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Trump's fake news and stock market returns

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ABSTRACT
We use a novel database that identifies allegedly Donald Trump's fake news during his presidency. We find that the number of daily fake news is positively related to contemporaneous US stock market returns. Fake news is typically positively biased in our context, increasing stock returns in the short term. We invalidate alternate explanations of the main relation, such as the notion that newly arrived information drives the relation. The mechanism of the relationship is the source used and the reliability of the fake news. Fake news matters to the extent that participants believe it is true. This positive relation reverses over the following days, indicating some evidence of correction. Overall, we find that a politician's fake news influences financial markets temporarily.

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'Everything is true and nothing is true' Barack Obama

1. Introduction

Fake news is defined as misinformation and disinformation, according to which someone unintentionally or intentionally spreads information with no factual basis (Moynihan and Roberts 2021). Fake news has become increasingly important with the use of the internet and online platforms, allowing anyone to disseminate information easily to a large audience (Finneman and Thomas 2018). We explore in this study the relationship between Trump's fake news and stock market returns.

Although not all empirical results are fully supportive (Bond and DePaulo 2006; Vrij 2008), studies tend to report that fake news influences the decisions of some market participants. Allcott and Gentzkow (2017) report that half of the people who see fake news believe it. Additionally, Vosoughi, Roy, and Aral (2018) find that fake news diffuses faster and farther than true news counterparts on Twitter. Within the context of our study, President Trump distributed fake news while in administration. He exaggerated positive news and downplayed the significance of negative news. For example, he often overstated the growth of the US economy, the magnitude of the reduction in regulations, and the increase in stock market returns to create a positive 'environment' during his administration. The frequency of repetition of fake news also impacted the perception of market participants regarding the importance of the news. High-frequency trading algorithms can further amplify the impact of fake news based on automated signals. Note that Trump often repeated the same statements without necessarily referring to newly arrived information. Most of the fake news in our context is thus likely to be positively biased to maximize the chance for Trump to be successful in the next general elections.

Considering that a significant percentage of market participants would likely believe the fake news (Allcott and Gentzkow 2017; Vosoughi, Roy, and Aral 2018), we expect that such fake news boosts short-term stock returns. Investors who are aware that such news may be fake face limitations to fully reflecting instantaneously their views in the stock market in the short term due to short-selling constraints (e.g. D'Avolio 2002), and so it is not easy to correct any mispricing instantaneously. On days with a high (low) number of fake news, we

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expect that the stock market to experience relatively stronger (weaker) stock market returns. Fake news is thus positively related to contemporaneous stock market returns.

We analyze allegedly fake news by Donald Trump while in administration as identified by reporters in the Washington Post. In line with our expectations, we find that the daily number of fake news is positively related to contemporaneous US stock market returns. A one standard deviation increase in the number of fake news is related to an increase in daily stock market returns by 0.059%. We find evidence showing that it is not likely that the relation is due to newly arrived information to the market. The relation holds after controlling for (i) contemporaneous volume and volatility, (ii) macroeconomic conditions, and (iii) general media attention toward Trump. We also find evidence of the reversal of this pattern later likely indicating mispricing. It is also unlikely that the relation is the result of main political events such as the Capitol attack and elections. We explore alternate potential mechanisms of the relation. We find that the relationship is most pronounced within fake news arriving from Twitter and Vlog that investors who follow them are more likely supporters of Trump. We also highlight the role of the reliability of fake news on the magnitude of the relation. The relationship is most pronounced on days when Trump experienced a relatively high approval rating in polls.

The remainder of this paper is structured as follows: Section 2 sets the study in comparison to the existing academic literature, Section 3 discusses the data used and the methodology followed, Section 4 reports the empirical findings, and finally, Section 5 concludes this study.

2. Literature review

Numerous studies have previously explored the interrelation of politics and financial markets. Government policies, privatization, regulations, political stability, uncertainty surrounding elections, and government contracts can impact financial markets (e.g. Tirtiroglou, Bhabra, and Lel 2004; Dinc and Gupta 2011; Goodell, McGee, and McGroarty 2020). Several studies even reported the role of political scandals for the benefit of individual firms. Cooper, Gulen, and Ovtchinnikov (2010), for example, show that firms which contribute to political parties tend to exhibit stronger abnormal stock returns. In comparison to these studies, we do not explore in this study the impact of a fundamental change on firms' benefit due to politicians' involvement. Instead, we test the role of a politician's statements and his perception of stale news. Stated differently, if markets were totally efficient, no response should have taken place due to Trump's fake news.

We focus on reviewing studies here on the impact of Trump's influence while in the administration that is closest to what we test empirically in this study. Allcott and Gentzkow (2017) empirically examine the 2016 US presidential election and find that President Trump's hoaxes were remembered more vividly, and more people supporting Trump shared them on Facebook compared to Hillary Clinton. Studies report the impact of the 2016 shock election of Trump on domestic stock returns (Wagner, Zeckhauser, and Ziegler 2018), well-being (Pinto et al. 2020), and international stock returns with relevant political connections (Fink and Stahl 2020). Tillmann (2020) also shows that President Trump's pressure made the Fed reduce interest rates. Several studies have also explored the impact of Trump's tweets. It is reported that his tweets influence negatively Russia's ruble (Afanasyev, Fedorova, and Ledyaeva 2021), are often covered on Fox News, and thus influence traditional media sources (Morales, Schultz, and Landreville 2021), and more often negatively influence financial markets (Brans and Scholtens 2020; Gjerstad et al. 2021; Machus, Mestel, and Theissen 2022). In comparison to these studies, we explore the impact of Trump's fake news on stock market returns. We explore separately the magnitude of the relation for fake news distributed through social media and traditional media sources.

Our work is also closely linked to a recently growing field to the extent that fake news influences financial markets. Both Clarke et al. (2021) and the concurrent study by Kogan, Moskowitz, and Niessner (2021) use fake news as identified later by the SEC between 2011 and 2013 that is distributed to investors through the Seeking Alpha platform. Clarke et al. (2021) find that fake news receives comparatively more investor attention, that readers cannot identify fake news, and that it is possible to predict fake news with the use of algorithms. They also find that fake news may generate high volume and volatility, but after controlling for legitimate articles' counterpart activity, fake news generates relatively fewer increases in volume and volatility showing some evidence of efficiency in the financial markets. Kogan, Moskowitz, and Niessner (2021) instead find that fake news is related to high volume and volatility potentially due to the disagreement on the eligibility of the fake news.

In comparison to these studies, we analyze the impact of fake news by President Trump, who has to an extent initiated 'fake news' in the modern era. The importance of fake news has risen significantly since the 2016 presidential election, and the news was spread especially by the former President of the United States of America, Donald Trump. We explore the relationship between fake news and stock market returns. Previous studies only explored the significance of fake news for individual stocks that can only explore mostly its impact on small capitalization firms. Mostly small-size firms tend to distribute fake news. Instead of exploring the dissemination of false news, as previous studies have done, we focus here on the impact of generalized fake news and its influence on changing investors' perceptions of the importance of stale news. In doing so, we investigate the impact of fake news on financial markets for the potential benefit of a powerful politician.

Overall, we contribute to the extensive academic literature that explores the impact of politicians on financial markets (e.g. Tirtiroglou, Bhabra, and Lel 2004; Cooper, Gulen, and Ovtchinnikov 2010; Dinc and Gupta 2011; Goodell, McGee, and McGroarty 2020). We focus on the impact of President Trump's statements that have received lots of attention in recent years (Wagner, Zeckhauser, and Ziegler 2018; Fink and Stahl 2020; Tillmann 2020; Brans and Scholtens 2020; Afanasyev, Fedorova, and Ledyaeva 2021; Morales, Schultz, and Landreville 2021; Gjerstad et al. 2021; Machus, Mestel, and Theissen 2022) while highlighting in this study the significance of Trump's fake news. We also contribute to the newly advancing literature on the impact of fake news. There has only been very little attention until now on the impact of fake news on financial markets (Clarke et al. 2021; Kogan, Moskowitz, and Niessner 2021), and to our knowledge, this is the first study that explores the importance of fake news to financial markets by a key politician. In comparison to these studies, we explore the relationship between fake news and stock market returns. The focus is on the impact of generalized fake news and its influence on changing investors' perceptions of the importance of stale news rather than on the distribution of false news.

3. Data and methodology

This study utilizes a novel dataset developed by journalists at The Washington Post, focusing on allegedly fake news attributed to Donald Trump during his presidency, spanning from January 20, 2017, to January 20, 2021. The selected fake news stories are available both online[1] and printed in The Washington Post's Fact Checker column, typically featured in the Sunday print edition. The selection process for identifying fake news begins with readers making initial claims, which are then evaluated by journalists who make the final determination.[2] The database provides the date of distribution for each fake news story but lacks specific timestamps, making intraday analysis unfeasible. We restrict our analysis to fake news categorized under the economy, excluding other categories such as biographical record, coronavirus, education, election, environment, foreign policy, guns, health care, immigration, jobs, miscellaneous, Russia, taxes, terrorism, trade, and Ukraine probe. Although some fake news in these categories may relate to stock market returns, a significant portion is considered noise and is thus omitted from our primary analysis.[3] It is worth noting that the database does not include instances where Trump refers to statements made by others as 'fake news.'

Figure 1 illustrates the reported number of fake news instances. Panel A displays fake news that includes repetitions, whereas Panel B only includes newly arrived fake news. According to the dataset, the majority of fake news comprises repetitions, which aligns with Trump's tendency to repeat certain content. Evidence suggests that investors respond to stale news (e.g. Tetlock 2011) and are more likely to believe repeated fake news as truth (Pennycook, Cannon, and Rand 2018). To our knowledge, The Washington Post's Fact Checker website, used in this study, is the only available source that includes repetitions, justifying our database selection.[4] Table 1 presents descriptive statistics of the main variables. As depicted in the figure, fake news exhibits outliers that we address by winsorizing at the top 5%.[5] We observe that the minimum number of fake news instances in a day is zero, while the maximum is 1,185 (inclusive of repetitions).[6]

We proceed with the following Ordinary Least Squares (OLS) estimation:

$$\begin{aligned} \textit{Stock market returns}_t &= \textit{constant} + b_1 \textit{Standardized fake news}_t + b_2 \textit{Stock market returns}_{t-1} + b_3 \textit{Covid}_t \\ &\quad + \textit{Fixed effects on the day of the week, month and year} + u_t \end{aligned} \tag{1}$$

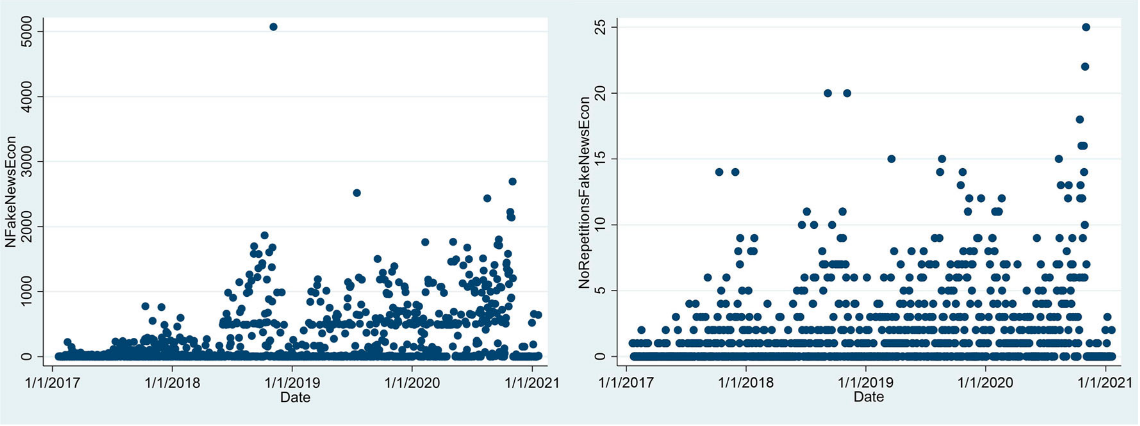

Figure 1. The first figure shows the number of fake news with repetitions and the second figure without repetitions.

Table 1. Descriptive statistics.

	# Fake news (not winsorized)	# Fake news	Standardized fake news	Stock market returns (%)
Minimum	0.00	0.00	−0.66	−11.98
Average	266.10	243.80	0.00	0.06
Median	12.00	12.00	−0.63	0.08
Maximum	5072.00	1185.00	2.55	9.38
Number of observations	1007	1007	1007	1007

Notes: This table displays the descriptive statistics of the main variables used in this study. # indicates the number of. The frequency of all variables is daily. We use the S&P500 index to measure stock market returns.

The dependent variable is daily stock market returns (S&P500)[7], sourced from Refinitiv Eikon Datastream. The primary independent variable is standardized fake news, calculated as each daily value minus the mean number of fake news during the sample period, divided by the standard deviation of the series. As discussed previously, we anticipate a positive parameter coefficient for b_1. Throughout all estimations in this study, we include control variables for one-day lagged stock market returns, considering the short-term reversal effect (Jegadeesh 1990).[8] These lagged returns also help to control whether market events prompt reactions that lead to the dissemination of fake news by Donald Trump (Machus, Mestel, and Theissen 2022). Additionally, we include a control variable for the impact of COVID-19, represented by a dummy variable that equals one from February 3, 2020, when Trump declared a health emergency due to the coronavirus, and zero otherwise.[9] As mentioned earlier, we only consider fake news related to the economy; therefore, Trump's fake news about COVID-19 is not included in our sample. We introduce dummy variables for the day of the week, month, and year to capture any potential seasonality in stock market returns, such as the Monday effect (e.g. French 1980). Given that the number of fake news instances may exhibit autocorrelation within nearby periods due to the repetition of the same fake news, we estimate cluster standard errors per year across all our estimations, following the approach outlined by Petersen (2009).[10]

4. Empirical results

4.1. Main results

We present the main results of this study in this section. We estimate equation (1) where the dependent variable is daily stock market returns, and the primary independent variable is contemporaneous standardized fake news. Column 1 of Table 2 shows the results when estimating the regression with the main independent variable and the fixed effects, column 2 includes lagged stock market returns and covid, and finally, column 3 reports results with all control variables.

Table 2. Main relation.

	Stock market returns{t}		
	(1)	(2)	(3)
Standardized fake news{t}	0.046*	0.043**	0.059***
	(0.074)	(0.025)	(0.001)
Stock market returns{t-1}		−0.260**	−0.274**
		(0.046)	(0.042)
Covid{t}		0.029	0.419***
		(0.557)	(0.004)
Constant	0.211*	0.070	0.417***
	(0.079)	(0.192)	(0.001)
Day of the week, month, and year fixed effects	Yes	No	Yes
Number of observations	1007	1006	1006
R-square adjusted	0.012	0.069	0.087

Notes: This table displays the relation between daily standardized fake news and contemporaneous stock market returns. *P*-values are reported in parentheses. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the ten, five, and one percent levels, respectively.

Consistent with our expectations, we find that the parameter coefficient of the standardized fake news variable is significantly positive, indicating that a politician's allegedly fake news influences investor decisions. This relationship is significant at the 1% level after the addition of all control variables. Furthermore, this relationship is also economically significant, with a one standard deviation increase in the number of fake news associated with a 0.059% increase in daily stock market returns, holding other variables constant. Additionally, we find that the parameter coefficients of the control variables align with expectations. For example, the parameter coefficient of lagged stock market returns is significantly negative, consistent with the short-term reversal effect (Jegadeesh 1990). For the remainder of the study, we do not tabulate the parameter coefficients of the control variables due to space constraints.

4.2. Does newly arrived information drive the relation?

An important consideration is whether the relationship is simply driven by fundamental news. We acknowledge that it is difficult to completely dismiss this possibility. Nonetheless, we anticipate that it is unlikely for the relationship to be driven solely by freshly announced news. The majority of the fake news in our sample is repetitive (99%), suggesting that at worst, the relationship may reflect 'stale' news rather than newly arrived information. Below, we conduct five tests aimed at further invalidating the argument that news drives the relationship.

First, Panel A of Table 3 explores the relationship after adding contemporaneous volume (LnVolume) and volatility (LnVIX) to our list of control variables as available from Refinitiv Eikon Datastream, and re-estimate the relation. Stock prices change to a large extent due to the arrival of news that is reflected in contemporaneous volume and volatility (e.g. Bollerslev, Li, and Xue 2018). While volume and volatility are not perfect measures, they provide useful indicators of the response to new information. If newly arrived news drives the relationship, the main relation should disappear after controlling for other contemporaneous responses in the stock market. However, we find that the parameter coefficient of the standardized fake news remains significantly positive even after including these additional controls.

Second, we examine whether the relationship simply reflects macroeconomic conditions. To ensure that the relationship is not solely driven by fake news closely linked to the economy, we exclude from the analysis fake news related to the economy. Specifically, we exclude Trump's statements containing any of the following terms: 'Economy', 'GDP', 'inflation', and 'interest rate', and re-estimate the main regression. As shown in column 1 of Panel B, we find that the relevant parameter coefficient remains significantly positive, indicating that the relationship is not solely driven by comments on the economy. Additionally, we control for daily macroeconomic conditions reflecting actual market conditions, accessing daily policy uncertainty data for the US market developed by Baker, Bloom, and Davis (2016)[11] and the daily Aruoba-Diebold-Scotti Business Conditions available from the Federal Reserve Bank of Philadelphia.[12] Several studies have previously demonstrated the significance of these macroeconomic measurements on investor decisions (e.g. Da, Engelberg, and Gao 2015). Re-estimating

Table 3. Alternate explanation I: News drives the relation.

Panel A: Controlling for contemporaneous volume and volatility

	Stock market returns{t}
Standardized fake news{t}	0.036*
	(0.056)
LnVolume{t}	−0.150
	(0.541)
LnVIX{t}	−1.375***
	(0.009)
Constant	6.924
	(0.171)
Previous control variables	Yes
Number of observations	1006
R-square adjusted	0.144

Panel B: Controlling for macroeconomics

	Stock market returns{t}		
	(1)	(2)	(3)
Standardized fake news without Trump's comments for the economy{t}	0.085***		
	(0.000)		
Standardized fake news without Trump's comments for 'stock'{t}			0.059***
			(0.001)
Standardized fake news{t}		0.047*	
		(0.055)	
ADS{t}		0.020**	
		(0.020)	
Policy index{t}		0.003**	
		(0.012)	
Constant	0.444***	0.046	0.417***
	(0.002)	(0.529)	(0.001)
Previous control variables	Yes	Yes	Yes
Number of observations	1006	1006	1006
R-square adjusted	0.088	0.105	0.087

Panel C: Controlling for general attention toward Trump

	Stock market returns{t}			
	(1)	(2)	(3)	(4)
Standardized fake news{t}	0.057***	0.058***	0.057***	0.059***
	(0.000)	(0.001)	(0.001)	(0.001)
Broadcast of 'President Trump'{t}	0.083			
	(0.258)			
Broadcast of 'Donald Trump'{t}		0.211		
		(0.463)		
Broadcast of 'Trump'{t}			0.037	
			(0.410)	
Broadcast of 'President Donald Trump'{t}				0.602
				(0.396)
Constant	0.214	0.27	0.222	0.299**
	(0.153)	(0.106)	(0.271)	(0.033)
Previous control variables	Yes	Yes	Yes	Yes
Number of observations	1006	1006	1006	1006
R-square adjusted	0.09	0.088	0.089	0.088

Notes: This table displays whether the news is driving the relationship. *P*-values are reported in parentheses. $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent levels, respectively.

the main regression with the addition of these two control variables, as shown in column 2 of Panel B, reveals that the parameter coefficient of standardized fake news remains significantly positive.

Third, column 3 of Panel B presents results after excluding fake news related to stock market performance to ensure that the relationship is not solely driven by Trump's reaction to stock market returns. We exclude Trump's statements containing the term 'stock' and re-estimate the main regression. Despite this exclusion, we

Table 4. Reversal effect.

	Stock market returns{t}	
	(1)	(2)
Standardized fake news{t}	0.068***	
	(0.008)	
Standardized fake news{t-1}	0.053	
	(0.175)	
Standardized fake news{t-2}	−0.104***	−0.084***
	(0.001)	(0.000)
Constant	0.399***	0.295***
	(0.003)	(0.004)
Previous control variables	Yes	Yes
Number of observations	1005	1005
R-square adjusted	0.092	0.088

Notes: This table displays the relation between lagged standardized fake news and stock market returns. *P*-values are reported in parentheses. ∗∗∗ indicates statistical significance at the one percent level.

find that the relevant parameter coefficient remains significantly positive, indicating that the relationship is not solely driven by Trump's comments on stock market returns.

Fourth, we investigate whether the relationship simply captures overall attention towards Trump, regardless of the content, and whether it is unrelated to fake news. We test whether Trump's statements alone drive stock market returns, regardless of their content. Using TV broadcasts on CNBC from the GDELT database,[13] which serves as a primary source for the TV News Archive, we access TV coverage of Trump using terms such as 'President Trump', 'Donald Trump', 'Trump', and 'President Donald Trump'. We individually add each of these terms to our main estimation and re-do the regression. Panel C demonstrates that the parameter coefficients of these terms are all insignificant. Therefore, mentions of Trump in the media do not appear to be related to stock market returns. After controlling for Trump's attention, we find that the parameter coefficient on standardized fake news remains significantly positive, indicating that the relationship is not solely driven by investor interest in Trump.

Finally, we explore the lagged relationship between fake news and stock market returns. Market participants who were aware that the news was fake would continuously try to take advantage of it by reducing buy and increasing sell transactions in the period after. Additionally, market participants who initially believed the fake news may reconsider its validity after potentially hearing others' criticism of Trump's statements. Given that fake news does not typically indicate new information, a reversal pattern is expected later. This reversed pattern is common in studies testing the relationship between sentiment and stock market returns (e.g. Lemmon and Portniaguina 2006; Siganos, Vagenas-nanos, and Verwijmeren 2014), demonstrating that market participants are capable of correcting mispricings. We acknowledge that some evidence in the literature shows that investors may overreact to fundamentals (e.g. Amini et al. 2013). However, it is more common for investors to underreact to fundamental news, as reported in key studies in the Accounting and Finance literature such as the momentum effect (e.g. Jegadeesh and Titman 1993) and post-earnings announcement drift (e.g. Bernard and Thomas 1989). Table 4 reports relevant results. We find that the parameter coefficient on the one-day-lagged fake news is positive but insignificant (0.053, with a p-value equal to 0.175). As stated in the Data Section earlier, we only know the day of the allegedly fake news and not the exact time of its dissemination. Therefore, it makes sense that a positive relationship would exist with tomorrow's stock market returns, given that some fake news may be distributed after the stock market is closed. More importantly, we find that the parameter coefficients of the two lagged stock market returns are negative at the 1% level. The sum of the parameter coefficients for days t and t-1 is 0.121, which is similar to the magnitude of the parameter coefficient with the day-two lag (−0.104). Thus, there is evidence of price recovery following the initial positive mispricing.

Overall, our evidence indicates that the relation is unlikely to be due to newly arriving news in the market.

Table 5. Alternate explanation II: Main political events drive the relation.

	Stock market returns{t}		
	Excluding days since the capitol attack (1)	Excluding days around mid-term and general elections (2)	Excluding all relevant days (3)
Standardized fake news{t}	0.067***	0.061***	0.073***
	(0.003)	(0.003)	(0.004)
Constant	0.432***	0.410***	0.429***
	(0.002)	(0.003)	(0.005)
Previous control variables	Yes	Yes	Yes
Number of observations	957	969	920
R-square adjusted	0.088	0.089	0.091

Notes: This table displays whether key political events drive the relation. *P*-values are reported in parentheses. *** indicates statistical significance at the one percent level.

4.3. Do key political events drive the relation?

We test here whether the relation is driven by major political events. We exclude days that are related to major events and re-estimate the main regression. To the extent that the relation is not driven by these events, it should be empirically valid when excluding these periods. We exclude days after the Capitol attack on January 6, 2021, as well as days around the midterm and final elections that took place on November 6, 2018, and November 3, 2020, respectively. In both elections, we exclude all days in October (2018 and 2020) before the elections and until November 10 to ensure that the initial impact of the elections is controlled.

Table 5 reports results after excluding the periods of the Capitol attack as shown in column 1, of both elections as shown in column 2, and all events as shown in column 3. We find that the relevant parameter coefficient remains significantly positive after these date exclusions. It is thus unlikely that major political events drive the relation.

4.4. Do confounding effects or reverse causality drive the relation?

It is not possible to control for all potential confounding effects that may drive stock market returns. There may also be reverse causality, such as poor stock market returns generating fake news. We have already controlled for lagged stock market returns across this study to address the potential loop in the relation. However, to invalidate such an explanation, we conduct a formal IV analysis. For the instrument, we use a dummy variable that takes one on days when Donald Trump is behind in the latest polls compared to his counterparts (e.g. Biden, Hawkins), otherwise zero. This analysis is based on several national polls found by FiveThirtyEight.[14] We expect that more fake news is present following disappointing poll results for Trump. Individual poll results would not significantly influence stock market returns, although we acknowledge that it is difficult to entirely disregard this path.

Table 6 reports these results. The first stage results indicate that our instrument is effective, showing that more fake news takes place when Trump is behind his competitors in polls. We use the predicted standardized fake news derived from the first stage to regress on the second stage with stock market returns. We find that the parameter coefficient of standardized fake news is still positively related to stock market returns. The relevant coefficient is 0.073 and significant at the 1% level. Overall, this result suggests that it is unlikely for the relationship to be in the reverse direction or due to confounding effects.

4.5. Potential mechanisms of the relation

We explore potential mechanisms of the relation here. One potential mechanism may be that small investors are more likely to believe fake news compared to professionals. Since small investors tend to trade in smaller

Table 6. Alternate explanation III: Confounding effects or reverse causation drive the relation.

	Standardized fake news{t} 1st stage regression (1)	Stock market returns{t} 2nd stage regression (2)
Dummy on days with Trump being lower than competitors in polls{t}	0.374**	
	(0.048)	
Standardized fake news{t}		0.073***
		(0.004)
Constant	−0.964***	0.431***
	(0.000)	(0.000)
Previous control variables	Yes	Yes
Number of observations	1006	1006
R-square adjusted	0.227	0.087

Notes: This table displays whether confounding effects or reverse causation drive the relation. An instrumental variable (IV) analysis is conducted. The instrument utilized is a dummy variable that takes a value of one on days when Trump is behind his competitors in the polls, and zero otherwise. *P*-values are reported in parentheses. ∗∗, and ∗∗∗ indicate statistical significance at the five, and one percent levels, respectively.

stocks (e.g. Lemmon and Portniaguina 2006), the relationship might be most pronounced within small capitalization firms. However, existing evidence in the literature on fake news (e.g. Clarke et al. 2021) suggests that identifying fake news is difficult regardless of investor background. If this is the case, the magnitude of the relation should be indifferent to firms' market capitalization. To test this, we re-estimate the relation using equal – and value-weighted stock market returns (rather than S&P500). Small investors' reaction to fake news may be better indicated by equal-weighted stock market returns, while large investors' reaction may be better indicated by value-weighted stock market returns. We conduct a DiD analysis to explore whether the difference in the parameter coefficient of interest is significant. As shown in columns 1–3 in Table 7, we find no evidence indicating that small and large investors react to fake news differently. The parameter coefficient on the standardized fake news is of similar magnitude with both stock market indexes used. The parameter coefficient of the interaction variable is insignificant. These results suggest that it is unlikely for the relation to be solely due to small investors' reaction to fake news.

To further explore this, we test whether difficult-to-value firms perform differently in relation to fake news. If investors can identify fake news, this may be the case for more difficult-to-value firms. Previously, we used the market capitalization of the firms, and here we expand on other proxies based on Baker and Wurgler (2006, 2007). We consider the following firm characteristics: size, return volatility, z-score, asset growth, book-to-market ratio, age, sales growth, and profitability. Small-capitalization, volatile, close-to-bankruptcy, high asset growth, high growth, and low-profitability firms are relatively more difficult to value. To test this, we download relevant daily US factors developed by Jensen, Kelly, and Pedersen (2023).[15] These indicate the difference in stock returns between firms that are hard to value versus easy to value, such as the stock returns of small minus large capitalization firms or the stock returns of high minus low volatility firms. We use these differences in stock returns as the dependent variable (rather than S&P500) and re-estimate the estimation. If the relationship is not influenced by the extent to which a firm is difficult to value (as we stated earlier), the parameter coefficient on the standardized fake news should be insignificant. As shown in columns 4 to 11, we indeed find that the parameter coefficients on the standardized fake news are all insignificant. These results indicate that it is unlikely that the relationship is driven by difficult-to-value firms.

Another potential mechanism of the relation is trust in Trump. On days with relatively high trust, it is expected that the relation is most pronounced. Investors respond to fake news as long as they believe them. To test this, we take advantage of two settings. First, Table 8 explores the relationship within days with different levels of support towards Trump. We access data from Gallup on the percentage of approval towards Trump.[16] These polls took place weekly, but there are a few missing days, especially toward the end of the sample period. The lowest support in the data towards Trump is linked to the Capitol attack. We undertake a threshold analysis that allows for changes in the relationship between independent and dependent variables at different values of a threshold variable (e.g. Gonzalo and Pitarakis 2002). The threshold variable is estimated at 43% approval for Trump. The sample is split into two regions: region 1 indicates the portion of the sample with approval less than

Table 7. Potential mechanisms of the relation: Difficulty to value and arbitrage.

	Equal-weighted market returns{t} (1)	Value-weighted market returns{t} (2)	DiD (3)	Size factor (4)	Return volatility factor (5)	Z-score factor (6)	Asset growth factor (7)	Book to market factor (8)	Age factor (9)	Sales growth factor (10)	Profitability factor (11)
Standardized fake news{t}	0.030*	0.055***		0.005	−0.030	−0.006	−0.011	0.006	0.008	−0.007	−0.003
	(0.085)	(0.003)		(0.658)	(0.249)	(0.525)	(0.348)	(0.703)	(0.686)	(0.452)	(0.745)
Standardized fake news as panel for the two groups{t}			0.047**								
			(0.033)								
Dummy = 1 for the first group, and Dummy = 0 for the second			−0.004								
			(0.860)								
Interaction variable{t}			−0.011								
			(0.165)								
Constant	0.422*	0.437***	0.434**	0.096	−0.257	0.030	−0.063	0.067	0.070	−0.117*	−0.031
	(0.076)	(0.007)	(0.027)	(0.381)	(0.216)	(0.555)	(0.199)	(0.503)	(0.336)	(0.050)	(0.691)
Previous control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1006	1006	2012	1006	1006	1006	1006	1006	1006	1006	1006
R-square adjusted	0.033	0.077	0.051	0.024	0.028	0.018	0.028	0.022	0.034	0.018	0.044

Notes: This table explores the role of difficulty-to-value and arbitrage firms as a potential mechanism of the relationship. *P*-values are reported in parentheses. $*$, $**$, and $***$ indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 8. Potential mechanisms of the relation: Trust in Trump.

	Stock market returns{t}						
	Region 1	Region 2	Threshold	BIC	HQIC	SSR	Number of observations
Standardized fake news{t}	0.032	0.397***	43	549	395	1102	883
	(0.533)	(0.000)					
Constant	0.470*	0.126					
	(0.053)	(0.822)					
Previous control variables	Yes	Yes					

Notes: This table explores the role of trust in Trump as a potential mechanism of the relationship. *P*-values are reported in parentheses. ∗, and ∗∗∗ indicate statistical significance at the ten, and one percent levels, respectively.

or equal to 43%, and region 2 with approval higher than 43%. The regression is then estimated in each region separately. Our results indicate that the relationship indeed becomes stronger on days when there is a relatively higher level of approval towards Trump. We find no relation between standardized fake news and stock market returns in Region 1 (with a relatively low level of support towards Trump), but a significantly positive relation is present in Region 2 (with a relatively high level of support).

Second, we expect that the relation is most pronounced within fake news arriving from Twitter and Vlog, given that investors who typically follow such sources are supporters of Trump. For example, over 88 million citizens followed Trump on Twitter.[17] According to surveys, a significant percentage of professional investors also read online sources for information, in addition to small investors.[18] Conversely, we expect the relationship to be less pronounced when using fake news from traditional sources. As shown in columns 1–3 in Table 9, we indeed find support for this expectation. The relevant parameter coefficient when using Twitter and Vlog sources is 0.074 and highly significant, with a t-statistic in untabulated results of 29.16. The parameter coefficient when using other sources is 0.057, still significant at the 1% level but with a relatively lower t-statistic of 7.24. We also introduce a dummy variable for fake news from Twitter and Vlog (otherwise zero) and interact this dummy with the standardized fake news from the respective sources. The parameter coefficient of the interaction variable reflects the difference in stock market returns between the two groups as influenced by the source of fake news. We find that the difference in these two parameter coefficients is statistically significant. Our evidence indicates that the source of the fake news matters for the magnitude of the relation.

Finally, we explore the 'reliability' of fake news. Although identifying fake news is challenging, some fake news is potentially less likely to be trusted compared to others, thus weakening the relationship. Criticisms of Trump's fake news on the Washington Post website often accuse him of changing his views.[19] This criticism is consistently mentioned in the dataset with the term 'flip-flop,' indicating that this type of fake news is likely to be less trusted. In untabulated results, we find that 4% of the received criticisms towards fake news refer to 'flip-flop.' We re-estimate the main regression separately using fake news with only the received criticism of a 'flip-flop' and then with fake news without such a comment. We expect that there should be no relationship with the use of fake news that received criticism as a 'flip-flop,' since investors are less likely to trust it. As shown in columns 4–6 in Table 9, we indeed find that the parameter coefficient on fake news is insignificant when using fake news with the 'flip-flop' comment, while it is significant without the 'flip-flop' comment. The parameter coefficient of the interaction variable is significant at the 10% level, indicating that the difference in these two parameter coefficients is significant. Our evidence thus indicates that the perceived trustworthiness of the fake news influences the magnitude of the relation.

4.6. Robustness tests

We conduct several robustness tests. In the previous analysis, fake news distributed over the weekend was excluded from the analysis since the market was closed. Column 1 of Table 10 reports the results when the number of weekend fake news is added to Monday's fake news. We find that the parameter coefficient of the standardized fake news remains significantly positive with the inclusion of weekend values.

We also test the relation within alternate sub-periods to ensure that the relationship is not driven merely by a few observations. Columns 2 and 3 show results when splitting the full sample into two equal sub-periods. Our

Table 9. Additional potential mechanisms of the relation.

	Stock market returns{t}					
	(1)	(2)	DiD (3)	(4)	(5)	DiD (6)
Standardized fake news from Twitter & Vlog{t}	0.074***					
	(0.000)					
Standardized fake news from other sources{t}		0.057***				
		(0.002)				
Standardized fake news as panel for the two groups{t}			0.058***			
			(0.001)			
Dummy = 1 for the first group, and Dummy = 0 for the second			−0.000			
			(0.997)			
Interaction variable{t}			0.015**			
			(0.012)			
Standardized fake news with 'flip flop'{t}				0.014		
				(0.600)		
Standardized fake news without 'flip flop'{t}					0.059***	
					(0.001)	
Standardized fake news as panel for the two groups{t}						0.052***
						(0.002)
Dummy = 1 for the first group, and Dummy = 0 for the second						0.000
						(0.998)
Interaction variable{t}						−0.041*
						(0.086)
Constant	0.424***	0.415***	0.419***	0.344***	0.417***	0.378***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.002)
Previous control variables	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1006	1006	2012	1006	1006	2012
R-square adjusted	0.088	0.086	0.087	0.085	0.087	0.086

Notes: This table displays additional potential mechanisms of the relation. *P*-values are reported in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

results show that the relationship remains strong within alternate sub-periods, and the relevant parameter coefficient remains significantly positive. In the main analysis earlier, we included both repetitive and newly arrived fake news. Only a few newly arrived fake news stories are available for our study. As shown in the literature (e.g. Tetlock 2011), investors respond even to stale news. Pennycook, Cannon, and Rand (2018) actually report that repeated fake news is more likely to be believed as truthful. Column 4 reports results when using only repetitive fake news. We find that the positive relationship between fake news and contemporaneous stock market returns is still empirically valid.

Throughout this study, we only used the economy category of fake news to exclude any unnecessary noise. However, apart from the fake news in the economy category, additional fake news may also be relevant, such as those regarding foreign policy. Due to the difficulty of identifying which fake news may or may not be relevant for this study, we only analyze fake news in the economy category and report results here when adding fake news from additional categories (biographical record, coronavirus, education, election, environment, foreign policy, guns, health care, immigration, jobs, miscellaneous, Russia, taxes, terrorism, trade, and Ukraine probe). Column 5 reports results when using all the available fake news across all categories. We still find that the relevant parameter coefficient remains significantly positive. The magnitude of the relation reduces from 0.059 as shown earlier in Table 2 to 0.040 and is now significant at the 5% level. Column 6 reports results for all fake news apart from the fake news in the economy category. The relation is now only marginally significant, at the 10% level. These results confirm our expectations.

Column 7 reports results when adding five-day lagged stock market returns to ensure that lagged stock returns are not behind the studied relation. We find that our empirical results hold with the addition of these extra control variables. If anything, the relation becomes stronger after the addition of further lagged control variables. Finally, column 8 reports results when not excluding any outliers while using the raw number of daily fake news. Once again, the relation holds, showing that extreme values do not necessarily contradict the pattern of this relation.

Table 10. Robustness tests.

	Stock market returns{t}							
	Including weekend values of fake news on Monday (1)	Split results into two equal sub-periods (2)	(3)	For only repetitive fake news (4)	(5)	(6)	Adding 5-day lags on stock market returns (7)	Using fake news without any win-sorization (8)
Standardized fake news{t}	0.066** (0.028)	0.080** (0.034)	0.060** (0.026)	0.060*** (0.001)			0.061*** (0.000)	
Standardized all fake news{t}					0.040** (0.014)			
Standardized non-economy fake news{t}						0.030* (0.057)		
# Fake news{t}								0.091** (0.036)
Stock market returns{t-1}							−0.241** (0.018)	
Stock market returns{t-2}							0.133 (0.201)	
Stock market returns{t-3}							0.018 (0.222)	
Stock market returns{t-4}							−0.124* (0.062)	
Stock market returns{t-5}							0.025 (0.375)	
Constant	0.391*** (0.002)	0.347** (0.017)	0.380* (0.051)	0.417*** (0.001)	0.396*** (0.002)	0.384*** (0.002)	0.446*** (0.002)	0.367*** (0.002)
Previous control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1006	503	503	1006	1006	1006	1002	1006
R-square adjusted	0.087	0.032	0.127	0.087	0.086	0.085	0.115	0.086

Notes: This table displays several robustness tests of the relation. *P*-values are reported in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

5. Conclusion

We explore in this study the role of fake news in financial markets. We utilize a novel dataset providing data on President Trump's allegedly fake news as identified by reporters at The Washington Post. Within our context, fake news tends to offer a relatively more positive angle, and thus, we find that the number of fake news articles is positively related to contemporaneous stock market returns. We invalidate several explanations for this main relation, such as the possibility of newly arriving news or major political events, such as elections, driving the relation. Our evidence indicates that both small and large investors seem to find it difficult to identify fake news. The source used to disseminate fake news and the likely reliability of the fake news influence the magnitude of the response to fake news. The relation is most pronounced within fake news arriving from Twitter and Vlog, indicating that investors who often follow such sources are supporters of Trump. We also find evidence showing that the mechanism of this relationship is trust in Trump. Finally, we find evidence of a reversal of this pattern in the subsequent days.

Overall, this study demonstrates that a politician's fake news temporarily impacts financial markets, offering further empirical evidence of the influence of politics on financial markets. This study also provides important insights for regulators, showing that fake news disrupts the efficiency of financial markets. Further efforts are needed to prevent fake news from being disseminated to market participants.

Notes

1. https://www.washingtonpost.com/graphics/politics/trump-claims-database/.
2. https://ballotpedia.org/The_Washington_Post_Fact_Checker#cite_note-kessler-3.

3. Fake news in other categories may or may not be linked with stock market returns, such as fake news related to Russia and the coronavirus. While the coronavirus may be linked with economics, it encompasses much more than that, with several instances of fake news not closely related to our interests. For example, a comment like "Biden failed with Swine flu" does not necessarily have any linkage with stock markets, even though it is categorized under the coronavirus category. One could even argue that some of the other categories are linked to some extent with economics, such as the Ukraine probe and foreign policy, which complicates the selection process. For robustness, we report later in this study results when using all fake news available from the database. We find that the relation between all fake news and stock market returns is positive but to a lower magnitude.
4. Newly arrived fake news does not offer enough variation in the data to base an empirical analysis. Politifact is another well-known fake news database. According to this database, Trump infrequently states more than one piece of fake news in a day, with most days exhibiting no fake news. Therefore, it is not feasible to use an alternate fake news database for the purposes of our study.
5. In a robustness check, we also report results later in this study without excluding any outliers. We find that our results hold regardless.
6. The 1,185 fake news took place on 16th October 2018 linked mostly with a lengthy interview.
7. We estimate discrete stock market returns.
8. In a robustness, we also add up to five day lags on stock market returns later in this study, and find that our results hold regardless.
9. https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020
10. For transparency, we conducted estimations with Newey-West standard errors, and the main relation was found to be slightly insignificant in untabulated results. The *p*-value of the relevant parameter coefficient was found to be 0.174. As discussed earlier, we believe there is justification within the context of our study to cluster our standard errors per year. Much of the fake news in our sample is repetitive and often reappears in nearby time periods.
11. http://www.policyuncertainty.com/
12. https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index
13. https://api.gdeltproject.org/api/v2/summary/summary?DATASET=IATV
14. https://projects.fivethirtyeight.com/polls/national/
15. https://jkpfactors.com/?country=gbr
16. https://news.gallup.com/poll/203198/presidential-approval-ratings-donald-trump.aspx
17. https://www.socialbakers.com/statistics/twitter/profiles/detail/25073877-realdonaldtrump
18. https://www.greenwich.com/asset-management/institutional-investing-how-social-media-informs-and-shapes-investing-process https://newsroom.bmo.com/2013-08-23-BMO-InvestorLine-Study-Despite-Rise-of-Social-Media-Investors-Still-Rely-on-Traditional-Media-Sources-for-Information
19. For example, strong stock market returns are not due to Obama leadership during Obama administration but due to Trump leadership during Trump administration.

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