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Elections, Emotional Asymmetry and Jumps in Stock Prices*

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This study investigates the role of emotional dynamics as captured by the Fear and Greed Index in explaining stock price jumps in the S&P 500. We focus on two distinct episodes: the aftermath of the 2016 U.S. presidential election and the early months of President Donald Trump's second term in 2025. Our findings reveal that during Trump's first term, stock price jumps were associated with oscillations between extreme fear and greed, creating short-term trading opportunities. In contrast, early in Trump's second term, extreme fear was the primary emotional driver of market jumps, that can be interpreted as herding behavior.

Key Words: Donald Trump's first and second terms; The Fear and Greed Index; Stock market jumps, Emotional asymmetry; Regime-switching models.

JEL Classification Numbers: F13, F31, G11.

1. INTRODUCTION

On November 5, 2024, Donald Trump was elected for a second non-consecutive term as the 47th president of the United States. Within days, his administration announced sweeping new tariffs under the banner of "Liberation Day" aimed at restoring economic sovereignty and reducing reliance on imports. This marked a decisive break from the post-Bretton Woods world order, spotlighting the end of several decades of global economic integration and signaled renewed volatility for the global economy. Trump's return introduced a period of elevated policy uncertainty, espe-

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Declaration of competing interest

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cially as his administration adopted a more isolationist stance with promises of tax cuts, deregulation, and reshaping trade relations.

In response to Trump's election victory and the imposition of new tariffs, both U.S. and global stock markets have fluctuated excessively with the potential for a trade war and its adverse effects on global trade. This high volatility reflects the fears surrounding the potential for a trade war and its adverse effects on global trade. Donald Trump's speech adds a dose of uncertainty for market participants. Accordingly, the CNN Fear and Greed Index (FGI) showed a spike in fear, highlighting growing anxiety among investors as uncertainty around Trump's tariffs and economic policies increased markedly. The U.S. trade policy uncertainty has exploded in 2025, whereas the global economic policy uncertainty index attains high levels (see Figure A1 in the Appendix.) Based on the economic policy U.S. uncertainty index proposed by Baker et al. (2016), the election of Donald Trump was the third highest driver of economic uncertainty in the U.S in the index's 30-year record.

Prior studies reveal that political uncertainty has significant effects on both the returns and the volatility of financial assets (e.g. Pantzalis et al., 2000; Nippani and Arize, 2005; Li and Born, 2006; He et al., 2009; Jones and Banning, 2009; Goodell and Bodey, 2012). Pantzalis et al. (2000) found that the stock returns across 33 countries react significantly to political election dates during the sample period 1974-1995. Moreover, Nippani and Arize (2005), Li and Born (2006), He et al. (2009), and Goodell and Bodey (2012) explored whether U.S. presidential elections affect stock markets and showed that the uncertainty surrounding the elections is reflected in stock prices. He et al. (2009) investigated the reaction of stock markets to the delayed result of the 2000 presidential election, and found that stock markets are negatively influenced by the rising uncertainty over the election result. Goodell and Vahamaa (2013) assessed how and to what extent the political uncertainty affects the implied stock market volatility during U.S. presidential election cycles. They showed that the stock markets tend to react to new information about political events that may influence the country's macroeconomic, fiscal and monetary policies. More precisely, the political events are followed by investors who form or revise their expectations based on the election outcome. Using an event study methodology, Selmi and Bouoiyour (2019) showed that the different U.S. sectors were varyingly influenced by Trump's victory in the 2016 US presidential elections and were heavily reactive during the days after the inauguration. Selmi et al. (2020) attempted to analyze the responses of the sectoral U.S. stock prices to the U.S.-China tariffs. They deduced that the initial effects of trade tensions appeared more significant than had been expected, and that the sentiment and confidence of investors are highly impacted by this uncertainty shock. More recently, Ahmed et al. (2025) examined the responses of the U.S. stock market to the 2024 U.S. presidential election outcome by conducting an event study. The election outcome yielded to significant abnormal returns during the immediate post-election trading session followed by a relatively moderate reversal, reflecting changing investor sentiment over time. By performing an event study including a novel textual-based measure at the firm level, Ferriani et al. (2025) found that firms aligned with Trump 2.0 policy priorities exhibit significant and positive abnormal returns, and that market optimism contrasts with increasing uncertainty surrounding the macroeconomic outlook.

The S&P 500 registered significant jumps since early November 2024 as Trump's election victory fueled expectations for a repeat of his growth- and market-bullish first term. It is important to point out at this stage that the S&P 500 in 2024 has more than tripled 2016 returns up to the elections (see Figure A2). Not surprisingly, Trump's return to the White House may bring back some familiar market dynamics, but the economic and geopolitical landscape in 2024 was markedly different from that of 2016. While Trump's first term witnessed an initial surge in investor optimism mainly owing to expectations of tax cuts, deregulation, and pro-business policies, Trump's second term began amid a far more fragile global economy. The market is now more attuned to his protectionist policies, such as tariffs and trade wars, which created volatility in his first term. In contrast to 2016, when investors were initially uncertain but eventually rallied, the market response to Trump 2.0 is more cautious and marked by significant fears of a renewed trade war and its resulting disruptions to global supply chains. The 2024 market dynamics are further complicated by inflationary pressures, post-pandemic recovery challenges, and rising geopolitical tensions, making investor sentiment more volatile and risk averse. A new survey[1] shows that most Americans expect that during his second term, there will be more executive orders and trade disputes. The FGI showed improvement in the overall market sentiment or "extreme greed" by attaining 84.45 in December 2024[2], reflecting optimism about corporate earnings growth under Trump 2.0 administration (Albori et al., 2024). However, the index moved to the "extreme fear" zone in February 2025.

The present research complements and extends the existing literature assessing the financial market reactions of the U.S. Presidential election (e.g. Selmi and Bouoiyour, 2019; Wagner et al. 2018) by comparing the

[1]For more information about what Americans expect more or less of Trump's second term compared to his first term as US President, refer to the following link: https://today.yougov.com/politics/articles/51468-what-do-americans-expect-from-donald-trumps-second-term

[2]For more details about the evolution of the fear and greed index after the Trump's second victory in the US presidential elections, refer to this link: https://edition.cnn.com/markets/fear-and-greed

emotions that drive the S&P 500 stock market dynamics during Trump's first and second terms. Unlike prior studies, this paper aims to contribute to the understanding of stock market behavior following Trump's victory in the U.S. presidential elections, particularly when investor behavior is likely to be driven by emotions. Specifically, we focus on two primary emotional states, greed and fear, that influence trading activity. Reflecting their greedy investors often exhibit optimism during market booms but experience fear or even anxiety when prices suddenly shift. Furthermore, investors oscillate between two activity levels: calm during periods of low market volatility and more reactive when volatility spikes (Westerhoff, 2004). It is crucial to understand the emotions driving market dynamics in times of heightened uncertainty, such as after the U.S. election outcomes. This analysis not only helps predict stock market movements but also provides new insights into developing more effective investment strategies by revealing how emotional swings may create both risks and opportunities for investors. Additionally, it offers regulators valuable insights into better controlling market fluctuations.

This paper's key contribution lies in distinguishing between S&P 500 stock price changes owing to normal innovations and stock price variation due to abnormal innovation (i.e., jumps). One source of excess kurtosis found in return data is related to jumps in the return series (see inter alia, Huang and Lin 2004; So and Yu 2006). According to Maheu and McCurdey (2004), the conditional variance of the jump innovation detects extreme price movements from significant information events. This technique is more flexible than the other GARCH models as the asymmetric effect of good versus bad news can be different for jump versus normal innovations. In the present research, we use the GARCH with Jump Intensity to decompose the S&P 500 stock price volatility into smooth and jump components and then assess whether the fear and greed index can predict S&P 500 jumps in a period of high uncertainty after the 2025 U.S. presidential elections, in comparison to the 2016 U.S. elections. As it is widely known that stock price dynamics inherently incorporate stochastic and nonlinear components, this study conducts a dynamic copula approach to appropriately capture the dynamic dependence between the fear and greed index and S&P 500 price jumps under low and high uncertainty periods. The copula-based approach presented here generalizes existing Markov-switching models (Fei et al., 2013; Balcilar et al., 2016). It captures extreme return clustering and asymmetry by allowing for two time-varying dependence regimes (i.e., low or normal, and high or crash at both the center and tails of the bivariate distribution). The dynamic copula approach is particularly appealing as it accounts for the fact that the behavior of time series often evolves through different phases.

The findings reveal a pronounced correlation between the FGI and S&P 500 stock price jumps in the extreme fear category compared to the extreme greed, highlighting the presence of emotional asymmetry in market behavior. This effect is particularly evident after 2024 U.S. election outcome. The current analysis underscores the pivotal role of investor emotions, particularly extreme fear, in driving large changes in U.S. stock prices due to surprising political or policy innovations.

The remainder of the article is organized as follows. Section 2 presents the data and outlines the empirical strategy. Section 3 reports the empirical findings. Section 4 concludes the paper, provides practical implications, and suggests future research directions.

2. EMPIRICAL STRATEGY AND DATA COLLECTION

Our empirical strategy is supported by financial econometrics and behavioral finance theories. We first carry out a GARCH model with jump intensity allowing us to decompose S&P 500 stock price volatility into continuous (smooth) and discontinuous (jump) components, consistent with jump-diffusion models of asset prices (Merton, 1976; Runggaldier, 2003), where jumps arise from unusual events or shocks. Jumps are recognized in the finance literature as a crucial component for modelling infrequent but large changes in asset prices (Cheng et al., 2020). Prior research also underscores the prominence of jumps, as they capture features of the information process underlying returns and illustrate the transmission channels of policy decisions (Rangel, 2011).

To examine the role of investor sentiment and to capture emotional asymmetry, we then model the dependence between the extracted jump components and the fear and greed index using a dynamic copula with regime switching. This approach is motivated by the behavioral finance theory suggesting that sentiment can play a significant role in generating jumps in asset prices (for instance, Li et al., 2021; Gao and Zhao, 2023). When stock prices react to unexpected information, sudden movements may occur. Arguably, Blacilar et al. (2017) showed that extreme emotions can yield to significant increases or decreases in volatility, and these effects are usually transmitted via the jump components of asset returns. This approach is also guided by theoretical models of market dynamics suggesting that investor sentiment and stock price responses differ across regimes characterized by distinct (i.e., low and high) uncertainty levels. This empirical choice is further motivated by theoretical models linking periods of high political uncertainty with significant changes in stock prices (Brograad et al., 2020) and more intense interconnection between investor sentiment and jumps (Chan and Smales, 2025), therefore offering a theoretical justification for our two-step empirical framework.

2.1. Detecting jumps in S&P 500 stock prices

Standard volatility models rely on the assumption of a time-invariant return distribution, which implies consistent expectation formation by economic agents across periods. Nevertheless, this assumption is unlikely to hold in practice. During periods of elevated volatility, such as economic downturns or geopolitical crises, the variance-covariance structure of asset returns can change widely. In such circumstances, traditional models may fail to properly capture conditional volatility dynamics, including transitory or permanent shifts. To address this limitation and better capture significant changes due to unusual events (i.e., jumps) in S&P 500 stock prices, we analyze the impact of the news process intensity on S&P 500 volatility. Let X_t corresponds to the log return of a particular stock from time $t-1$ to time t. Suppose investors know the information in ϕ_{t-1} when they make their investment decision at time $t-1$. Thereafter, the expected return μ_t to the investors is the conditional expected value of X_t,

$$\mu_t = E(X_t|\phi_{t-1}) \tag{1}$$

The expected volatility (σ_t^2) corresponds to the conditional variance of X_t,

$$\sigma_t^2 = Var(X_t|\phi_{t-1}) \tag{2}$$

and the unexpected return at time t is

$$\varepsilon_t = X_t - \mu_t \tag{3}$$

Following Maheu and McCurdy (2004), we interpret the innovation to returns extracted from price data as the effect of latent news. The latent news process is assumed to comprise two components, namely normal and unusual innovations. These news innovations are identified through their impact on return volatility. The impact of unobservable normal news innovations is assumed to be captured by the return innovation component, $\varepsilon_{1,t}$. This component of the news process causes relatively modest changes in the conditional variance of returns. The second component of the latent news process causes infrequent wide changes in the conditional variance of returns or jumps, $\varepsilon_{2,t}$.

Given the information set at time $t-1$, which consists of the history of returns $\phi_{t-1} = \{r_{t-1}, \ldots, r_1\}$, the two stochastic innovations, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$, determine the returns in the mean equation expressed as follows,

$$r_t = \mu + \varepsilon_{1,t} + \varepsilon_{2,t} \tag{4}$$

where $\varepsilon_{1,t}$ is specified as a normal GARCH error term such that $E[\varepsilon_{1,t}|\phi_{t-1}] = 0$, and $\varepsilon_{2,t}$ is a jump innovation such that $E[\varepsilon_{2,t}|\phi_{t-1}] = 0$. Each component of ε_{t-1} affects future expected volatility distinctly.

The total conditional variance of returns is also divided into two components, a smoothly evolving conditional variance component $\sigma^2_{1,t} = Var(\varepsilon_{1,t}|\phi_{t-1})$ associated with the diffusion of past news effects, and a conditional variance component $\sigma^2_{2,t} = Var(\varepsilon_{2,t}|\phi_{t-1})$ related to the occurrence of unusual events which induce jumps. The total conditional variance of returns is thus,

$$Var(r_t|\phi_{t-1}) = Var(\varepsilon_{1,t}|\phi_{t-1}) + Var(\varepsilon_{2,t}|\phi_{t-1}) \tag{5}$$

The first component of the conditional variance is expressed as a GARCH function of the past return innovations, that is

$$\sigma^2_t = \omega + g(\Lambda + \varphi_{t-1})\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \tag{6}$$

where the parameter function $g(.)$ is a function of the parameter vector Λo, and $\varepsilon_{t-1} = \varepsilon_{1,t-1} + \varepsilon_{2,t-1}$ is the total return innovation observed at time $t-1$.

The GARCH volatility component captures the smooth autoregressive changes in the conditional variance that are predictable based on past news impacts. It should be stressed that volatility can be highly sensitive to either good or bad news or whether a jump occurred last period. Accordingly, the following equations controls for these possible responses

$$g(\Lambda+\phi_{t-1}) = exp(\alpha+\alpha_j E[\eta_{t-1}|\phi_{t-1}]+I(\varepsilon_{t-1})(\alpha_a+\alpha_{a,j}E[\eta_{t-1}\phi_{t-1}])) \tag{7}$$

where the model parameters are collected in the parameter vector $\Lambda = \{\alpha, \alpha_j, \alpha_a, \alpha_{a,j}\}$ with α denoting the number of jumps, α_j the most recently inferred number of jumps, α_a the period where no jumps happened, and $\alpha_{a,j}$ the difference in the propagation of previous news effects that result in jumps versus news events that cause normal innovations. $I(\varepsilon_{t-1})$ is an indicator function that takes the value 1 when $\varepsilon_{t-1} \prec 0$ and 0 otherwise. $E[\eta_{t-1}|\phi_{t-1}]$ is the expected number of jumps that occurred between $t-2$ and $t-1$ using the $t-1$ information.

The conditional variance component associated with the jump innovation is

$$Var(\varepsilon_{2,t}|\phi_{t-1}) = (\theta + \delta)\lambda_t \tag{8}$$

where θ is the jump-persistence coefficient, δ the jump-size standard deviation parameter, and λ_t the conditional jump intensity.

The unconditional variance is for $\alpha_j = \alpha_a = \alpha_{a,j} = 0$,

$$Var(r_t) = \frac{\omega}{(1-\alpha-\beta)} + \frac{\alpha(\theta^2+\delta^2)}{(1-\alpha-\beta)}\frac{\lambda}{(1-\rho)} + (\theta^2+\delta^2)\frac{\gamma}{(1-\rho)} \tag{9}$$

where the first term corresponds to the usual unconditional variance, the middle term the interaction of unusual news with anticipated news ($\varepsilon_{t-1} =$

$\varepsilon_{1,t-1}+\varepsilon_{2,t-1}$), and the last term the unconditional variance from the jump innovation.

2.2. Capturing regime switches in the dependence between fear and greed index and jumps in the S&P 500 stock market

To capture the evolving relationship between the FGI and S&P 500 stock price jumps, we apply a dynamic copula with a Markov-switching model developed by Fei et al. (2013). This method captures possible nonlinear dependencies and potential regime shifts in the joint distribution of the two variables. It controls for potential asymmetries by distinguishing between distinct market conditions including as high-dependence (characterized by extreme fear and low levels of greed) regime and low- or normal-dependence regime (low fear and extreme greed)[3], thereby offering a more flexible and accurate representation of the underlying dynamics. Interestingly, the use of the CNN Fear & Greed Index enables us to capture market sentiment based on various market indicators and investor behavior. This index mainly concerns emotional reactions to market circumstances with varying uncertainty levels rather than formal model uncertainty as studied in Hansen and Sargent (2005) and Barrillas et al. (2009). Although both concepts relate to uncertainty in financial markets, Knightian or model uncertainty reflects ambiguity about the underlying generating process of asset returns which cannot be reduced to a change in sentiments. The Fear & Greed Index used throughout this analysis measures observable market emotions can interact with periods of increased uncertainty. The fact that investor sentiment will have the greatest effect in highly uncertain conditions is in line with an extensive literature in psychology on deviations from rationality under uncertainty (see inter alia, Kahneman and Tversky, 1973; Kahneman, 2003).

Accordingly, the dynamic copula parameters are estimated conditional on distinct market conditions. Patton (2006) suggested a time-varying copula mainly consisting of copula dependency θ to evolve in an ARMA fashion:

$$\theta_t = \Lambda(\omega + \varphi\theta_{t-1} + \Psi\Gamma_t) \tag{10}$$

where $\Lambda(.)$ denotes the modified logistic function[4] with the parameters ω, φ and ψ enabling a dynamic way of modelling the dependency between the time series. ω refers to the weight that determines the structure of the dependency, φ the degree of the dependency, and ψ the copula rank

[3]This assumption is based on how the FGI is constructed. High fear correlates with risk-off behavior (market stress), whereas low greed signals a lack of speculative enthusiasm. Both tend to occur in bearish or volatile markets.

[4]The dynamic parameter is the conventional correlation measure, $\theta_t = \rho_t$, and $\Lambda(y) = (1-e^{-y})(1+e^{-y})^{-1}$ is the modified logistic transformation to ascertain $\rho_t \in (-1, 1)$.

correlation. The duration of the persistence of the dependency is measured by the sum $(\varphi + \psi)$.

Γ_t called the forcing variable is expressed as

$$\Gamma_t = \frac{1}{m} \sum_{j=1}^{m} F_1^{-1}(\mu_{1,t-j}) F_2^{-1}(\mu_{2,t-j}) \tag{11}$$

where $F_n^{-1}(\mu_{n,t}),\ n = 1, 2$ denotes the inverse cumulative distribution function of the margins. It is derived from filtered time series through the probability integral transform.

Following Fei et al. (2013), let S_t be a state variable that represents the prevailing regime. The joint distribution of X_{1t} and X_{2t} conditional on being in the states is expressed as

$$(X_{1t}, X_{2t} | X_{1,t-1}, X_{2,t-1}; S_t = s) \sim C_t^s(\mu_{1t}, \mu_{2t} | \mu_{1,t-1}, \mu_{2,t-1}; \theta_t^s) \tag{12}$$

where $s \in \{H, L\}$; H is the high dependence regime and L is the low dependence regime. $C_t^s(.|.)$ corresponds to the copula function at time t and conditional on being at a state S or a time-varying copula function. The parameteris θ_t^s the copula parameter at time t and conditional on being at a state S.

The random variable S_t follows a Markov chain of order one

$$\pi = \begin{pmatrix} \pi_{HH} & 1 - \pi_{HH} \\ 1 - \pi_{LL} & \pi_{LL} \end{pmatrix} \tag{13}$$

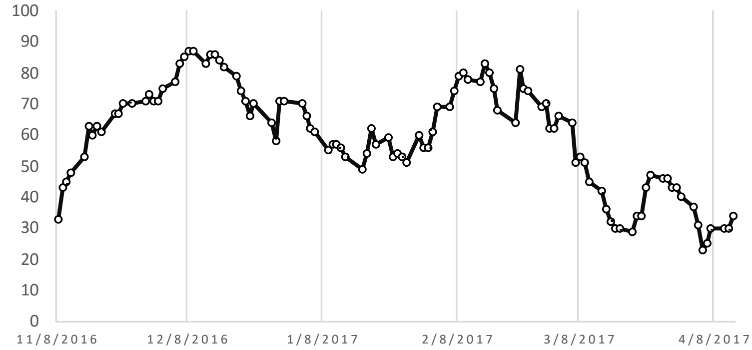
where $\pi_{HH}(\pi_{LL})$ is the probability of being in the high (low) dependency regime at time t conditional on being in the same regime at time $t - 1$.

2.3. Data collection and descriptive statistics

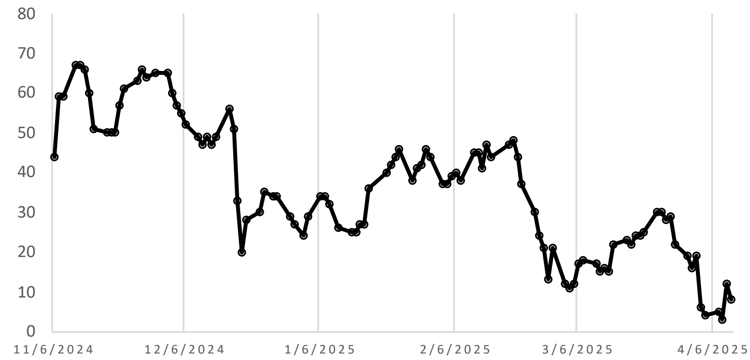
The responses of S&P 500 stock price jumps to the FGI are compared for the two periods following Trump's victories in the 2016 and 2024 U.S. presidential elections (Period 1: November 8, 2016, to April 12, 2017; Period 2: November 6, 2024, to April 10, 2025; with 159 observations for each period). The FGI data was collected from two different sources. for Period 1 the values were sourced from a GitHub repository, where they had been scraped from the CNN Business website. For Period 2 the data was retrieved directly from the CNN website by employing the Wayback Machine. This developed index synthesizes seven distinct indicators to measure stock market behavior including market momentum, stock price strength, stock price breadth, put and call options, junk bond demand, market volatility, and safe-haven demand. The FGI allows proper tracking of how much these individual indicators deviate from their averages, often

FIG. 1. Evolving trends in the CNN fear and greed index during Trump's two presidential terms

a) Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)



b) Period 2: November 6, 2024 to April 10, 2025 (Trump's second term)

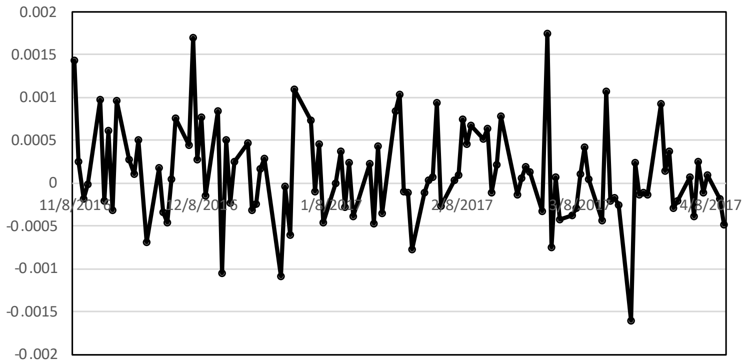


Source: CNN website; GitHub (https://github.com/hsauers5/FearAndGreed).

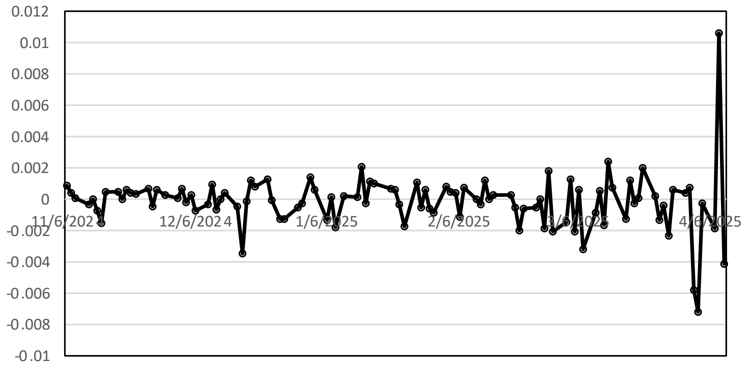
reflecting price trends and trading activity. The index gives each indicator equal weighting in calculating a score from 0 to 100, with 100 denoting maximum greediness and 0 maximum fear. Figure 1 illustrates the contrasting patterns in the FGI across Trump's two non-consecutive presidential terms. Following his election in November 2016, the index surged into "Extreme Greed" territory, as markets reacted positively to anticipated tax cuts, deregulation, and rising infrastructure spending. By contrast, the onset of Trump's second term was characterized by an index remaining neutral to modestly greedy levels. This reflected a market environment still adjusting to post-pandemic conditions and sustained fiscal policies. However, by early 2025, the index had decreased substantially attaining 20, underscoring "Extreme Fear."[5] In other words, investors were likely to be scared, possibly owing to heightened geopolitical uncertainty surrounding the introduction of new tariffs targeting China and other countries, as well as shifts in U.S. foreign policy concerning Ukraine and Russia.

FIG. 2. S&P 500 return patterns across Trump's two presidential terms

a) Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)



b) Period 2: November 6, 2024 to April 10, 2025 (Trump's Second term)



Source: Bloomberg (https://www.bloomberg.com/quote/SPX:IND).

The data of S&P 500 index data was downloaded from Bloomberg. Figure 2 depicts the contrasting evolution of S&P 500 returns across Trump's two presidential terms, highlighting key differences in the market performance and the investor sentiment. While the first term was marked by significant returns mainly driven by pro-business policies such as tax cuts and

[5]If the index is low (typically below 25), it implies "extreme fear" in the market.

deregulation, the second term shows a more volatile trajectory influenced by increasing geopolitical uncertainty and instability in trade dynamics.

Table 1 reports the descriptive statistics for daily returns, showing that the average daily returns for both the S&P 500 (STR) and the FGI are positive across all return series. Volatility in the S&P 500 is notably higher in Period 2 than in Period 1. In both periods, the return distributions exhibit negative skewness and kurtosis values exceeding three, indicating asymmetry and leptokurtosis characteristics that deviate from normality. These features are sustained by the Jarque-Bera test statistics, confirming significant non-normality in the return distributions of both STR and FGI.

TABLE 1.

A Statistical Comparison of log-transformed time series during Trump's first and second terms

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)								
STR	0.0001	5.3940E-05	0.0085	−0.0189	0.0552	−0.1845	4.059	371.62^{+}
FGI	4.0019	4.1190	4.3438	3.1354	0.5028	−0.2976	37.026	91.88^{+}
Period 2: November 6, 2024 to April 10, 2025 (Trump's Second term)								
STR	−0.0002	3.2854E-05	0.0125	−0.0167	0.0776	−0.3127	14.882	56.81^{+}
FGI	3.4030	3.5553	4.2046	1.0986	0.6976	−0.4836	6.447	78.92^{+}

Notes: STR denotes the S&P 500 stock returns; The logarithmic (log) return between t and $t-1$ is determined by $\ln(P_t/P_{t-1})$; FGI corresponds to the logarithm of the CNN Fear and Greed Index; $^{+}$ denotes the rejection of the null hypotheses of normality at the 1% level of significance.

To check the validity of the dynamic copula model which is a nonlinear technique, the BDS test (Brock et al., 1996) of nonlinearity on the residuals recovered from the OLS models is performed. This test is flexible in detecting various forms of nonlinearity, such as deterministic chaos and other complex patterns. It does not necessitate the specification of a particular nonlinear model, making it a broad test for general nonlinearity. More importantly, this test can be carried out for distinct embedding dimensions (m), enabling it to properly detect complex dependencies at several scales. The findings displayed in Table 2 show strong evidence of nonlinearity by rejecting the null hypothesis of independent and identical distribution (i.i.d). It is found that the residuals of time series are nonlinearly dependent, therefore justifying the prominence of controlling for nonlinearity when analysing the association between fear and greed emotions and jumps in the U.S. stock market prices. Accordingly, the Copula with Markov-switching regime effectively controls for possible nonlinearities and regime shifts.

TABLE 2.

The BDS test based on the residuals of the log-transformed series

Dimensions	$m = 2$	$m = 3$	$m = 4$	$m = 5$	$m = 6$
Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)					
STR	6.478^{*}	2.998^{*}	3.653^{***}	4.043^{***}	2.756^{**}
FGI	4.934^{**}	5.061^{***}	4.867^{***}	6.117^{***}	3.469^{***}
Period 2: November 6, 2024 to April 10, 2025 (Trump's second term)					
STR	9.523^{***}	4.692^{**}	2.799^{**}	4.038^{***}	5.1026^{**}
FGI	2.110^{*}	3.587^{*}	3.065^{***}	2.571^{*}	2.384^{**}

Notes: m denotes the embedding dimension of the BDS test; STR denotes the S&P 500 stock returns; The logarithmic (log) return between t and $t-1$ is determined by $\ln(P_t/P_{t-1})$; FGI corresponds to the logarithm of the CNN Fear and Greed Index; ***, ** and * indicate the rejection of the null of the residuals being iid at the 1%, 5% and 10% levels of significance, respectively.

3. DISCUSSION OF RESULTS

3.1. Jumps in S&P 500 stock prices: Comparing Trump's first and second terms

Table 3 reports the estimation results of the GARJI model for S&P 500 stock price volatility across Trump's two non-consecutive presidential terms. In both periods, the mean equation coefficient μ is statistically significant and close to zero. During Trump's first term, the GARCH equation indicates that α, the coefficient capturing the immediate impact of innovations on volatility, is relatively modest, while β, the coefficient reflecting the persistence of volatility shocks, is notably high. In contrast, Trump's second term shows stronger effects for both α and β, suggesting that shocks to the S&P 500 returns had a more substantial and longer-lasting impact on conditional variance. This implies that innovations during the second term not only triggered sharper changes in volatility but also had a more persistent influence on the volatility process.

Following the 2016 U.S. election outcome, the coefficient referring to the leverage effect in the variance equation (η) is positive suggesting that negative shocks in the return series increase volatility more than positive shocks. In addition, the mean coefficient of jump size (θ) is negative, suggesting that, on average, sudden jumps had a downward impact on the return series. Since jumps are often triggered by unanticipated news, this suggests that the market responded more strongly to negative news than to positive ones. A similar pattern emerges following Trump's 2024 victory, where both the leverage effect and the negative influence of jump events remain evident. This sustains the evidence that during both Trump's presidential terms adverse news had a disproportionate effect on market volatility compared to positive news. Regarding the coefficients that govern the frequency

TABLE 3.
S&P 500 stock price changes during Trump's first and second terms: Output of the GARJI model

	Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)	Period 2: November 6, 2024 to April 10, 2025 (Trump's Second term)
Mean Equation		
μ	-0.0671^{***} (0.0002)	0.0094^{*} (0.0558)
STR_{t-1}	0.0195^{**} (0.0034)	0.0214^{***} (0.0007)
Variance Equation		
ω	3.1021 (0.1197)	1.9406^{**} (0.0035)
α	0.0039^{*} (0.0611)	0.1207^{*} (0.0889)
β	0.1583^{***} (0.0004)	0.2246^{*} (0.0159)
η	0.1951^{**} (0.0062)	0.1285^{*} (0.0401)
δ	0.0569^{***} (0.0000)	0.0813^{**} (0.0041)
θ	-0.0443^{**} (0.0082)	-0.0491^{*} (0.0196)
λ	0.1690^{***} (0.0001)	0.2311^{**} (0.0052)
γ	0.1014^{*} (0.0595)	0.1372^{***} (0.0003)

Notes: STR_{t-1} corresponds to the lagged S&P 500 stock returns; ***, ** and * imply significance at the 1%, 5% and 10%, respectively.

of jumps and the potential for jump clustering, we find that the jump persistence coefficient (λ) is higher during Trump's second term compared to his first term. This clearly suggests a pronounced degree of persistence in jump intensity during Trump's second term. It is also shown that the jump standard deviation (δ) is stronger in that period. This means that the S&P 500 stock market was hit by a larger range of unusual shocks, and investor responses are likely to be more chaotic, reflecting huge uncertainty in the magnitude of market reactions to surprising news. This could mainly be attributed to wider and more frequent global disruptions and weakening investor confidence in predictability. Furthermore, the coefficient detecting the impact of innovations on jump intensity (γ) is positive and statistically significant in both terms, which implies that unexpected shocks consistently contributed to rising jump activity in the S&P 500 stock market across both time frames. In sum, the results robustly indicate that market reactions to shocks were more intense and persistent during Trump's second term compared to the first term.

3.2. Detecting the impact of emotional asymmetry on jumps in S&P 500 stock prices via a dynamic copula model: Trump's first term versus his second term

To effectively assess the utility of a dynamic copula model in exploring the dependency structure between the CNN FGI and jumps in S&P 500 stock prices during Trump's first and second terms, we first use time-invariant copulas as benchmarks. More specifically, we carry out both Gaussian and Student-t copulas for comparison. The estimated parameters are presented in Table 4. It is clearly noticed that the Student-t copula offers better goodness of fit, as indicated by the lowest AIC and BIC values. Using the Student-t copula, we find a positive linkage between the FGI and S&P 500 stock price jumps during Trump's second term, but an insignificant relationship during his first term. Gaussian and Student-t Copulas do not control for possible asymmetries and nonlinearities in the dependency structure. The two considered time-invariant copulas might still serve as a valuable baseline for detecting average dependency structures between variables, providing initial insights into the role of emotional asymmetry in driving jumps in stock prices. However, inability to adapt to varying market circumstances limits efficacy in capturing some hidden features that may be embedded in the dependency between FGI and S&P 500 stock price jumps, especially during periods of high uncertainty. Overall, these techniques may cause a significant underestimation of the risk from joint extreme events (Selmi et al., 2021).

Table 5 summarizes the estimation findings of the dynamic copula with Markov-switching model. During Trump's first term, the parameters ω_H and ω_L of dynamic copula with Markov-switching indicate that the dependency between the FGI and jumps in S&P 500 stock prices is positive and statistically significant in the periods of extreme fear (ω_H) and extreme greed (ω_L). More specifically, FGI exhibited a strong correlation with stock price jumps across both regimes, namely high dependency (associated with extreme fear and low greed) and low dependency (low fear and elevated greed). This implies that investor emotions, whether rooted in fear or greed, may play a pivotal role in driving market dynamics. The observed outcome also corroborates that of Farrell and O'Connor (2024) who demonstrate the strong predictive power of the FGI for U.S. stock price changes, highlighting its usefulness in forecasting market movements especially during times of heightened investor emotion. It is important to add that the fact that both extreme fear and extreme greed strongly af-

TABLE 4.
The connection between FGI and jumps in S&P 500 stock prices during Trump's first and second terms via time-invariant copulas

Copulas		Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)	Period 2: November 6, 2024 to April 10, 2025 (Trump's Second term)
Normal copula	ρ	0.1081^{***}	0.0773
	p-value	0.0002	0.8045
	AIC	−112.85	−135.17
	BIC	−99.05	−110.21
Student -t copula	κ	−0.0912	0.1372^{**}
	p-value	0.1586	0.0061
	AIC	−169.54	−200.11
	BIC	−155.37	−189.03

Notes: ρ denotes the correlation coefficient; κ, also called the kappa parameter, refers to the tail dependence coefficient. A higher κ (closer to 1) means a great dependence on the tails or extreme co-movements; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

fect stock price jumps suggests balanced emotional sensitivity in the U.S. market responses. Fear usually results from high uncertainty surrounding unusual shocks including trade war and unexpected policy shifts. This could lead to panic selling, flight to safe-haven assets, and sharp downward price jumps (Naeem et al., 2024). Nevertheless, times when market shows optimism (or "extreme greed") seems likely to be attributed to tax reform promises that might fuel speculative behavior and risk-taking. Interestingly, the dual effect of extreme fear and extreme greed might offer opportunities for short-term trading, while requiring heavy vigilance in response to policy shifts or market euphoria. Moreover, and consistently with Hoyer et al. (2023), we find no empirical evidence that investors with higher levels of greed or fear behave fundamentally differently from their less emotional counterparts.

Conversely, FGI shows that Trump's second term was mainly characterized by an extreme fear-dominated market dynamic (values below 25) with stock price jumps highly correlated with the index, whereas the connection between the focal variables appears relatively moderate in low dependency regime (associated with extreme greed and low fear levels, values above 25). It should be pointed out that low greed levels may not necessarily be associated with high optimism, but rather with a lack of speculative enthusiasm (Shefrin, 2002). These results are, however, inconsistent with Johnson (2023) revealing that the European and Asia Pacific stock indices tend to be strongly correlated with the FGI when the index is in the "Greed" categories compared to when it is in the "Fear" categories. The asymmetry underscores that markets may be more reactive to optimistic emotions than to fearful ones, possibly owing to the effect of greed-driven buying behavior

(Shefrin, 2002). Both the present study and that of Johnson (2023) still sustain the relevance of accounting for emotional asymmetry in investment decision-making (Chen et al., 2013; Li et al., 2017).

TABLE 5.

Estimation of the dynamic copula with Markov-switching: The connection between FGI and jumps in S&P 500 stock prices during Trump's first and second terms

	Period 1: November 8, 2016 to April 12, 2017 (Trump's first term)	Period 2: November 6, 2024 to April 10, 2025 (Trump's Second term)
ω_H	0.1809^{**} (0.0041)	0.3115^{***} (0.0000)
ω_L	0.1592^{***} (0.0000)	0.0048^{***} (0.0005)
φ	0.1173^{**} (0.0089)	0.1354^{*} (0.0389)
ψ	0.0910^{*} (0.0559)	0.1126^{**} (0.0038)
π_{HH}	0.8123^{***} (0.0000)	0.9355^{***} (0.0007)
π_{LL}	0.6974^{***} (0.0001)	0.1132^{**} (0.0024)

Notes: Superscript $H(L)$ indicates the high (low) dependence regime. The high-dependence regime is distinguished by extreme fear and low levels of greed; The low dependence regime is characterized by extreme greed and low fear levels; π_{HH} (π_{LL}) is the probability of staying in the high (low) dependence regime. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

The identified differences between Trump's terms suggest heightened investor risk aversion predominantly exacerbated by rising trade tensions including waves of tariffs, retaliatory measures, and breakdowns in negotiations. Indeed, the unpredictability of the trade agenda would exert a significant influence on investment decisions and market volatility. This underscores the necessity of effective risk management strategies and the use of safe-haven assets. Additionally, the significance of the estimated dependence parameters φ and ψ across the two terms under study indicates that rank correlations are time-varying, implying that the structure of dependencies between jumps in S&P 500 stock prices and investor sentiment evolves with uncertainty over political developments. The transition probabilities, particularly π_{HH} and π_{LL}, consistently indicate greater persistence of the high dependency regime across all cases under investigation. This persistence seems more pronounced in fear-dominated markets when investors focus on avoiding losses rather than achieving gains. This may reflect prolonged episodes of systemic stress, during which investors are more likely to engage in herding behavior (Bikhchandani and Sharma, 2001) and flight-to-safety dynamics (Baur and Lucey, 2010).

Overall, the dynamic copula with regime switching offers a significant advantage over time-invariant copulas by capturing asymmetric and nonlinear dependencies between the focal variables. Unlike Gaussian and Student-t copulas, which assume constant relationships over time, dynamic copulas can account for temporal fluctuations in the dependency structures while controlling asymmetry and nonlinearity. This seems very prominent when modeling complex phenomena such as financial markets where extreme events change investor emotions. The inclusion of these characteristics would give more appropriate risk assessments and improved forecasts of tail dependence, volatility clustering, and other nonlinear market dynamics.

4. CONCLUSIONS

By underscoring the asymmetric influences of investor emotions such as fear and greed on stock price jumps during periods of heightened political and policy uncertainty, the present results contribute to the growing research in behavioral finance investigating the role of emotions in stock markets (Hishleifer, 2015; Nofsinger, 2005), preceded by a similar trend in behavioral research on judgment and decision making (Greifeneder et al., 2011; Lerner et al., 2015; Pham, 2007; Phelps et al., 2014). While the prior finance research has established by means of both experiments and observational field studies (Duxbury, 2015; Duxbury et al., 2020) that emotions significantly shape behavior in stock markets, the present research enriches the understanding of market dynamics by revealing which emotions exert influences on stock price jumps as well as the states (high or low dependency regime) under which the influences are the strongest.

Focusing on the periods following the 2016 and 2024 U.S. presidential elections of Donald Trump, mainly distinguished by increasing tariff-related uncertainty, we apply a novel nonlinear model to disentangle regular stock price movements from wide changes due to unusual innovations (referred to as jumps). The results indicate that the CNN Fear and Greed Index (FGI) exhibits statistically significant predictive power for stock price jumps across both periods, with a sharply wider dependency shown during the 2024 presidential term. Therefore, traders and speculators in the S&P 500 market could rely on the FGI as a powerful signal for market behavior.

It is found that extreme fear is more strongly correlated with S&P 500 stock price jumps than extreme greed. This reveals the presence of an emotional asymmetry in market behavior, where negative emotional states provoke more pronounced market responses than their positive states, presumably reflecting loss aversion (Charpentier et al., 2016; Kahneman and

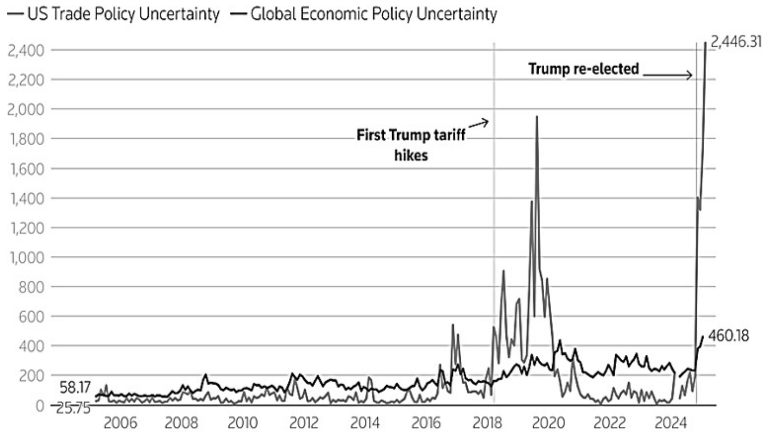
Tversky, 1979; McGraw et al., 2010) implying that individuals are more emotionally influenced by possible losses than the prospect of equivalent gains. A similar asymmetry is demonstrated in studies of trading in experimental asset markets known to induce bubbles and crashes (Breaban and Noussair, 2017). By inferring emotions from observations of traders' facial expressions positive (anger) and negative emotions (fear) are found to have different importance for the irrational exuberance driving bubbles and crashes. It is also confirmed that fear is related to loss aversion. Besides, the dominance of extreme fear-induced jumps after Trump's 2024 inauguration can be interpreted as herding behavior since high policy uncertainty due to unpredictable shifts in tariffs might lead to collective emotionally driven responses while overlooking their own information, beliefs or analysis (Scharfstein and Stein, 1990; Spyrou, 2013).

Overall, this study reinforces the evidence provided by prior research showing that negative emotions, specifically fear, prompt stronger market reactions than positive emotions, a result sustained by Bouri et al. (2024) showing that extreme fear significantly affects US stock market volatility. These results underscore the importance of emotional asymmetries in financial markets and demonstrate that shifts in the prevailing emotional climate can help explain and potentially predict market dislocations in times of political uncertainty. By accounting for emotional asymmetries in risk management and hedging strategies, investors can furthermore strengthen their portfolio resilience during extreme fear-driven periods. Moreover, regulators should integrate emotion-sensitive indicators such as FGI in their monitoring systems to improve market stability assessments during uncertain times.

Future research may benefit from a disaggregated decomposition of emotions beyond the binary fear-greed spectrum by differentiating between distinct negative emotions (e.g. anger, anxiety, doubt, despair) and positive emotions (e.g. hope, optimism, desire) by the means of natural language processing techniques. Another promising direction consists of assessing whether the variation in investor composition (retail versus institutional) influences how and to what extent fear and greed drive market dynamics under various regimes. In some research (Fenton-O'Creevy et al., 2011, 2012) more sophisticated investors have been found to be more skilled at controlling negative emotions such as fear.

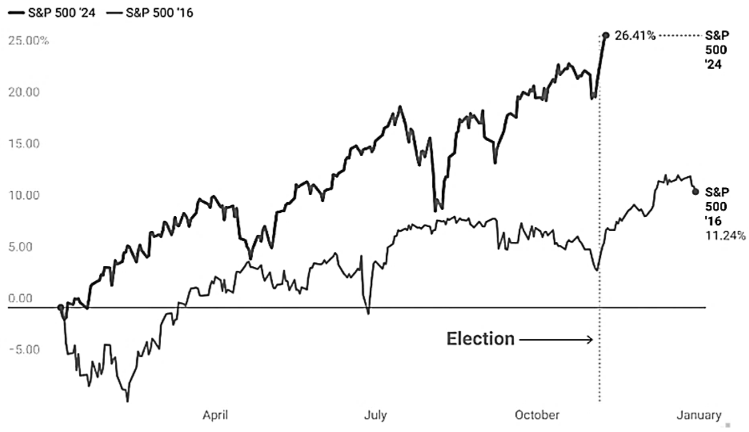
APPENDIX

FIG. A1. US trade policy uncertainty vs. global economic policy uncertainty: A comparison across Trump's first and second terms



Source: Economic Policy Uncertainty Unit/ LSEG DataStream.

FIG. A2. The evolution of S&P 500 stock prices a few days after the election: Comparing Trump's first and second terms



Source: Bloomberg; Opening Bell daily (https://www.openingbelldailynews.com).

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