Trump's statements—which often characterized China as an "enemy"—added an element of uncertainty to the trading relationship between the world's two largest economies. All of these findings proved robust even after including controls for macroeconomic factors such as changes in each country's import dependence and interest rates.

Viewed as a whole, the study adds to the economics and finance literature by investigating the cross-border volatility effects of changes in investor attention or interest associated with trade developments under differing political environments. In the final analysis, the results of the study strongly suggest that—at least in the case of U.S./China trade—words matter.

CRediT authorship contribution statement

Nathan Mauck: Conceptualization, Writing – original draft, Writing – review & editing, Methodology. **Stephen Pruitt:** Conceptualization, Writing – original draft, Writing – review & editing. **Wenjia Zhang:** Conceptualization, Writing – original draft, Methodology, Formal analysis, Writing – review & editing.

Table 5
Regressions on spillover effects controlling for monetary policies and import dependence.

Panel A: Regressions on daily volatility changes of Shanghai Stock Exchange 50 (SSE 50)					
	Change of SSE 50 Volatility (t)				
C	0.001	0.001	0.001	0.000	0.001
	[0.322]	[0.226]	[0.444]	[0.125]	[0.297]
Change of SVI (t-1)	0.005**	0.005**	0.005**	0.005**	0.005**
	[2.544]	[2.537]	[2.549]	[2.558]	[2.554]
Change of S&P 500 Volatility (t-1)	0.061***	0.076***	0.070***	0.043*	0.038
	[2.990]	[2.907]	[2.608]	[1.916]	[1.159]
Bush		0.000			
		[0.088]			
Obama			−0.001		−0.001
			[−0.315]		[−0.283]
Trump				0.002	0.002
				[0.319]	[0.246]
Change of S&P 500 Volatility (t-1)*Bush		−0.039			
		[−0.927]			
Change of S&P 500 Volatility (t-1)*Obama			−0.021		0.011
			[−0.504]		[0.246]
Change of S&P 500 Volatility (t-1)*Trump				0.092*	0.098*
				[1.776]	[1.728]
China Base Rate Adjustment	0.015	0.015	0.015	0.014	0.014
	[0.304]	[0.303]	[0.293]	[0.279]	[0.276]
Change in Import Dependence of China	−0.211	−0.187	−0.108	−0.127	−0.047
	[−0.478]	[−0.389]	[−0.201]	[−0.271]	[−0.086]
FOMC Meeting	−0.005	−0.005	−0.005	−0.006	−0.006
	[−0.567]	[−0.565]	[−0.563]	[−0.590]	[−0.581]
Change in Import Dependence of US	−0.162	−0.162	−0.160	−0.138	−0.140
	[−0.943]	[−0.932]	[−0.929]	[−0.769]	[−0.777]
N	3459	3459	3459	3459	3459
Adjusted	0.003	0.003	0.003	0.004	0.003
F-Statistic	2.811	2.216	2.151	2.521	2.030

Panel B: Regressions on the daily volatility changes of S&P 500 Index					
	Change of S&P 500 Volatility (t)				
C	0.002	0.002	0.004	0.002	0.004
	[1.462]	[0.842]	[1.665]	[1.234]	[1.508]
Change of SVI (t-1)	0.004***	0.004***	0.004***	0.004***	0.004***
	[2.649]	[2.637]	[2.675]	[2.584]	[2.594]
Change of SSE 50 Volatility (t)	0.025*	0.043**	0.011	0.021	0.001
	[1.752]	[2.283]	[0.587]	[1.432]	[0.070]
Bush		0.003			
		[0.763]			
Obama			−0.003		−0.003
			[−0.921]		[−0.922]
Trump				0.001	0.000
				[0.171]	[−0.040]
Change of SSE 50 Volatility (t)*Bush		−0.042			
		[−1.474]			
Change of SSE 50 Volatility (t)*Obama			0.027		0.037
			[0.961]		[1.269]
Change of SSE 50 Volatility (t)*Trump				0.053	0.073
				[0.964]	[1.283]
China Base Rate Adjustment	0.059	0.059	0.059	0.059	0.058
	[1.165]	[1.151]	[1.148]	[1.164]	[1.146]
Change in Import Dependence of China	−0.067	0.066	0.171	−0.032	0.188
	[−0.182]	[0.165]	[0.381]	[−0.083]	[0.414]
FOMC Meeting	−0.004	−0.004	−0.004	−0.004	−0.004
	[−0.543]	[−0.513]	[−0.509]	[−0.536]	[−0.500]
Change in Import Dependence of US	−0.265*	−0.280*	−0.260*	−0.254*	−0.258*
	[−1.854]	[−1.934]	[−1.819]	[−1.700]	[−1.722]
n	3460	3460	3460	3460	3460
Adjusted R^2	0.003	0.003	0.003	0.002	0.003
F-Statistic	2.615	2.303	2.183	2.081	1.910

This table reports the results from multivariate regressions on the daily changes of volatility for both stock markets Indices. The sample period is Jan 1st, 2004-June 30th, 2018. The dependent variable equals the change of index volatility multiplied by 100. *SVI,* the search volume index from Google Trends with “U.S. China trade” as the search query string, is scaled by its standard deviation. *Bush/Obama/Trump* is a dummy variable, which equals 1 if it is in his presidency. Spillover effects are also tested using the cross term of lagged volatility changes from the counterpart market and different presidencies. *China Base Rate Adjustment* equals the change of the base rate for demand deposits set by the People's Bank of China on the announcement day, with the percentage sign omitted. *FOMC Meeting* is a dummy variable, which equals 1 when it is on the day the FOMC meeting is closed, and 0 otherwise. *Change in Import Dependence* equals *Import Dependence* in year *t* minus import dependence in year *t-1*. *Import Dependence of China (U.S.)* equals the import from U.S. (China) in year t divided by its total import in year t. The coefficient estimates, t-statistics (in brackets), adjusted R^2 and F-statistic are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

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