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Do US states' responses to COVID-19 restore investor sentiment? Evidence from S&P 500 financial institutions



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Abstract

This paper specifically investigates the effects of US government emergency actions on the investor sentiment-financial institution stock returns relationship. Despite attempts by many studies, the literature still provides no answers concerning this nexus. Using a new firm-specific Twitter investor sentiment (TS) metric and performing a panel smooth transition regression for daily data on 66 S&P 500 financial institutions from January 1 to December 31, 2020, we find that TS acts asymmetrically, nonlinearly, and time varyingly according to the pandemic situation and US states' responses to COVID-19. In other words, we uncover the nexus between TS and financial institution stock returns and determine that it changes with US states' reactions to COVID-19. With a permissive government response (the first regime), TS does not impact financial institution stock returns; however, when moving to a strict government response (the overall government response index exceeds the 63.59 threshold), this positive effect becomes significant in the second regime. Moreover, the results show that the slope of the transition function is high, indicating an abrupt rather than a smooth transition between the first and second regimes. The results are robust and have important policy implications for policymakers, investment analysts, and portfolio managers.

Keywords: COVID-19, Financial institution stock returns, Investor sentiment, US states' responses

Introduction

Despite the classical financial theory that believes the market is efficient and that security prices sufficiently reflect all market information, behavioral finance rejects the premise of investors' perfect rationality. Behavioral finance explains many anomalies and argues that investors are more likely to be influenced by investor sentiment (IS) (e.g., emotion, anxiety) in making decisions, leading to a bias of irrationality in investment decisions. A work by Baker and Wurgler (2006) stated that IS can be conceptualized as a belief about returns and risk that is not rationalized by truths. Therefore, based on behavioral finance, sentiment is considered an outstanding way to explain financial selections and is likely to affect investors' investment decisions in stock markets (Nofsinger 2005). Reviewing the literature, several works have empirically revealed that IS



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could be an essential determinant that considerably affects asset pricing (e.g., Li et al. 2017; Shen et al. 2019).

For example, Fang et al. (2021) revealed that companies with optimistic IS have considerably higher stock returns, while those with pessimistic IS experience considerably opposing results. Kim and Lee (2022) highlighted that IS has a considerable positive impact on stock returns in the Korean stock market. Liu et al. (2023) showed a particularly significant positive interaction between IS and stock prices, implying that a rising stock price leads to an increasing IS and vice versa. Cevik et al. (2022) revealed a significant positive relationship between IS and stock market returns globally. Tiwari et al. (2022) highlighted directional and bidirectional nonlinear causality between sentiment and the returns of industry stocks in Australia. The authors also found that the likelihood between IS and industry stock returns is high (low) in a normal (extremely bearish or bullish) market state. In addition, some studies (e.g., Baker and Wurgler 2006; Schmeling 2009) have shown that IS is negatively linked with expected stock returns. Brown and Cliff (2005) argued that if IS causes stock prices above (below) original values, future stock returns would be low (high). Chakraborty and Subramaniam (2020) showed that lower sentiment stimulates fear-induced selling, thus reducing returns, and high sentiment is followed by lower future returns as the market reverts to fundamentals. Wang et al. (2021) also uncovered a negative relationship between IS and future stock returns globally.

What about the IS–financial institution stock returns relationship during COVID-19? When analyzing the financial sector's performance during COVID-19 and comparing the S&P 500 Bank Industry Group Index to the S&P 500, Year to Date change in value as of July 22, 2020, it is evident that the value of the S&P 500 Bank Industry Group Index dropped by 34.31% in contrast to a 0.82% increase in the S&P 500. The anticipation of spikes in COVID-19 cases or deaths caused substantial uncertainty and high volatility in worldwide financial markets and led to psychological resilience and unbearable psychological pressure among investors, with the financial industry being no exception (Baig et al. 2023). Researchers showed that uncertainty is a key factor affecting investment decisions (Vickman et al. 2012; Zhu et al. 2021). Work by Loewenstein et al. (2001) argued that investor mood (optimistic or pessimistic) has a significant role in decisionmaking during the uncertainty period. Based on a report by Bank of America, IS collapsed following the coronavirus outbreak due to recession fears, the extremely bearish positioning of the market, and surging debt default risk.

Chen et al. (2020) and Ftiti et al. (2021) determined that pandemic-related news (e.g., death rate) stimulates concern among investors and impacts investors' beliefs, perceptions, moods, and sentiments. Consequently, a higher (lower) pandemic death rate generates pessimistic (optimistic) anticipations. Haroon and Rizvi (2020) found that sentiment generated from news of the coronavirus is linked to rising instability in equity markets. Huynh et al. (2021) documented the persistence of the predictive power of IS in describing stock returns (negatively) and volatility (positively) at the inception of COVID-19. Liu et al. (2023) showed that rising external anxiety due to the lockdown significantly affects the IS–stock prices nexus. Mili et al. (2023) revealed that COVID-19 news has an important impact on IS, and IS is influenced relatively more by undesirable news about COVID-19 than by positive news. Bai et al. (2023) showed that adverse

financial market sentiment intensifies the impact of COVID-19 on the stock market, whereas positive sentiment can reduce losses caused by the pandemic shock.

Nevertheless, governments made prompt financial decisions and offered various health and economic emergency policy packages to offset recessions and resurrect IS. For instance, on June 25, 2020, the US Federal Reserve Bank began its annual stress test to limit Q3 dividends for banks and block share repurchases until Q4. For the emergency policy packages, the US government, for instance, initiated emergency actions, such as lockdowns, travel restrictions, testing and guarantining, and economic packages with the primary aim of controlling the spread of the disease on the one hand and minimizing adverse economic impacts on the other hand. Regarding the emergency policy packages, the US government's responses to COVID-19 are as follows. First, the combined containment and health index demonstrates how many forceful measures were implemented to contain the virus and protect citizen health care (this combines lockdown limitations and closures with health actions such as testing policies and contact tracing). Second, the economic support index shows how much financial help was made accessible (e.g., income support, debt relief). Third, the stringency index records the strictness of lockdown-style closures and containment policies that mainly limit people's behavior. Finally, the overall government response index (GRI) records how state responses have varied according to general indicators, capturing the full range of responses.¹

While COVID-19 adversely impacted IS and stock markets,² we expect that implementing these government actions (through the overall GRI) has both direct and indirect threshold effects on the IS-financial industry stock returns relationship. Similarly, work by Goel and Dash (2022) uncovered that government policy responses to COVID-19 have a moderating role on the IS-stock returns nexus globally. Regarding the direct threshold effects, social distancing measures might negatively affect stock market returns by negatively influencing economic growth. Conversely, there is a likelihood that government containment, health responses, and income support packages lead to positive market reactions, as they tend to reduce unfavorable economic impacts from the disease. The indirect threshold impact of these government actions is through IS (e.g., improving investor confidence by decreasing the intensity of COVID-19). Studies by Irresberger et al. (2015) and Kadilli (2015) discussed that changes in IS and perception of the economic situation are likely to affect financial industry stock returns. Strict government actions, including stringent social distancing actions, aggressive analysis, quarantining policy, and substantial government income support plans might decrease the rate of new infections, which would both improve the investment climate and increase the credibility of governments' commitment, thereby enhancing investors' confidence and mood. However, the strictness of the lockdown measures has raised concerns about a potential wave of bankruptcies. Terminations of global events and new initiatives to motivate social distancing have made it more challenging to predict when economic activity might hit bottom, creating more uncertainty for investors.

 $^{^1}$ Note: Each index reports a number ranging from 0 to 100, reflecting the level of government response along specific dimensions.

² For instance, a work by Apostolakis et al. (2021) showed that volatility spillovers peaked, and more volatility was transmitted from mid-cap firms to large-cap firms during COVID-19. Athari and Hung (2022) uncovered that the nexus between asset classes intensified during COVID-19, and Athari et al. (2023) showed that the world pandemic uncertainty adversely impacted the German stock market.

By reviewing prior studies, we found a significant gap in comprehensively examining the IS-financial industry stock returns nexus, especially during the pandemic period by considering the government intervention actions. Hence, we aim to fill this gap by answering how the US government's responses to COVID-19 have impacted the ISfinancial industry stock returns nexus. To be precise, this study is specifically designed to determine whether any observable variations in the IS-financial industry stock returns relationship are attributed to US states' responses to COVID-19. This may be the first study to conduct this nexus, and the results could open a new discussion within the literature. To achieve this purpose, we employ the panel smooth transition regression (PSTR) approach to a panel dataset of the daily stock returns of 66 financial institutions in the S&P 500, government responses, and firm-specific Twitter investment sentiment (TS) from January 1 to December 31, 2020. Based on Bloomberg, firm-specific TS is calculated using tweets from the overall Twitter and Stock-Twits that Bloomberg classifies as being about a given company. Bloomberg uses supervised machine learning algorithms that, among other capabilities, can help detect financial tweets about a company, decide whether the tweet is positive, negative, or neutral, and assign it a confidence score. A firm's daily TS is derived from its story-level sentiment and related confidence scores over the previous 24 h. The sentiment values are released every morning before the stock market's opening.

TS includes retweets in their analysis, which can provide a more accurate representation of the overall sentiment toward a topic, as retweets indicate that the original tweet resonated with other users. When it comes to handling foreign languages, the TS index relies on machine translation to translate tweets into a language the algorithm is trained on. Using Bloomberg's TS makes our study replicable and transparent. We find that TS demonstrates asymmetrical, nonlinear, and time-varying behavior in response to the pandemic situation and the actions taken by different US states to combat COVID-19. This means that the relation between TS and stock returns in the financial industry fluctuates depending on changes in government responses to the pandemic. Specifically, in a permissive government response scenario (the first regime), TS does not substantially affect stock returns. However, when the government response becomes stricter (as indicated by the overall GRI surpassing a threshold of 63.59), the positive influence of TS on stock returns gains importance in the second regime. This can be attributed to the attenuation impact of government responses to COVID-19 on TS. Thus, the GRI serves as a moderating factor that affects the linkage between TS and stock returns.

Our work makes multiple contributions to the current literature. First, this work contributes to the existing literature on market and government responses to COVID-19 (e.g., Funke and Tsang 2020; Nepp et al. 2022; Goel and Dash 2022; Zhang et al. 2022). Second, unlike most previous studies (e.g., Baker and Wurgler 2006; Chakraborty and Subramaniam 2020; Bai et al. 2023), which have mainly focused on market sentiment, this work contributes by focusing on Bloomberg's firm-specific TS. With the help of Bloomberg's TS data, we can contribute to the literature on the informational content of Twitter messages without performing a daunting and potentially subjective analysis of tweet content. This makes it possible to probe the predictive content of TS for many individual firms over a long sample period. Third, it acts as an intermediary between behavioral finance theory and classical financial theory that rejects the influence of sentiment because it supposes that rational investors dominate the market. Unlike irrational IS, rational IS will depend, to a much larger extent, on external factors (such as the pandemic crisis and government policies). In such situations, a heterogeneous panel data model is needed to examine firms' investment behavior.

Fourth, this study provides valuable insight into IS's frequency dynamic. The effect of government responses to COVID-19 on the IS-financial industry stock returns nexus is divided into a small number of homogeneous regimes, with various coefficients for each regime. This feature makes our model more interesting, as investors are not limited to similar behavior during all periods. This is because investors may have different reactions to government responses due to different cultural dimensions, market integrity, intelligence, and education. Furthermore, our threshold variable (government responses to COVID-19) is time-varying. Fifth, it improves our comprehension of the speed at which investor responses can happen, abruptly or smoothly. Previous studies assume that investors primarily underreact to news and are slow to update their beliefs and moods according to new evidence in the market (Odean 1998). Whether this dynamic still holds during government intervention actions during the COVID-19 pandemic is of interest.

This study provides some interesting results. First, the results reveal that TS acts asymmetrically, nonlinearly, and time varyingly according to the pandemic situation and US states' responses to COVID-19. This finding implies that the nexus between TS and financial institution stock returns varies with changes in US states' reactions to COVID-19. Second, the results highlight that with a permissive government response (the first regime), TS does not affect financial institution stock returns; however, when moving to a strict government response (the overall GRI exceeds 63.59), this positive impact becomes significant in the second regime. This finding implies that US government intervention actions are only effective from a certain threshold point in further stimulating TS and reverting the stock market from a crash to a normal stage. Third, the results show that the slope of the transition function is high, indicating that an abrupt rather than a smooth transition takes place between the first and second regimes. Overall, the results imply a key role for the overall US government response to COVID-19 in determining the IS-financial industry stock returns nexus.

The rest of the study proceeds as follows. Sect. "Methodology" explains the data collection procedure and indexes that measure government responses during the COVID-19 pandemic. Sect. "Empirical results" explains the results. Sect. "Conclusion" concludes.

Methodology

Sample selection and variables

This study's first sample covers all financial institutions within the S&P 500, which constitutes a diverse segment of the US equities market. Businesses in the New York City stock market and Nasdaq are used for this index. Notably, banking institutions with incomplete information are removed from the database. Therefore, the final sample includes 16,380 observations spread among 66 financial firms from January 1, 2020, to December 31, 2020. In gathering financial data and IS, Bloomberg is used. Additionally,

Variables	Definitions	Sources
Dependent variable		
Stock return Independent variables	The daily return is calculated using the return index from Bloomberg	Bloomberg
Government response index (GRI)	An overall national reaction indicator tracks how the US has responded to different measures and captures the complete variety of government interventions	Oxford Covid- 19 government response tracker
The daily average of Twitter sentiment (TS)	The total daily emotion on Twitter. The scale ranges from -1, represent- ing the most negative attitude, to 1, meaning the most significant high level of engagement, with 0 representing a balanced mood	Bloomberg
Size	The logarithm of the company's market capitalization	As above
Beta	The ratio of stock price volatility to market index volatility	As above
Fed_Asset	Assets: (M\$)	Federal Reserve System's gov- erning board (US)

Table 1 Variable descriptions

we used the Oxford COVID-19 government response tracker website³ to gather daily information on the US GRI for COVID-19. The GRI is typically a tool for systematically tracking and comparing policy measures that governments worldwide take in response to a crisis like COVID-19. It includes health system policies, containment and closure policies, economic support, and governance and policy measures. It is usually calculated by scoring each of the above policy areas on a scale (for example, from 0 to 100) and then averaging these scores. Each policy area can be weighted equally, or some policy areas can be given more weight depending on the objectives of the index. The index can vary across states based on the specific policies and measures implemented by each state. For example, some states may have implemented stricter containment and closure policies, while others may have focused more on economic support measures. Likewise, the GRI can change over time as governments adjust their policies in response to changing circumstances.

In addition, we collected data for federal assets from the Federal Reserve System's Board of Governors. All variables used in the econometric investigation are formally defined in Table 1.

Panel smooth transition regression model

The PSTR approach of González et al. (2017) is used to investigate the threshold influence of the GRI on the IS–financial industry stock market returns relationship. This novel approach differs somewhat from the typical econometric techniques used in prior research.

First, we generate regression parameters based on the PSTR estimates that vary between businesses, over time, and with different government response regimes, incorporating variations across firms, temporal instability, and government policy dynamics and offering more consistent estimators. Second, the PSTR model challenges the assumption of uniform interpretations of IS across firms; it brings

³ https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker



A map of states, counties, and county-equivalents in the United States that have imposed mandatory stay-at-home orders (sometimes as "shelter-in-place orders" or "safer-at-home orders") as part of U.S. state and local government responses to the 2020 coronavirus pandemic, color-coded by the week on which each order went into effect.

Fig. 1 Policies Responses to COVID-19 Across States of the USA. The map was taken from https://en.m.wikip edia.org/wiki/File:COVID-19_outbreak_USA_stay-at-home_order_county_map.svg

reasonable responses to the discrepancies, omissions, and incongruities in existing research and proposes an approach that transcends the simplistic linear association between IS and firm stock returns. This is likely because the government's response to COVID-19 can influence IS during the pandemic. Third, unlike discrete switching models (e.g., Hansen 1999), PSTR modeling is more flexible because it allows for both gradual changes and actions that may deviate between extreme regimes and the incorporation of regime-switching behavior, which adds to knowledge about variable dynamics. It remains adequate for both abrupt transitions and smooth regime shifts (González et al. 2017).

Fourth, the PSTR technique can be applied to more than two phases, highlighting disparities in government attitudes in response to the COVID-19 pandemic. The PSTR model explicitly accounts for the presence of regime shifts or nonlinearities in relationships between variables. This is particularly relevant when studying the impact of policy thresholds, as the effects of policies on IS and stock returns may not follow a linear pattern. We believe that thresholds are justified because policy effects are often nonlinear and may not follow a monotonic pattern. By considering different thresholds, we can capture the nuanced effects of policy changes on IS and stock returns.

To further motivate our paper, we included a simple figure of different states or regions that demonstrates the variations in policy responses. Figure 1 highlights how these differences in policy responses can influence IS and subsequently affect stock returns. This additional analysis strengthens the empirical relevance of our research and provides a clearer connection between the research question and the estimation methodology preference.

The PSTR concept with two distinct domains and a singular turn-up can be described as follows, according to González et al. (2017):

$$Return_{it} = \mu_i + \beta'_0 x_{it} + \beta'_1 x_{it} W(GRI_{it}; \gamma, c) + \varepsilon_{it}$$
(1)

The number of financial institutions is i = 1, 2... N, and the number of periods is t = 1, 2... T. *Return_{it}* is the return on investment. x_{it} represents TS, the GRI, federal assets, and company size and risk. $W(GRI_{it}; \gamma, c)$ is the normalized transition function restricted between 0 and 1, and 1. (GRI_{it}) is the threshold parameter. The transitioning and threshold variables are the remnant and/or a single time-invariant effect. The logistic description can be used for the input signal, according to González et al. (2017):

$$W(GRI_{it};\gamma,c) = \left[1 + \exp\left(-\gamma \prod_{j=1}^{m} (GRI_{it} - c_j)\right)\right]^{-1}$$
(2)

where $\gamma > 0$ and $c_1 \le c_2 \le \dots \le c_m$. The PSTR model is reduced to a panel change over the predictor variable when m = 1 and $\gamma \to \infty$. According to González et al. (2017), to exploit the nonlinearity generated by regime-switching, it is necessary to investigate only the situations of m = 1 or m = 2.⁴

For m = 1, the analysis shows that higher and lower concentrations of GRI_{it} are linked to a gradual transformation of the variables from β_0 to $\beta_0 + \beta_1$ as it grows, with the shift concentrated at c_1 as $GRI_{it}GRI_{it}$. When $\gamma \rightarrow \infty$, g ($GRI_{it}GRI_{it}$; γ , c) transforms into an indicator unit I [$GRI_{it}GRI_{it}$ > c_1], denoted as I [A] = 1 when the incident A occurs and 0 otherwise. The equation in (1) simplifies the PSTR model to Hansen (1999)'s parallel design model equation.

The transition function for m = 2 has a low at $(c_1 + c_2)/2$ and a maximum value at both low and high values of GRI_{it} . When $\gamma \rightarrow \infty$, the framework is now a three-regime cutoff model, with outer regimes similar to the mid-regime and unique.

When m > 1 and $\gamma \rightarrow \infty$, in general, the number of separate zones is maintained at two, with the process stage flipping across zero and one at c1, cm. Finally, when m = 0, the transition function (2) remains constant $\gamma \rightarrow 0$, resulting in a uniform or homogeneous panel data regression framework with explanatory variables for any integer value m.

The PSTR model can also be expanded to include more than two modes:

$$Return_{it} = \mu_i + \beta_0 x_{it} + \sum_{j=1}^r \beta_j x_{it} W_j (GRI_{it}; \gamma_j, c_j) + \varepsilon_{it}$$
(3)

where r+1 is the number of regimes and $W_j(GRI_{it}; \gamma_j, c_j) W_j(GRI_{it}; \gamma_j, c_j)$, j=1...r, are the transition functions (Eq. (2)).

Panel smooth transition regression procedure

The PSTR procedure consists of three steps: (1) detailed description, which involves homogeneity checking and a sequential homogeneity analysis to check the transition function's order m, (2) based evaluation; and (3) assessment, which includes parameter constancy testing and no residual heterogeneity. If they take the following forms a homogenous process, the PSTR paradigm is unidentifiable. Furthermore, homogeneity

⁴ The case m = 1 corresponds to a logistic PSTR model, and m = 2 refers to a logistic quadratic PSTR specification.

must be evaluated first to avoid the estimate of unidentifiable models. According to Luukkonen et al. (1988), the null hypothesis used in the homogeneity test is H_0 : $\gamma = 0$. However, the PSTR model contains unknown nuisance parameters. To resolve this issue, g (*GRI*_{*it*}; γ , *c*) QUOTE in Eq. (1) is replaced by its first-order Taylor expansion around $\gamma = 0$, and the model becomes

$$Return_{it} = \mu_i + \beta_0^{'*} x_{it} + \beta_1^{'*} x_{it} GRI_{it} + \dots + \beta_m^{'*} x_{it} GRI_{it}^m + \varepsilon_{it}^{'*}$$
(4)

Accordingly, testing $H_0: \gamma = 0$ in Eq. (1) is equivalent to testing the null hypothesis $H_0^*H_0^*: \beta_0^*\beta_0^* = \cdots = \beta_m^*\beta_m^* = 0$ in Eq. (4) (González et al. 2017). The homogeneity test⁵ confirms the null hypothesis of proportionality using LM-type analyses predicated on asymptotic χ^2 averages, Fischer variants, resistant HAC editions, and wild bootstrap (WB) and wild cluster bootstrap (WCB) LM analyses.⁶ González et al. (2017) recommended using WCB tests when assessing linearity.

If uniformity is denied, the model chooses the right value of m in Eq. (2) and uses a series of homogeneity evaluations to identify the suitable shape of the transition function. Terasvirta et al. (2010) developed a set of tests for determining whether m=1 or m=2 should be used. The validation process is as such when applying it to our system. Test the null hypothesis $H_0^*H_0^* : \beta_3^*\beta_3^* = \beta_2^*\beta_2^* = \beta_1^*\beta_1^* = 0$ using the auxiliary model Eq. (4) with m=3. Test $H_{03}^*H_{03}^* : \beta_3^*\beta_3^* = 0$, $H_{02}^*H_{02}^* : \beta_2^*\beta_2^* = 0|\beta_3^*\beta_3^* = 0$, and $H_{01}^*H_{01}^* : \beta_1^*\beta_1^* = 0|\beta_3^*\beta_3^* = \beta_2^*\beta_2^* = 0$ if it is rejected. If the denial is the greatest, choose m=2; otherwise, choose m=1. See Terasvirta for the explanation behind this basic rule (1994).

The simultaneous equation model is estimated; nonlinear regression methods are used to produce an estimate in the PSTR framework (1) (NLS). Independent variables are first eliminated by subtracting different averages, and NLS is then applied to the altered information.

Assessment of the estimated PSTR model is critical. Misspecification tests are run on the estimated model to see if it defines a sufficient data description. The evaluations of variable stability over time and the absence of residual nonlinearity were fitted. The parameter constancy test is more promising when the time dimension is more important. As a result, the greater the time aspect, the more useful this test becomes. This test compares parameter stability's null hypothesis (H₀) to the alternate explanation (H₁) of smooth changes in slope coefficients over time. When the PSTR model is discarded, it becomes a moment PSTR. Using the no residual heterogeneity test, the PSTR has a

⁵ The findings of the linearity experiments are divided into four categories:

 $[\]chi^2$ -version under the anthropic principle of linearity, the stationarity LM test with terminal 2 distribution is used.

F-version under the null hypothesis of linearity, the regression LM test with exponential F probability is used. The size of the finite sample should be increased.

HAC χ^2 -version Under the normality test of regression, which is a heteroscedasticity problem and latency compatible, the linearity LM test with terminal χ^2 distribution is used.

HAC F-version under the anthropic principle of linearity, which is heteroskedasticity and latency consistent, the linearity LM test with asymptotic F probability is used. The size of the specified threshold should be increased.

The wild bootstrap (WB) analyses are heteroskedasticity-resistant, while the wild cluster bootstrap (WCB) analyses are heteroskedasticity-resistant and cluster-dependent. Cluster-dependence indicates that within an individual, there can be dependency (autocorrelation), but no connection between entities.

⁶ The linearity testing is conducted for a collection of "candidate" transition variables in the lack of a conceptual framework for picking the transition variable, and the one that offers ascent to the greatest repudiation of proportionality (if any) is selected as the transition parameter.

successful outcome if the number of phases has recorded all nonlinearity present in the data. This test explicitly pits the PSTR leftover nonlinearity hypothesis H_0 with a solitary equation given (r = 1) versus the equivalent with two different values (r = 2).

Empirical results

Descriptive statistics

Table 2 summarizes the descriptive statistics of the investigated factors in this study. The mean (median) of financial industry stock returns is 8.4% (7%), with a standard deviation of 3.713. Likewise, it shows GRI has a range between zero to 69.27, with a mean (median) of 53.471 (64.580). Table 2 also reveals that TS has a mean (median) value of 1.7% (0.3%). Moreover, Table 2 indicates that size and beta have a mean value of 23.954 and 0.879, respectively.

Table 3 (Panels A and B) shows Pearson's correlation matrix between used variables and lagged values of TS for testing multicollinearity problems. Panel A shows that stock returns and TS have a positive correlation coefficient. The correlation coefficient between stock returns and GRI is also positive. Panel (B) indicates the absence of a multicollinearity problem when including lagged values of TS in our regression.

Figures 2 and 3 display a scatter plot of financial industry stock returns on IS (i.e., TS) during COVID-19 by considering government response actions (i.e., the GRI).

Variables	Observations	Mean	Std. Dev	Median	Minimum	Maximum
Stock return	16,380	0.084	3.713	0.070	-26.835	31.700
GRI	16,380	53.471	22.950	64.580	0.000	69.270
TS	16,380	0.017	0.117	0.003	-0.987	0.927
Size	16,380	23.954	1.019	23.850	21.465	27.051
Beta	16,380	0.879	2.664	1.044	-6.326	6.487
Fed_Asset	16,380	6,358,694.2	1,176,861.7	6,990,418	4,145,912	7,404,039

Table 2 Descriptive statistics

Tabl	e 3	Correl	ation	matrix

Panel (A): Pearson's correlation between variables									
Variables	Stock return	TS	Beta	Size	GRI	Fed_Asset			
Stock return	1.000								
TS	0.027	1.000							
Beta	0.058	- 0.006	1.000						
Size	0.014	- 0.078	-0.012	1.000					
GRI	0.077	0.002	-0.007	- 0.075	1.000				
Fed_Asset	0.087	0.027	-0.018	- 0.045	0.950	1.000			
Panel (B): Pear	son's correlation bet	tween lagged v	alues of TS						
	TS _(t - 1)		TS _(t - 2)	TS _{(t –}	3)	TS _(t – 4)			
TS _(t - 1)	1.000								
TS _(t - 2)	0.354		1.000						
TS _(t - 3)	0.303		0.395	1.000					
TS _(t - 4)	0.288		0.286	0.353		1.000			

Especially, we use a regime-switching model that helps us more accurately describe the degree of this relationship. To achieve this purpose, the GRI is divided into two groups, namely permissive and strict responses, based on its mean. These charts do not allow for accurate or succinct characterization of the extent of correlation.

The scatter plots depict how the connection between TS and company share liquidity fluctuates in response to changes in the GRI. However, this graphical representation alone is not sufficiently comprehensive. Hence, implementing a regime-switching model that provides a more precise depiction of this correlation proves beneficial.

To examine the correlation between the stock-specific Twitter index and broader IS measures, Fig. 4 shows variations in the Twitter index and the VIX, also known as the fear index, to further support the validity and relevance of our approach.

While the Twitter index reveals more volatility, it should be noted that the stock-specific Twitter index primarily captures sentiment at the firm level, whereas indices like the VIX represent overall market sentiment.



Fig. 2 Scatter plot of stock return on twitter investor sentiment (TS) during the COVID-19 Pandemic



Fig. 3 Scatter plot of stock return on twitter investor sentiment (TS) based on government response status



Fig. 4 Variations in the Twitter index and the VIX

Linear panel regression with fixed effects

Table 4 shows the linear regressions' fixed-effect estimates for various models. In Model (1), we exclude monetary factors and assume that time effects are not fixed. Model (2) is similar to Model (1). It assumes that time effects are fixed to consider economic and financial shocks and noticeable and inherently unknowable systematic changes between identified time steps. In Model (3), we exclude the effect of GRI and include monetary factors that affect stock returns within the financial sector (e.g., FED total assets, FED announcement following its annual stress test of banks) by assuming that time effects are not fixed. Model (4) includes the lagged TS measured at times (t-1) through (t-4)and excludes monetary factors by assuming that time effects are fixed. Lastly, Model (5) is similar to Model (4) and includes lagged dependent variables, indicating that stock returns are quite persistent. Overall, the results reveal that the coefficient of TS is significant and positive, supporting the behavioral economics hypothesis that argues that an increase (decline) in TS leads to increasing (decreasing) stock market returns. In addition, the results reveal that the coefficient of GRI is positive and significant, implying that government interventions likely result in a favorable market reaction by controlling the negative economic repercussions of COVID-19. Notably, because this specification assumes linearity, the result about the variability of the opinion impact from government reform responses to COVID-19 should be verified as another more rigorous and suitable requirement that allows consideration of a nonlinearity relationship.

Nonlinear specification

Table 5 illustrates compelling evidence that homogeneity is decisively disproven for the GRI as a threshold variable for ma = 1, 2, and 3. The LM-type test based on the

Independent variables	Dependent variable: Stock return									
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)					
Stock return _(t-1)	_	_	-	-	- 0.075***					
	_	_	_	_	(0.0248)					
TS	0.717**	0.808***	0.671*	-	_					
	(0.274)	(0.198)	(0.369)	-	-					
TS _(t - 1)	-	-	-	0.867**	0.999***					
	-	-	-	(0.330)	(0.306)					
TS _(t - 2)	-	-	-	- 0.387	-0.452					
	-	-	-	(0.379)	(0.375)					
TS _(t - 3)	-	-	-	- 0.063	- 0.052					
	-	-	-	(0.421)	(0.413)					
TS _(t - 4)	-	-	-	- 0.649*	- 0.670*					
	-	-	-	(0.356)	(0.371)					
Beta	0.089***	0.060***	0.086***	0.068***	0.069***					
	(0.011)	(0.009)	(0.008)	(0.022)	(0.021)					
Size	3.164***	1.341***	3.072***	0.798**	0.889**					
	(0.182)	(0.157)	(0.202)	(0.369)	(0.385)					
GRI	0.023***	0.008***		0.0007	0.0003					
	(0.001)	(0.001)		(0.002)	(0.002)					
Fed_Asset	-	-	3.239***	-	_					
	-	-	(0.275)	-	-					
Fed_Announcement	-	-	-0.671***	_	_					
	-	-	(0.058)	_	_					
Bank fixed effect	Yes	Yes	Yes	Yes	Yes					
Time fixed effect	No	Yes	No	Yes	Yes					
Num. of Obs	16,380	16,380	16,380	16,380	16,380					

Table 4 Linear panel regression with fixed effects

The numbers in parentheses denote robust standard errors that account for potential heteroskedasticity and time-series autocorrelation within each bank. The use of asterisks ***, **, and * signifies statistical significance at the 1%, 5%, and 10% levels, respectively. Year dummies are unreported

Table 5 Horn	noaeneitv	v tests
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Tra	Transition variable: government response index (GRI)											
m	LM_X	PV	LM_F	PV	HAC_X	PV	HAC_F	PV	WB_PV	WCB_PV		
1	63.36	5.71E-13	15.77	6.93E-13	39.78	4.81E-08	9.901	5.34E-08	0	0		
2	167.7	0.00E+00	20.87	0.00E+00	57.86	1.22E-09	7.199	1.44E-09	0	0		
3	227.1	0.00E+00	18.84	0.00E+00	58.48	4.27E-08	4.849	4.99E-08	0	0		

asymptotic χ^2 distributions, their F-versions, HAC tests, and WB tests confirms that nearly all p-values⁷ equal zero.

The transition function's order m is then determined via a series of tests. Table 6 shows the outcomes of our transition variable's specification test sequence. The optimal choice for the GRI, as per the HAC and WB tests, is m=2. The transition function for m=2

⁷ The linearity testing is conducted on all our independent variables as a collection of "candidate" transitional factors, and GRI is the one that results in the most significant rejection of normality. As a result, it gets selected as the transition variable.

Transition variable: government response index (GRI)										
	LM_X	PV	LM_F	PV	HAC_X	PV	HAC_F	PV	WB_PV	WCB_PV
H* ₀₃	63.36	5.71E-13	15.77	6.93E-13	39.78	4.81E-08	9.901	5.34E-08	0	0
H* ₀₂	104.8	0.00E+00	26.07	0.00E+00	49.81	3.95E-10	12.39	4.58E-10	0	0
H* ₀₁	60.05	2.84E-12	14.94	3.45E-12	37.42	1.48E-07	9.309	1.64E-07	0	0

 Table 6
 Sequence of homogeneity tests for selecting order M of transition function

Select m = 2 if the rejection of $H_{02}^* H_{02}^*$ is the strongest one, otherwise select m = 1

has a minimal at (c1+c2)/2 and the highest amount at both minimum and maximum quantities of GRI_{it} . When $\gamma \rightarrow \infty$, the paradigm does become a multiple threshold system, with outer phases that are similar to the mid-regime and distinct from it.

Estimation and evaluation of panel smooth transition regression

Before analyzing the estimation results, we evaluate the suitability of the two-regime PSTR model by conducting misspecification tests to assess the absence of remaining heterogeneity and parameter constancy. Table 7 presents the findings of these tests. The WB and WCB tests, which consider both heteroskedasticity and potential within-cluster dependence, indicate that the estimated model with two regimes is appropriate.

Table 8 presents parameter estimates derived from the PSTR model.

using cluster-robust and heteroskedasticity-consistent standard errors. To better understand the estimation results in Table 8, we plot Figs. 3 and 4.

The threshold value is chosen so that the shift from the bottom phase connected with a liberal state reaction (low GRI) to the upper regime, which is associated with a rigorous political situation (high GRI), is seamless. Figure 4, plotted versus GRI for each ring as an observation, demonstrates this. Furthermore, given that the transition function's minimum is (61.33+65.85)/2, the midpoint estimation is c=63.59. Figure 3 illustrates this. The point estimate value falls between the 25th and 50th percentile rank of the GRI observed distribution. As a result, the model recognizes the TS-financial institution stock returns relationship influenced by a liberal government reaction to COVID-19 as a discrete subgroup that is separate when the GRI exceeds 63.59 (Figs. 5, 6).

Discussion

This paper primarily aims to determine whether any observable variations can be found in the connection between TS-financial institution stock returns attributed to US states' responses to COVID-19. To do so, three general questions are posed. First, the PSTR results in Table 8 point to two regimes running from TS to the stock return proxy. Looking at the PSTR model, it can be inferred that TS has a positive impact on stock return dynamics within each regime, and any improvement in TS leads to enhanced financial institution stock returns. The observed TS coefficients for the first regime (0.267, standard error = 0.230) and second regime (1.308, standard error = 0.639) indicate that optimistic TS can cause a stock return to rise significantly, which is similar to a study by Namouri et al. (2018) that showed a positive and asymmetric relationship between TS and stock return. Nevertheless, the COVID-19

Table 7 Misspecification tests

Transition variable: government response index (GRI)										
	LM_X	PV	LM_F	PV	HAC_X	PV	HAC_F	PV	WB_ PV	WCB_ PV
No rema	aining he	terogeneity								
ma = 2	388.3	0.00E+00	24.14	0.00E+00	59.48	6.40E-07	3.697	7.49E-07	0.58	0.58
Paramet	er consta	incy								
$h_a = 2$	607.3	0	37.75	0	59.97	5.29E-07	3.728	6.20E-07	1	1

Table 8 Estimated results for panel smooth transition regression model

Independent variables	Parameter estimates						
	Government response index (GRI)						
	First extreme regime $eta_0 eta_0$	Second extreme regime $eta_0 + eta_1 \ eta_0 + eta_1$					
TS	0.267	1.308**					
	(0.230)	(0.639)					
GRI	0.026***	0.044***					
	(0.010)	(0.002)					
BETA	0.019**	0.184***					
	(0.007)	(0.015)					
SIZE	3.156***	3.210***					
	(0.252)	(0.256)					
Transition parameters							
Thresholds (c1, c2)	[61.33***, 65.85***] [(0.064), (0.012)]						
(c1 + c2)/2	63.59						
Slope (y)	4.71 (0.193)						

Values in parentheses are robust standard errors. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% statistical levels, respectively



Fig. 5 Transition function plot of two-regime panel smooth transition regression model with r = 1 and m = 2

outbreak may result in different situations. Our outcomes are consistent with the theoretical proposition in behavioral finance (e.g., Baker and Stein 2004; Liu 2015; Debata et al. 2021) that optimistic (pessimistic) sentiment leads to higher (lower) share returns. Such an optimistic view is generated by the US government's responses to COVID-19 (Narayan et al. 2021).



Fig. 6 Transition function plot of government response index

Second, we test whether variations in US government responses to COVID-19 affect the relationship between TS and financial institution stock returns. In our PSTR model, the estimated slope is 0.2671 for the first regime, where GRI is less than 63.59, is 0.2671, whereas it is 1.308 for the second regime, where GRI is greater than 63.59. Thus, the magnitude of the effect of the TS impact can vary per regime, resulting in the highest value being obtained in the second regime. This validates the role of US government responses to COVID-19 in enhancing the effect of TS on stock returns.

Since the TS coefficient for the second regime is significant and greater than the TS coefficient for the first regime, the former, being the superior sentiment, is optimal, as explained by the positive effect of US government responses to COVID-19 on TS. One plausible reason for this could be that government policy interventions boost investors' optimism and demonstrate confidence in the government's ability to handle a pandemic (Goel and Dash 2021). Hence, government policy responses affect TS, leading to increased investor optimism (Rahman et al. 2021). This suggests that the US government's reactions to COVID-19 have become a medium through which the impact of TS on stock returns is transmitted. Understanding the effects of government responses on TS and financial institution stock returns provides valuable insights into the transmission channels through which government actions impact financial markets. During crises, such as the COVID-19 pandemic, government interventions play a crucial role in stabilizing financial markets and restoring investor confidence. The outcomes of this study highlight the primary role of government responses in shaping TS, which in turn influences financial institution stock returns (Bouri et al. 2022). This understanding helps in better comprehending the mechanisms through which government policies and actions impact financial markets, thereby contributing to a more comprehensive understanding of economic dynamics.

Earlier research indicated that TS might depend on various psychological factors wherein any additional change is unlikely to be significant. Yet, it is the authors' understanding that previous studies have never investigated this relationship for financial institutions during a pandemic crisis. The study of the transition function's slope results revealed that US government policy responses to COVID-19 substantially changed investor perceptions. It is worth mentioning that the transition function exhibits a high speed of transition ($\gamma = 4.71$). That is, an abrupt rather than smooth transition takes place between the first and second regimes, as illustrated in Fig. 3. The threshold distinguishing the two rules is 63.59.

The impact of US states' policy responses to COVID-19 (GRI) on stock returns must also be observed. The GRI coefficients of the two regimes are positive and significant at the 1% level. The coefficient in the second regime is greater than that in the first regime, indicating that the more effective government interventions are, the higher stock returns are, consistent with the findings of Goel and Dash (2022).

The identified link between TS and financial institution stock returns has direct implications for traders and investors. The research reveals that TS acts asymmetrically, nonlinearly, and varyingly over time based on the pandemic situation and government responses (Goel and Dash 2022). Traders can leverage this knowledge by incorporating sentiment analysis into their decision-making processes. By monitoring and analyzing TS, traders can gain insights into potential shifts in stock returns for financial institutions. During strict government response regimes, when sentiment becomes a significant driver of stock returns, traders can incorporate sentiment-based strategies into their investment approaches, capitalizing on the observed positive influence of TS on financial institution stock returns. This information can assist traders in formulating more informed and effective trading strategies, potentially leading to enhanced portfolio performance.

Moreover, the findings have crucial implications for policymakers. By understanding the impact of government actions on TS and subsequent stock market outcomes for financial institutions, policymakers can tailor their interventions to achieve desired economic and financial outcomes. During crises, policymakers can design and implement policies that foster positive TS, thereby supporting financial institutions and contributing to market stability. The research emphasizes the importance of effective government responses in influencing TS and financial markets, highlighting the need for policymakers to consider the interplay between government actions, TS, and financial institution stock returns when formulating policy measures. This finding underscores the importance of considering regional differences and specific state-level policies when examining how government responses influence financial markets. Policymakers can use this information to tailor their policies and interventions at the regional level by considering the varying dynamics of TS and financial institution stock returns across different states. This targeted approach can enhance the effectiveness of policy measures and contribute to more efficient resource allocation within the financial system.

With regard to control variables, firm size is measured by market capitalization, with a positive and statistically significant sign, albeit with varying magnitudes of impact. Firm risk, measured by beta, has a positive and statistically significant sign but with multiple degrees of influence, indicating that the impact of firm risk on stock return is more meaningful when the GRI rate exceeds 63.59. These results are consistent with the prior literature that maintains stock returns are positively related to the firm size and firm beta (e.g., Namouri et al. 2018; Ftiti et al. 2021). Overall, the presence of these two different regimes side by side with each other is a representative illustration of behavioral finance theory conclusions.

Independent Variables	Parameter estimates Stringency index					
	First extreme regime β_0	Second extreme regime $eta_0 + eta_1$				
TS	- 0.096	1.189**				
	(0.361)	(0.573)				
Stringency index	-0.013***	0.027***				
	(0.011)	(0.003)				
Beta	0.015**	0.151***				
	(0.007)	(0.015)				
Size	3.901***	3.801***				
	(0.345)	(0.326)				
Transition parameters						
Thresholds (c1, c2)	[66.18 ***, 72.18 ***] [(0.0399), (0.0115)]					
(c1 + c2)/2	69.48					
Slope (y)	2.37 (0.092)					

 Table 9 Estimation results for the panel smooth transition regression model for the stringency index

Values in parentheses are robust standard errors. Asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% statistical levels, respectively

Robustness checks

We corroborate the robustness of the results by employing another government response to COVID-19, which is the stringency index. This index measures the stringency of closure and containment policies, commonly referred to as "lockdown style" measures, that primarily restrict people's behavior. Table 9 shows similar results. The findings emphasize that TS has a significant and nonlinear impact on stock returns that varies with policy responses to COVID-19 across US states. Table 9 reveals that the coefficient of TS (1.189, standard error = 0.573) for the second regime (stringency index > 69.48%) is significant and greater than the insignificant coefficient of TS (-0.096, standard error = 0.361) for the first regime (stringency index < 69.48%).

Conclusion

While several studies have examined the TS and stock returns relationship, the literature still has not addressed this nexus in particular by considering the role of government interventions in COVID-19. Therefore, this study fills the gap by specifically investigating the effects of US government emergency actions on the TS–financial institution stock returns relationship. To achieve this purpose, the present study uses a new firm-specific Twitter investment sentiment and performs the PSTR applied for daily data on 66 S&P 500 financial institutions from January 1 to December 31, 2020. We also employ a PSTR methodology to more accurately capture asymmetric investor behaviors and temporal instability.

Our results reveal some consistent highlights. First, the results show that TS is acting nonlinearly, asymmetrically, and time varyingly according to the pandemic situation and US states' responses to COVID-19. In other words, we uncover that the link between TS and financial institution stock returns fluctuates in response to changes in US states' reactions to COVID-19. Second, the results reveal that government policy responses indirectly move stock returns through the channel of TS. Under a permissive government response (the first regime), TS does not influence financial institution stock returns; however, when moving to a strict government response (the overall GRI exceeds the 63.59 threshold), this positive effect becomes significant in the second regime. This can be explained by the attenuation effect of government responses to COVID-19 on TS. In other words, the GRI is a moderator estimator of Twitter content on stock return. Third, the results show that the transition function's slope is high, indicating that an abrupt rather than a smooth transition takes place between the first and second regimes.

The research highlights the crucial role of government responses in shaping TS and its subsequent effect on stock market outcomes for financial institutions. This finding has significant implications for policymakers, especially during times of crisis like pandemics or emergencies. Policymakers can leverage these insights to inform their decision-making processes, allowing them to tailor interventions that promote stability and instill confidence among investors. By understanding how government actions influence TS and financial markets, policymakers can implement strategies that maintain market equilibrium and foster a positive investment climate.

For investor analysts, this study emphasizes the importance of considering the dynamic and nonlinear nature of TS. They must go beyond overall sentiment analysis and consider contextual factors, such as the government's response to the crisis. These contextual factors can significantly influence investor behavior and ultimately affect stock market performance. Therefore, incorporating sentiment analysis and closely monitoring government actions should be integral parts of the investment analysis process for investor analysts.

Portfolio managers can also benefit from the findings of this research by adjusting their investment strategies based on the observed connection between TS and financial institution stock returns. During periods of permissive government response, when sentiment has a limited impact on stock returns, portfolio managers may prioritize other factors, such as financial performance indicators, to guide their investment decisions. However, during times of strict government response, when sentiment becomes a significant driver of stock returns, portfolio managers should allocate resources to closely monitor and analyze TS. This allows them to incorporate sentiment-based strategies into their portfolios and make more informed investment decisions.

Furthermore, the study has implications for risk management practices within financial institutions. Understanding the asymmetrical and time-varying nature of TS can assist risk managers in assessing the potential impact of government actions and changes in sentiment on financial institution stock returns. This knowledge enables them to better evaluate and manage risk exposures, make necessary adjustments to risk models, and develop appropriate hedging strategies. By doing so, financial institutions can mitigate potential losses or capitalize on opportunities that arise from shifts in TS.

The results are robust and have important policy implications for policymakers, investor analysts, and portfolio managers. This study uses the overall GRI as a proxy for measuring government policy interventions. Therefore, it would be a compelling area of study to delve into each component of the GRI, which includes containment, health measures, economic support, and policy stringency. Unraveling these aspects would give us an indepth understanding of their individual and collective effects on the intricate relationship between TS and stock return.

Such a comprehensive study could illuminate various new perspectives and dimensions. It could help us better understand how different policy responses affect investor behavior and, in turn, stock market performance. This could be a valuable resource for policymakers, investors, and academics alike, providing insights that could help shape future crises responses, inform investment strategies, and contribute to theoretical understanding within the field. It's valuable for further studies to probe this relationship for other countries by including oil price (Kondoz et al. 2019) and domestic-specific political, economic, and financial risks (Athari and Irani 2022; Saliba et al. 2023) control variables.

Abbreviations

IS Investor sentiment

- TS Twitter investor sentiment
- GRI Government Response Index

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