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Effects of the GFC and COVID-19 on U.S. Financial Indicators: An Integrated Short-Term Econometric Approach

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Abstract

The 2008 Global Financial Crisis (GFC) and the 2020-2021 COVID-19 pandemic disrupted financial markets, causing volatility, liquidity issues, and shifts in investor behavior. This study analyzes the immediate impacts and recoveries of these events, comparing their characteristics and the effectiveness of policy responses. An event study methodology and a GARCH approach are applied. Results show that -in the GFC Crisis- Lehman Brothers bankruptcy has greater negative impact than the first date of subprime mortgages bad news. In the COVID-19 crisis, closures and vaccines announcements has greater impact than the first COVID-19 case date in US. Also, the GFC Crisis decreased the valuation levels of key financial indicators as equal as the COVID-19, but this last was less volatility pronounced. These results highlight the importance of timely and effective public policy interventions to mitigate the adverse effects of such crises on financial markets.

JEL Classification: G10, G14, C10, C22
Keywords: GFC-2008, COVID-19, stock markets, abnormal returns, event study, VIX, S&P 500, DJIA.

Efectos de la Crisis Financiera Global y el COVID-19 en los indicadores financieros de EE. UU.: un enfoque econométrico integrado de corto plazo

Resumen

La Crisis Financiera Global (CFG) de 2008 y la pandemia de COVID-19 de 2020-2021 afectaron a los mercados financieros, causando volatilidad, problemas de liquidez y cambios en el comportamiento de los inversores. Este estudio analiza los impactos y las recuperaciones inmediatas, comparando sus características y la efectividad de las políticas públicas mediante un estudio de eventos y un GARCH. Los resultados muestran que la quiebra de Lehman Brothers tuvo un impacto negativo mayor que las noticias sobre las hipotecas subprime. Para el COVID-19, los cierres y anuncios de las vacunas tuvieron un mayor impacto que el primer caso de COVID-19 en Estados Unidos. Hay que añadir que, tanto la CFG de 2008 como la del COVID-19 disminuyeron la valoración de los indicadores financieros, pero en el segundo evento la volatilidad fue moderada. Estos resultados resaltan la importancia de las intervenciones de políticas públicas oportunas y efectivas para mitigar los efectos adversos de tales crisis sobre los mercados financieros. La originalidad de este análisis radica en la metodología aplicada para analizar los indicadores en medio de crisis financieras.

Clasificación JEL: G10, G14, C10, C22
Palabras clave: Crisis Financiera Global 2008 (GFC-2008), COVID-19, mercados bursátiles, rendimientos anormales, estudio de eventos, VIX, S&P 500, DJIA.

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1. Introduction

The 2008 Global Financial Crisis (GFC) and the 2020-2021 COVID-19 pandemic represent two of the most significant economic shocks to occur in this century. Both events precipitated profound disruptions in financial markets, resulting in unprecedented volatility, liquidity constraints, and shifts in investor behavior (Rodriguez Canfranc, 2020). These crises not only tested the resilience of financial institutions and regulatory frameworks but also highlighted the interconnectedness of global financial systems.

At first, the GFC originated from the collapse of the housing bubble in the U.S. This led to a widespread default on subprime mortgages, the failure of major financial institutions, and a severe credit crunch. The subsequent recession had a ripple effect across the global economy, triggering a reevaluation of risk management practices and regulatory oversight (Agatón Lombera et al., 2024). Conversely, the COVID-19 pandemic brought about an entirely different kind of disruption. The rapid spread of the virus necessitated lockdowns and social distancing measures, leading to a sudden halt in economic activity and unprecedented fiscal and monetary responses from governments and central banks worldwide (Agatón Lombera et al., 2024).

This paper aims to explore the effects of these two crises on key U.S. financial indicators, employing an integrated short-term econometric approach. By analyzing a range of financial metrics, including the Volatility Index (VIX), Standard & Poor's 500 Index (S&P 500), and the Dow Jones Industrial Average (DJIA), we seek to understand the immediate impacts and subsequent recoveries associated with each event. This comparative analysis is essential for several reasons. First, it provides insights into the varying nature of economic shocks and their transmission mechanisms. Second, it offers a perspective on the effectiveness of policy responses in stabilizing financial markets. Lastly, it contributes to the broader literature on financial market resilience and the role of systemic risk during periods of extreme economic uncertainty.

We divide this paper as follows. After this introduction, we present a brief literature review covering the GFC and COVID-19 empirical studies. In the third section we describe the methodology and data used in this paper. The descriptive analysis and empirical results are presented in the fourth and fifth sections, and the conclusions depicted in the sixth section.

2. Literature review

Global financial markets, particularly in the U.S., have experienced a phase of overreaction marked by high volatility and a decline in the valuation of economic assets. This trend has been especially notable in the context of the GFC and the COVID-19 pandemic, showing characteristics comparable to the 1929 crisis (Chowdhury et al., 2022; Kinateder et al., 2021). Many studies have investigated the efficiency of financial markets during periods of economic uncertainty in the U.S. and examined risk-adjusted returns during such crises without a clear consensus result (Alfaro, L Chari, A Greenland, A Schott, 2020; Baker et al., 2020; Breuss, 2011; Brunnermeier, 2009; Cheung et al., 2010; Lamba & Jain, 2023; Malhotra et al., 2023).

For example, Logan (2021) argues that financial crises are influenced by the magnitude of shocks and the financial system's vulnerabilities. The duration of these crises is driven by market uncertainty. Both types of crises reduce global liquidity demand, disrupt short-term financing, and destabilize credit markets, creating negative feedback loops. These loops, marked by deteriorating financing conditions and increased volatility, lead to asset sales and falling prices, exacerbating the crises. This literature review, thus, examines the financial market consequences of both types of crises.

2.1. Global Financial Crisis (GFC): Impact on Financial Markets

It is publicly known that the 2008 GFC was caused by multiple factors: i) the relaxation of borrowing policies; ii) excessive consumption; and iii) the global trade of complex and high-risk financial products (Baily et al., 2008). This crisis had severe repercussions on aggregate demand, characterized by the devaluation of real estate, a reduction in global consumption, and the destruction of value chains. These factors drastically diminished growth prospects for countries, spreading the negative effects from developed to developing economies.

Breuss (2011) examines the overreaction of the exchange rate in the United States during periods of uncertainty such as the GFC and economic stabilization, influenced by the Dornbusch model. Using an error correction model, the authors aim to quantify the long-term adjustment speed of the series in both open and closed economies, measuring the time required to reach long-term equilibrium. The results indicate that markets which are more integrated with the global economy exhibit more significant effects on exchange rate overreaction compared to those less globally integrated. These findings support the notion of economic contagion when an economy like the U.S. is more interconnected with the world (Breuss, 2011).

According to Cheung et al. (2010), the financial crisis in the U.S. had multiple repercussions on international financial markets, particularly affecting countries with greater economic integration. The authors examined the case of the U.S. in relation to the United Kingdom, Hong Kong, Japan, Australia, Russia, and China, assessing the contagion effects of the crisis on these countries' key financial indicators and observing short- and long-term relationships. Cheung et al. (2010) indicate that international markets are closely linked to the U.S. market, leading to widespread declines in global financial markets. Moreover, they found that the intensity of contagion was quicker in countries with higher economic integration.

Similarly, regarding the BRIC countries, Bianconi et al. (2013) conducted an analysis of the Dow Jones Industrial Average (DJIA) in relation to the major financial indicators of these countries, using impulse-response analysis and dynamic correlation between 2003 and 2010, covering the period of the GFC. The results show that Brazil and Russia tend to be more integrated with the U.S. economy, making them more susceptible to declines in asset values or financial indicators. This susceptibility is primarily due to financial market pressures from the U.S., driven by reduced derivative transactions originating from these regions.

Chevallier (2012) explores the relationship between global imbalances, credit levels, the structure of the real estate market, and macroeconomic variables in stock prices and the valuation of major U.S. financial indices from 1987 to 2011. Using multivariate Markov Switching models, this study demonstrates that speculation in the real estate market and global imbalances profoundly impact the valuation of the U.S. financial market. This is attributed to the growth of bubbles, global current account deficits, and the absence of market regulations (Chevallier, 2012).

Casarin et al. (2013) examines risk-adjusted returns using the VIX employing a range of Bayesian and non-Bayesian models in the context of the GFC. The authors utilize non-Bayesian alternatives such as EGARCH or GJR models, alongside Bayesian specifications of time series models, to observe whether returns tend to be similar and to identify performance levels before, during, and after the financial crisis. The results suggest that the Bayesian approach provides a more robust analysis of GFC returns, identifying potentially higher returns compared to the non-Bayesian alternative. Additionally, the authors determine that despite the presence of the economic crisis, there were also opportunities for returns during the period (Casarin et al., 2013).

2.2. COVID-19: Impact on Financial Markets

The COVID-19 health crisis dealt a severe blow to the economy in 2020, impacting both aggregate supply and demand due to local and international lockdowns and reduced trade in goods and services (Gunay & Can, 2022). Additionally, it caused widespread loss of human capital across societies (Centers for Disease Control and Prevention, 2022). Focusing on the U.S. economy, the COVID-19 pandemic quickly escalated into a large-scale economic and financial crisis, affecting multiple sectors and economic agents (Goldstein et al., 2021).

At the firm and household levels, the supply and demand for goods and services plummeted exponentially due to virus exposure, prioritizing essential products and services. Moreover, government mobility restrictions aimed at reducing contagion levels led to economic contractions, shrinking the U.S. Gross Domestic Product (GDP) by 3.5% in 2020, akin to the Great Recession of 1929 (Goldstein et al., 2021). In financial markets, the COVID-19 crisis heightened market uncertainty, driving volatility and reducing market valuations of major indices such as the S&P 500, while boosting the derivatives market as a haven (Goldstein et al., 2021).

Furthermore, the economic stress from the health crisis constrained liquidity in markets, particularly in corporate bond markets. Institutional demand for cash intensified, leading to a preference for liquidity and downward pressure on stock prices (Goldstein et al., 2021). Similarly, Kargar et al. (2021) delves into the COVID-19 effects on financial market liquidity, particularly in corporate bond markets. The authors note that one immediate effect observed was increased transaction costs for corporate bonds, as demand decreased and supply remained high, resulting in fewer bonds traded and stable bond holding costs, which were more pronounced in technology and medical product sectors.

Additionally, during the initial stages of the global COVID-19 pandemic, volatility in financial markets led investors to shift towards leveraging more tangible assets such as derivatives and precious metals, which tend to serve as a hedge. This trend reduced the tradability of financial products like bonds and stocks (Kargar et al., 2021). On the other hand, Cheng (2020) argues that uncertainty in financial markets during the early months of the COVID-19 pandemic resulted in an underreaction in derivative markets, where derivative prices did not fully reflect the magnitude of pandemic risks. Cheng (2020) calculates VIX futures premiums adjusted for perceived risks and compares them with actual VIX futures prices, highlighting asymmetric information among investors regarding protection against future market movements at the outset of the pandemic, implying a higher risk tolerance (Cheng, 2020).

Gupta et al. (2022) conduct a meta-analysis examining the effects of COVID-19 on financial indicators in the United States and the top five largest global economies (China, Japan, India, United Kingdom, and Germany), which collectively account for approximately 56.6% of the global GDP. They compile key financial indicators worldwide and construct a financial market return indicator during COVID-19, assessing impacts before and after the pandemic. The study finds that COVID-19 caused a widespread decrease in daily financial market valuations worldwide, with developing economies experiencing broader spillover effects due to increased global economic uncertainty (Gupta et al., 2022). Albulescu (2021) investigates how COVID-19-related news or events regarding infection rates and fatality levels affect volatility in the U.S. markets using the S&P 500 index. Employing Ordinary Least Squares (OLS) regression, the author determines that announcements about increasing infection-to-fatality ratios early in the pandemic had a negative impact on the S&P 500, though these effects tended to diminish over time.

2.3. Literature review on event study and GARCH models

There are many examples in the literature where event study and GARCH models have been applied together in the financial area or with high volatility variables. In this subsection, a few are described to depict a picture about how both methods are related in literature. For example, McKenzie et al., 2004 use traditional event study methods, designed for daily stock price returns, and adapted for agricultural futures data, to test hypotheses about market efficiency and the informational content of events. They incorporate GARCH models into this framework, allowing them to account for the unique characteristics of these markets, providing more accurate estimates of abnormal returns and volatility responses to events.

The use of GARCH models in conjunction with event studies has also been instrumental in examining the impact of specific events, such as stock crises, on market volatility. Naik et al. (2020) finds that GARCH models are particularly useful in determining future crisis periods, while Belke et al. (2018) apply event study around Brexit referendum dates with GARCH models for market indices volatility. Endri et al. (2021) uses the same framework to study the response of stock prices on the Indonesia Stock Exchange (IDX) to COVID-19. Singh, Roca and Li (2021) uses event study and GARCH models to evaluate policy interventions during financial crisis in China and Rusia. Finally, Harjoto & Rossi (2021) use the same approach to examine the market reaction to the World Health Organization (WHO) announcement of COVID-19 as a global pandemic on the emerging equity markets and compares the reaction with developed markets. This study also compares the market reactions to the COVID-19 with the market reactions to the GFC.

3. Methodology and Data

To quantify the effects of the GFC and the COVID-19 crisis, this analysis proposes a three-stage estimation approach to address the hypotheses previously stated. In the first stage, it evaluates the impacts within a specified date window of key events occurring during both crises on the returns of major financial indicators in the U.S. economy, using the Event Study Method through a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model with extensions. Daily returns of selected indicators, such as the VIX, S&P 500, and DJIA, are analyzed before and after events to determine market reactions via mean difference tests, as proposed by Pandey & Kumari (2021).

In To define the event study, three aspects are crucial: 1) the event date; 2) the event window surrounding the event date (days before and after the key event); and 3) the model estimation of indicators related to the event study. Three key dates are selected between both crises, encompassing positive and negative news within the crisis duration spectrum (see table 1). Following Pandey & Kumari (2021), an event window of 120 trading days is defined, excluding weekends and holidays. Within this 120-day window, 90 days are allocated before the event date and 30 days after (including the event day), using the closing index value on each trading day (Pandey & Kumari, 2021).

Table 1. Event Dates considered in the GFC and COVID-19 Crisis.

Dates	Description
GFC	
09/08/2007	First recognition of the risk of subprime mortgages by BNP Paribas bank.
21/09/2008	Lehman Brothers declares bankruptcy, triggering financial panic, and investment banks change their status to seek rescue.
16/12/2008	The Fed sets a target range for the interest rate between 0% and 0.25%.
COVID – 19 Crisis	
19/01/2020	The first case of COVID-19 is detected in the United States.
15/03/2020	Closures in institutions and businesses due to preventive lockdowns.
24/12/2020	More than one million vaccines are administered in the United States.

Source: Prepared by authors based on Centers for Disease Control and Prevention (2022) and Kingsley (2012).

In a second stage, the study it verifies the causal effects of the mentioned events and a set of macroeconomic control variables on key financial indicators using a Dynamic Regression Model (DRM). This model type offers several advantages: 1) It facilitates the examination of short-term causal relationships, and 2) It allows for the inclusion of exogenous variables and temporal trends (Chowdhury et al., 2022).

Finally, in the third stage focuses on estimating risk-adjusted returns during periods associated with the health and financial crises. In this regard, Exponential GARCH in mean estimation is employed. This analysis aims to compare mean estimates associated with the estimation process to determine which context yields higher returns per unit of risk. This helps identify under which conditions greater returns can be achieved. The stages are explained in full in the following sections.

The methodological approach adopted in this study is carefully aligned with the objective of capturing both the immediate and dynamic effects of financial and health crises on major financial indicators. The use of the Event Study Method combined with a GARCH framework in the first stage is justified by its proven ability to isolate and measure market reactions to specific, time-bound events characterized by volatility shocks, as observed during the GFC and the COVID-19 pandemic. In the second stage, the application of a Dynamic Regression Model enables the analysis of short-term causal relationships while accounting for exogenous macroeconomic factors and time trends, thus providing a deeper understanding of the transmission mechanisms between crisis events and financial performance. Finally, the use of Exponential GARCH-in-Mean estimation in the third stage offers a robust means of assessing risk-adjusted returns, essential for comparing the performance of financial indicators under varying crisis conditions. Together, these methods form a coherent framework that allows for a comprehensive evaluation of crisis impacts from multiple analytical angles.

3.1. Event Study Methodology

This document presents an impact assessment using the event study method (ESM) (Tweneboah-Koduah et al., 2020). The estimation focuses on daily returns or closing movements of each index within the defined event window. The base model is a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model The estimation process focuses on daily returns or closing movements of the index estimates adjusted within the event window. Although Ordinary Least Squares (OLS) methodology is widely accepted in the literature (Dyckman et al., 1984), the base model for the estimation is a GARCH model (Chowdhury et al., 2022).

This modeling choice is appropriate because financial time series often display volatility clustering and time-varying variance, particularly during periods of economic crisis. GARCH models address these issues by allowing conditional variance to depend on past squared residuals and past variances, offering a more robust framework than traditional OLS. Moreover, residuals from GARCH estimation are more likely to satisfy standard regression assumptions, including normality and homoskedasticity. The rationale behind this choice is that GARCH models can handle the volatile nature of time series and capture conditional variance patterns in financial data, and the residuals from the estimation process are more likely to meet the linear regression assumptions compared to OLS estimation

In this context Following the event study approach, both abnormal returns (AR) and cumulative abnormal returns (CAR) are calculated computed to capture the market's response to selected crisis-related events. Abnormal returns (AR) are defined as the difference between the actual returns of a financial asset and the expected return (Equation 1). Cumulative abnormal return (CAR) is the cumulative sum of abnormal returns, where:

$$AR_t = R_t - (\hat{\beta} X_t + \varepsilon_t) \tag{1}$$

Where AR_t, R_t, and X_t represent abnormal returns, returns on the stock index, and a vector of covariates of financial indicators (including such as the VIX index, the S&P 500 Standard & Poor's 500 index (S&P 500), and the DJIA index Dow Jones Industrial Average (DJIA)) on day t. The expected return is estimated through the market model parameters, with corresponding parameters $\hat{\alpha}$ and $\hat{\beta}$, obtained via GARCH estimation. To assess the cumulative impact of an event, the following measure is computed: from the market model. Based on this calculation, the reaction of the index within the period is estimated, and the following is computed

$$CAR_{t-120,t,t+29} = \sum_{1}^{t} AR_t \tag{2}$$

Where $CAR_{t-120,t,t+29}$ represents the cumulative price reaction to an event within the time window from day 1 to day t (Equation 2)The market model is estimated using a GARCH model, chosen primarily based on information criteria and likelihood derived from the estimation process (Kao et al., 2020; Sorin, 2012). Additionally, it is selected the selection of regression coefficient orders heavily depends on achieving maximum likelihood and minimizing information criteria. According to Nelson & Cao (1992), the GARCH model order can be either balanced (same order) or unbalanced (different orders), with the correct model choice focusing on minimizing estimation errors and selecting the best model through estimation test satisfaction.

$$\widehat{R_t} = \hat{\alpha} + \hat{\beta} X_t + \varepsilon_t$$
$$\varepsilon_{i,t} | \Omega_{t-1} = N(0, h_{jt}) \qquad (3)$$
$$h_{i,t} = c_j + \sum_{i=1}^{q} \lambda \varepsilon_{(i,t)}^2 + \sum_{i=1}^{p} \theta h_{t-k}$$

Here, ε_t denotes the return innovation or shock, and $h_{i,t}$, is the volatility must have a mean of zero and conditional variance of errors. This structure allows the model to capture the persistence and clustering behavior observed in financial volatility (Equation 3). To evaluate the statistical significance of mean return changes before and after the events, a two-sample mean difference test is employed. A significant difference in AR estimates across time windows indicates distinct market reactions to the events. These empirical estimates—based on Equations (1) to (3)—are presented in Tables 3, 5 and, 7, where the statistical significance of AR values across pre- and post-event periods is tested.

3.2. Dynamic Regression Model

To assess the impacts of the respective financial and health crises on U.S. financial indicators, a dynamic regression model is developed applied using quarterly data from 2000-Q3 to 2022-Q4 and. Additionally, a vector of control covariates X_{nt} is employed, measuring economic efficiency as follows: 1) U.S. Gross Domestic Product (GDP): the aggregate production of the economy; 2) University of Michigan Consumer Sentiment Index: gauges consumer confidence and economic expectations; 3) Industrial Production Index: measures industrial sector development via production volume variation; 4) Unemployment Rate: proportion of the workforce unemployed; and 5) Sales-to-Inventory Ratio: assesses economic efficiency through production and consumption capacity (Agatón Lombera et al., 2024; Federal Reserve Bank, 2023; Ratanapakorn & Sharma, 2007).

It's important to note that most of these indicators are reported monthly or daily, hence it needs to be transformed into quarterly data for better management. Data were sourced from the Federal Reserve Bank database, and then. It is important to define that the variables to be analyzed will be transformed into natural logarithms. This transformation seeks to maintain stationarity in the time series data (Ratanapakorn & Sharma, 2007). In this context, the following the model in equation 4 is estimated. Here, Y_t represents the vector of dependent variables, comprising our main financial indices, Additionally, the model includes a vector of covariates X at time t and $t-1$ to incorporate the dynamic nature of the series, along with the lagged dependent variable. To measure the effects of the crises and two dummy variables are implemented to reflect the quarters during which the crises occurred ($D_{2007-2009}$ y $D_{2019-2021}$). Also, it is important to note that the estimation process will it is used robust standard errors, to mitigate heteroscedasticity.

$$Y_{nt} = \hat{\alpha} + \hat{\beta}Y_{nt-1} + \hat{\varphi}D_{2007-2009} + \hat{\rho}D_{2019-2021} + \hat{\delta}X_{nt-1} + \varepsilon_{it} \quad (4)$$

3.3. Risk-Adjusted Return Analysis (EGARCH in Mean)

The analysis of r Risk-adjusted returns is used helps to identify the levels of returns for each unit of risk assumed in an investment or portfolio of investments. In this case, it evaluates the return levels associated with financial and health crises.

The return per unit of risk represents the opportunity costs of holding an asset instead of a risk-free asset. Here, r_{it} shows the returns associated with asset i over time t, and μ represents the fixed returns derived from asset i, aspects that are evident in the structure of an exponential GARCH model (Núñez Mora & Chávez Gudiño, 2010).

To identify the existence of significant assets that associate returns with a unit of risk, the coefficient associated with conditional variance (σ^2) must be positive and significant (Equation 6). This indicates the presence of returns. Additionally, the variable representing fixed returns from the asset during the eGARCH estimation process (μ) should be significant, showing the number of return units per unit of risk. An exogenous component related to a dummy variable reflecting the crisis period (D_{it}) and a variable associated with economic growth (X_{it}) is included (Equation 5).

To avoid issues related to data asymmetries and the presence of heavy-tailed distributions, meaning the higher probabilities of observing extreme values, we would use a Generalized Hyperbolic (GHYP) distribution helping to reduce biases in the estimation process. The use of GHYP is crucial because financial asset prices often exhibit patterns that do not fit a typical normal distribution as they may have heavy tails or skewness in their distribution.

The ability of the GHYP distribution to capture these specific characteristics of financial data makes it a valuable tool for analyzing and modeling returns and volatility in financial markets (Núñez Mora & Chávez Gudiño, 2010; Núñez-Mora et al., 2023; Agatón Lombera et al., 2024). The analysis of returns per unit of risk focuses particularly on the dependent variables. Likewise, exogenous variables, such as the dummy variables for the presence of crises and economic growth, are included. This inclusion helps capture the effects derived from the crises and how they relate to economic growth.

$$r_{it} = \mu + \beta_0\sigma_{it-1} + \epsilon_t + D_{it} + X_{it} \quad (5)$$
$$\sigma_{it}^2 = \omega + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{it-1}^2 \quad (6)$$
$$\epsilon \sim N(0, \sigma_{it}^2) \quad (7)$$

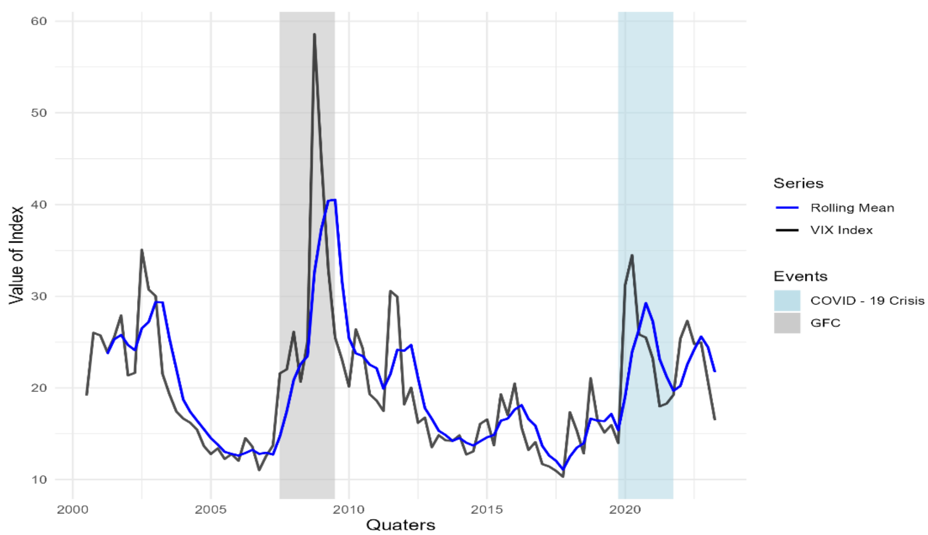
4. Descriptive Analysis

This chapter aims to establish a rolling analysis of time series for financial indicators in the United States. While this is not a causal or predictive analysis, it serves multiple purposes: 1) It quantifies changes in expectations associated with the behavior of the series, identifying movements in volatility under conditions of symmetrical information, and 2) It measures market recovery under conditions of certainty (Sheng et al., 2023). By examining the VIX index, it is evident that during both events, volatility levels were higher compared to periods without economic crises, reaching significant peaks (see Figure 1). During the GFC, the indicator reached peaks higher than in other quarters; however, under certainty, the associated duration and magnitude might have been smaller (Agatón Lombera et al., 2024).

In the case of COVID-19, the same pattern occurred as during the financial crisis, with the peak being neither as high nor as prolonged as that observed during the GFC. This could be attributed to several factors, including a faster and more coordinated response by governments and central banks, which implemented aggressive economic stimulus measures and supportive policies to mitigate the impact of the pandemic on the economy (Kinateder et al., 2021).

Additionally, in the interim periods between the two crises, the VIX experienced several minor fluctuations. These fluctuations reflect temporary volatility episodes that did not reach crisis levels. This indicates a market that, while experiencing occasional uncertainties, managed to maintain a more controlled level of volatility overall.

Figure 1. Dynamic Analysis of VIX Index Rolling Statistics

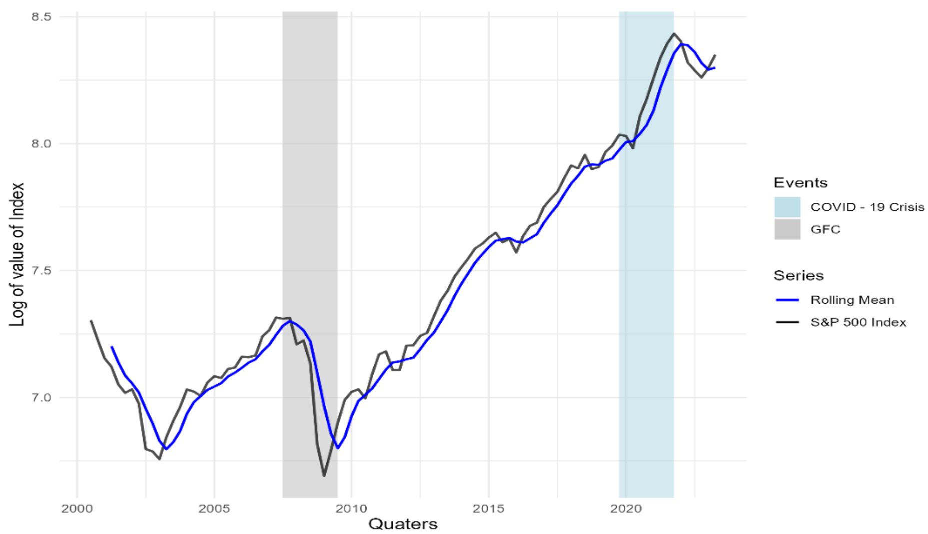


Source: Prepared by the authors.

For the logarithm of the S&P 500, it is evident that the two crises had disparate effects over the time series (see Figure 2). During the GFC, the market valuation of companies within the index decreased significantly. Compared to its moving average, the index experienced a more prolonged and severe decline.

In contrast, the recovery from the COVID-19 pandemic was swift, with the moving average quickly resuming its upward trajectory. This rapid recovery is associated with aggressive economic stimulus policies and the growth of essential sectors, such as technology.(Agatón Lombera et al., 2024; Baiardi et al., 2020).

Figure 2. Dynamic Analysis of Log of S&P 500 Index Rolling Statistics



Source: Prepared by the authors.

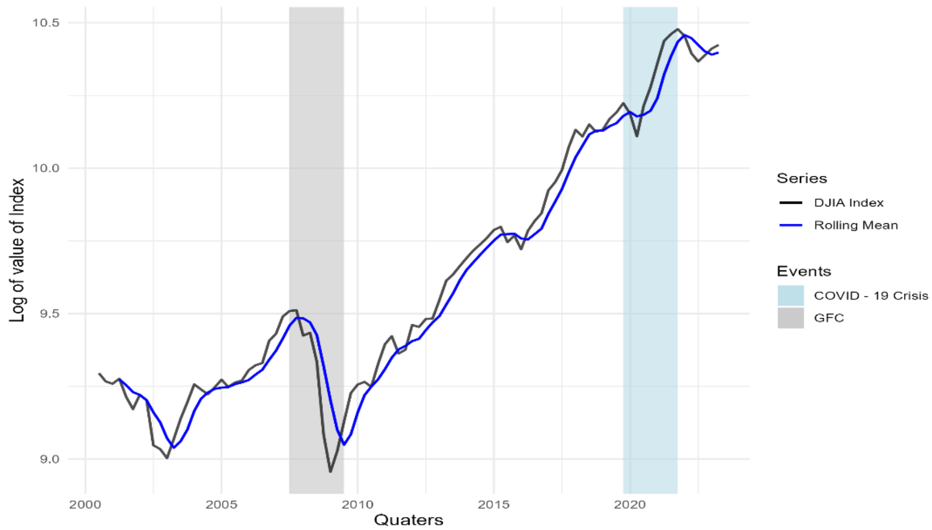
In Figure 3, a comparable pattern can be observed in the behavior of the logarithm of the Dow Jones Industrial Average (DJIA) relative to the S&P 500. This similarity stems from the fact that both indices encompass major U.S. market participants, with the DJIA including 30 prominent companies and the S&P 500 encompassing a broader array of 500 firms (Anagnoste & Caraiani, 2019; Tabash et al., 2024). Despite this difference in scope, their responses to economic shocks are closely aligned. The analysis of these indices provides a clear depiction of how both the Global Financial Crisis (GFC) and the COVID-19 pandemic impacted key financial indicators in the United States.

The GFC resulted in a significant and prolonged decline in market valuations for companies within both indices, with the DJIA and S&P 500 displaying extended and severe downturns when compared to their respective moving averages. This indicates a deep and enduring negative impact on market sentiment and valuation during the GFC. In contrast, the recovery from the COVID-19 crisis was markedly swift. Both indices experienced a rapid rebound, with the moving averages quickly resuming their upward trajectories. This rapid recovery can be attributed to the aggressive economic stimulus measures implemented during the pandemic, along with the growth of critical sectors such as technology, which played a significant role in driving the market's resurgence.

The results presented in Figure 3 descriptively highlight the distinct effects of the two crises on these major financial indicators. The GFC's impact was more profound and prolonged, reflecting systemic issues and a more extended period of market instability. Conversely, the COVID-19 crisis, while initially severe, was followed by a faster recovery phase, influenced by supportive fiscal policies and the resilience of key sectors.

In the subsequent sections of this document, we will further investigate the specific effects of each crisis on the indices. This analysis will focus on understanding how these events shaped the financial indicators and identifying periods where returns per unit of risk were maximized. By examining these factors, we aim to provide a comprehensive understanding of the crisis impacts and recovery dynamics within major U.S. financial indices.

Figure 3. Dynamic Analysis of Log of DJIA Index Rolling Statistics



Source: Prepared by the authors.

5. Empirical Results

This section aims to report the results of the Event Study models with GARCH estimation, Dynamic Regression models, and Risk-Adjusted Return Analysis for the VIX, the S&P 500, and the DJIA in the context of the GFC and the COVID-19 Crisis. These methods are employed to capture both the immediate market reactions to crisis events and the underlying causal dynamics and risk-return profiles associated with each period, thereby providing a comprehensive assessment of financial market behavior under extreme stress conditions.

5.1. Event Study

In the analysis, key dates were selected that significantly impacted the financial market during both crises. Based on these dates, multiple variations of GARCH models were estimated to identify the best-fitting model that minimizes intrinsic estimation errors. The financial crisis was analyzed first, followed by the health crisis. The dynamics of the VIX were examined first, followed by the S&P 500 and DJIA. Accordingly, the following table presents the estimation results for key events: August 9, 2007, (initial recognition of subprime mortgages) and September 21, 2008, (Lehman Brothers bankruptcy and ensuing financial panic). For the first date, parameter estimates are significant except for the conditional variance constant (ω) and the lagged conditional variance error (ϵ_{t-2}^2). Additionally, autoregressive effects are evident in the model. For the second date, the exponential GARCH model shows all parameters as significant, influenced by both volatility model components and ARMA. These results are validated by the minimization of information criteria and the maximization of the likelihood index (Table 2). In the case of the third model within the context of the GFC, examining the results reveals that both the autoregressive components of volatility (GARCH) and the lagged observations of data alongside the moving average of past volatility (ARMA) are significant for calculating abnormal returns.

For the first two dates linked to the VIX index, Abnormal Returns are expected to increase after receiving bad news, as a higher VIX indicates heightened market volatility. These findings align with Günsür & Bulut´s (2022) analysis, suggesting that such events typically yield positive and accelerated growth in expected returns on the VIX index. This trend is driven by significant bankruptcies among US investment banks and reduced consumer credit lines, which amplified market volatility levels (Günsür & Bulut, 2022). In contrast, the third date shows a gradual decline in abnormal returns due to the implementation of countercyclical policies (Figure 4 1A in column A).

The analysis of the COVID-19 crisis identifies three key dates: 1) January 19, 2020 (First case of COVID-19 detected in the United States); 2) March 15, 2020 (Institution and business closures due to preventive lockdowns); and 3) December 24, 2020 (Administration of over one million vaccines in the United States). For each of these pivotal events, GARCH models are estimated accordingly.

The first date, marking the detection of the first COVID-19 case in the US, shows a significant trend in its GARCH parameters. In contrast, models extended to cover the start of preventive lockdowns and the milestone of one million vaccines administered in the US demonstrate greater significance and efficiency. Notably, both the AR (Autoregressive) and MA (Moving Average) components play significant roles in these models. These findings corroborate the study by Pandey & Kumari (2021),which highlights the identification of COVID-19 as a global public health threat with adverse impacts on financial asset markets, driven by widespread panic. These trends are visually represented in the first two dates (Figure 1A, Column B).

Table 2. GARCH Estimates Applied to the Event Study of the VIX Index – (GFC and COVID-19 Crisis)

Dates	09/08/2007	21/09/2008	16/12/2008	19/01/2020	15/03/2020	24/12/2020
			VIX Index			
	GARCH (2,1) ARMA (2,0)	GARCH (2,2) ARMA (2,2)	gjrGARCH (1,2) ARMA (1,2)	GARCH (1,2) ARMA (1,2)	eGARCH (2,2) ARMA (2,1)	gjrGARCH (2,2) ARMA (2,1)
Constant	14.40***	21.27***	39.93***	15.18***	24.54***	16.21***
	(0.61)	(0.00)	(0.11)	(1.70)	(0.00)	(0.02)
ω	0.05	3.54***	0.23***	0.11	1.84***	0.16***
	(0.06)	(0.00)	(0.00)	(0.11)	(0.00)	(0.00)
ϵ_{t-1}^2	0.24*	0.11***	0.33***	0.64***	0.14***	0.00***
	(0.14)	(0.00)	(0.00)	(0.18)	(0.00)	(0.00)
σ_{t-1}^2	0.75***	0.09***	0.09***	1.00***	-0.90***	0.77***
	(0.13)	(0.00)	(0.00)	(0.21)	(0.00)	(0.00)
ϵ_{t-2}^2	0.00	-0.30***	-	-	0.15***	0.41***
	(0.15)	(0.00)	-	-	(0.00)	(0.00)
σ_{t-2}^2	-	-0.35***	0.77***	-0.12	-	0.14***
	-	(0.00)	(0.00)	(0.22)	-	(0.00)
Y_{nt-1}	0.70***	1.70***	0.99***	0.95***	0.31***	0.09***
	(0.08)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
Y_{nt-2}	0.25***	-0.72***	-	-	0.46***	0.86***
	(0.08)	(0.00)	-	-	(0.00)	(0.00)
ε_{nt-1}		-0.93***	-0.09***	-0.14	0.33***	0.89***
		(0.00)	(0.00)	(0.15)	(0.00)	(0.00)
ε_{nt-2}		0.23***	-0.27***	0.02	-	-
		(0.00)	(0.00)	(0.11)	-	-
AIC	3.37	5.76	5.74	4.36	4.05	3.25
BIC	3.58	6.03	5.99	4.57	4.28	3.51

Likelihood	-193.68	-333.64	-333.63	-252.79	-233.45	-184.20
R^2	0.49	-0.22	-0.19	0.89	0.23	0.90
Adjusted R^2	0.48	-0.23	-0.20	0.89	0.22	0.90

Source: Prepared by the authors.
Note: *** p-values<0.01; ** p-values<0.05; * p-values<0.10.

A statistical test for mean differences was applied to assess differences in returns before and after events. Significant differences were found in the return index means, indicating market inefficiency according to Pandey & Kumari (2021).

During the GFC, there was a substantial increase in volatility returns post-event, suggesting heightened volatility levels. For the COVID-19 crisis, volatility significantly increased on the first two dates but was less significant on the last date, ultimately reducing volatility levels.

Table 3. Estimates of Mean Difference Tests Applied to Abnormal Returns Associated with the VIX Index

GFC			
Dates	Mean ex–ante	Mean ex–post	P–value
09/08/2007	-0.370	3.361	0.000
22/09/2008	-5.109	5.746	0.000
16/12/2008	-0.755	-4.493	0.000
COVID–19			
19/01/2020	-6.149	2.364	0.000
16/03/2020	-0.128	22.664	0.000
24/12/2020	0.995	-0.112	0.035

Source: Prepared by the authors.

After analyzing the VIX, the effect of key dates on the logarithm of the Standard & Poor's 500 (S&P 500) index will be examined. Abnormal Returns are expected to decrease following negative news and increase following positive news. For the initial dates, GARCH model results indicate higher efficiency compared to a base estimate. In the event of the first recognition of the Subprime crisis, both ARMA and GARCH components are significant. Similarly, in the event of investment bank bankruptcies, ARMA and GARCH components are significant, except for the squared error of the conditional variance in a lagged period.

For the last date during the GFC, most parameters are significant in consolidating abnormal returns series. Negative events such as the initial recognition of the financial crisis and bank bankruptcies had negative effects on the returns series.

Conversely, news related to interest rate cuts showed growth in the returns series, especially during the FED's interest rate reduction event (Table 4). Balubaid (2015) noted a gradual decline in S&P 500 returns days before the financial crisis events, demonstrating the ability of the index to anticipate drops during crucial economic periods (Figure 2A).

Table 4. GARCH Estimates Applied to the Event Study of the S&P 500 Index Log – (GFC and COVID-19 Crises)

Dates	09/08/2007	21/09/2008	16/12/2008	19/01/2020	15/03/2020	24/12/2020
			Log (S&P 500 Index)			
	eGARCH (2,1) ARMA (2,2)	eGARCH (2,2) ARMA (2,0)	gjrGARCH (1,2) ARMA (2,1)	gjrGARCH (2,2) ARMA (1,2)	eGARCH (2,2) ARMA (1,2)	gjrGARCH (2,2) ARMA (2,1)
Constant	7.28***	7.16***	6.93***	8.01***	8.03***	8.13***
	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)
ω	-0.55***	-0.84	0.00*	0.00***	-1.23***	0.00**
	(0.01)	(0.51)	(0.03)	(0.00)	(0.44)	(0.00)
ϵ_{t-1}^2	-0.54***	-0.23	0.01	0.00	-0.56***	0.24
	(0.12)	(0.17)	(0.04)	(0.76)	(0.14)	(0.18)
σ_{t-1}^2	0.94***	0.16	0.82	0.14	0.16*	0.00
	(0.00)	(0.00)	(1.22)	(0.25)	(0.08)	(0.53)
ϵ_{t-2}^2	0.17*	0.03	-	0.00	-0.33**	0.00
	(0.09)	(0.17)	-	(0.56)	(0.15)	(0.57)
σ_{t-2}^2	-	0.72***	0.00	0.22	0.69***	0.27
	-	(0.16)	(0.25)	(0.20)	(0.08)	(0.18)
Y_{nt-1}	0.07***	0.78***	0.04***	1.00***	0.99***	0.31
	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(2.23)
Y_{nt-2}	0.91***	0.23***	0.97***	-	-	0.68
	(0.00)	(0.02)	(0.01)	-	-	(2.21)
ε_{nt-1}	0.97***	-	1.00***	0.02	-0.09	0.58
	(0.00)	-	(0.00)	(0.21)	(0.10)	(2.60)
ε_{nt-2}	-0.10***	-	-	0.08	0.10	-
	(0.00)	-	-	(0.21)	(0.08)	-
AIC	-6.71	-3.95	-3.91	-7.18	-5.75	-6.11
BIC	-6.45	-3.72	-3.65	-6.92	-5.49	-5.86
Likelihood	413.74	247.24	245.59	442.04	355.94	377.99
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Adjusted R^2	0.99	0.99	0.99	0.99	0.99	0.99

Source: Prepared by the authors.
Note: *** p-values<0.01; ** p-values<0.05; * p-values<0.10.

We will now proceed to analyze the behavior of the S&P 500 financial index during the COVID-19 pandemic. For the first and third dates, the GARCH component is found to be significant; however, except for the second-order autoregressive component, both the first-order autoregressive and first- and second-order moving average components tend to be significant. Regarding the second date, it is significant, except for the constant components and the conditional variance constant (Table 3).

The analysis of S&P 500 financial index returns during both the GFC and the COVID-19 pandemic reveals notable differences before and after pivotal events. During the GFC, events such as the initial recognition of the crisis and Lehman Brothers' bankruptcy resulted in negative returns, while interest rate cuts had a positive impact. In contrast, during COVID-19, the initial event unexpectedly saw returns following negative news, whereas subsequent events aligned with expectations: negative developments decreased returns, and positive milestones such as vaccination efforts boosted expected returns from the financial index (Table 2A).

Table 5. Estimates of Mean Difference Tests Applied to Abnormal Returns Associated with the S&P 500 Index Log

Dates	Mean ex–ante	Mean ex–post	P–value
GFC			
09/08/2007	0.279	-0.839	0.035
22/09/2008	18.634	4.453	0.000
16/12/2008	11.622	13.571	0.000
COVID–19			
19/01/2020	1.354	2.571	0.000
16/03/2020	6.181	-7.989	0.000
24/12/2020	-7.054	0.906	0.000

Source: Prepared by the authors.

This section also aims to examine the behavior of abnormal returns associated with the logarithm of the DJIA series. The analysis of the three key dates reveals that both GARCH and ARMA components are significant, influencing the parameters used to calculate derived returns (Table 6). On evaluating the COVID-19 pandemic using GARCH models with ARMA extensions, it is evident that both components are significant and influential in the return calculations for the first two key dates. However, for the third date, the GARCH estimators do not show complete significance in the analysis.

Plotting the abnormal returns during the financial crisis events shows that average returns for the first two dates were below zero, indicating a reduction in returns following negative news. Conversely, news such as the FED's interest rate cuts led to an increase in returns (Figure 3A column A). For the first key date, following the announcement of the first COVID-19 cases, there was a significant reduction in returns one month after the event. On the second date, the speed at which returns reached their lowest point was much faster, with the start of quarantine having a negative effect on returns. Finally, during the event marking the administration of the first million vaccines, there was a rapid increase in DIJ financial indicator returns. However, these returns remained negative, reflecting the market's lack of confidence (Figure 3A column B).

Table 6. GARCH Estimates Applied to the Event Study of the DJIA Index Log – (GFC and COVID-19 Crises)

Dates	09/08/2007	21/09/2008	16/12/2008	19/01/2020	15/03/2020	24/12/2020
	Log (DJIA Index)					
	eGARCH (2,2) ARMA (0,2)	eGARCH (2,1) ARMA (1,1)	eGARCH (2,2) ARMA (2,1)	gjrGARCH (2,2) ARMA (1,2)	eGARCH (2,2) ARMA (1,2)	gjrGARCH (2,2) ARMA (2,1)
Constant	9.51***	9.47***	9.33***	10.21***	10.22***	10.23***
	(0.00)	(0.04)	(0.00)	(0.01)	(0.01)	(0.01)
ω	-1.99***	-0.24***	-0.64***	0.00***	-1.27**	0.00**
	(0.00)	(0.51)	(0.00)	(0.00)	(0.51)	(0.00)
ϵ_{t-1}^2	-0.19***	-0.03	-0.16***	0.00	-0.48***	0.11
	(0.00)	(0.07)	(0.00)	(0.00)	(0.12)	(0.11)
σ_{t-1}^2	-0.07***	0.97***	0.48***	0.19***	0.03	0.07
	(0.00)	(0.00)	(0.00)	(0.05)	(0.21)	(0.12)

ϵ_{t-2}^2	0.26***	-0.17	-0.29***	0.00	-0.44***	0.00
	(0.00)	(0.11)	(0.00)	(0.09)	(0.14)	(0.12)
σ_{t-2}^2	0.84***	-	0.44***	0.23	0.82***	0.51***
	(0.00)	-	(0.00)	(0.15)	(0.27)	(0.14)
Y_{nt-1}	-	0.99***	1.67***	1.00***	0.99***	0.38***
	-	(0.02)	(0.00)	(0.01)	(0.01)	(0.09)
Y_{nt-2}	-	-	-0.67***	-	-	0.62***
	-	-	(0.01)	-	-	(0.10)
ε_{nt-1}	0.75***	-0.19***	-0.86***	-0.04	-0.09	0.48***
	(0.00)	(0.04)	(0.00)	(0.10)	(0.10)	(0.12)
ε_{nt-2}	0.53***	-	-	-0.01	0.07	-
	(0.00)	-	-	(0.21)	(0.10)	-
AIC	-5.75	-4.88	-4.28	-6.90	-5.61	-6.27
BIC	-5.47	-4.67	-4.02	-6.64	-5.35	-6.01
Likelihood	357.15	302.12	267.89	425.26	347.84	387.04
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Adjusted R^2	0.99	0.99	0.99	0.99	0.99	0.99

Source: Prepared by the authors.
Note: *** p-values<0.01; ** p-values<0.05; * p-values<0.10.

Applying mean difference tests to examine returns associated with the DJIA reveals the impact of key events. The Lehman Brothers' bankruptcy had a negative effect, reducing returns by about 11 points. Conversely, the reduction in interest rates led to an increase in returns, raising the average by around 5 points. Positive news should positively drive returns associated with this indicator.

These findings align with Pineda (2015), who noted that the collapse of major banks resulted in reduced returns on financial assets (Table 7). For the COVID-19 pandemic, significant changes in series movements before and after events indicate breakpoints. Initially, the emergence of COVID-19 cases in the U.S. did not threaten financial markets, as returns increased following the event. However, subsequent dates highlight market sensitivity to the crisis: returns fell with the announcement of quarantine measures but rose with the administration of the first million vaccines.

Table 7. Estimates of Mean Difference Tests Applied to Abnormal Returns Associated with the DJIA Index Log

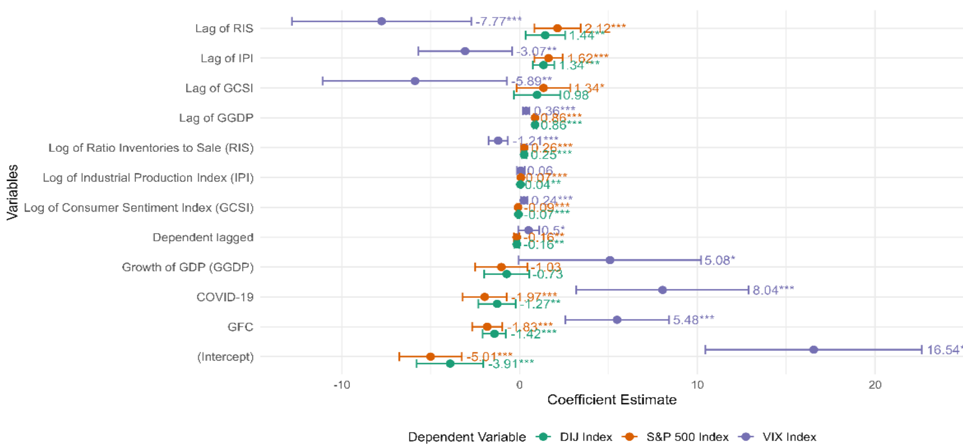
	GFC		
Dates	**Mean ex–ante**	**Mean ex–post**	**P–value**
09/08/2007	-0.684	-1.165	0.268
22/09/2008	12.582	1.358	0.000
16/12/2008	12.668	17.460	0.000
	COVID–19		
19/01/2020	1.354	2.571	0.000
16/03/2020	6.181	-7.989	0.000
24/12/2020	-7.054	0.906	0.000

Source: Prepared by authors.

5.2. Dynamic Regression Analysis

This analysis aims to explore the causal relationships between multiple crises and a set of control variables concerning three key dependent variables. By employing a dynamic regression modeling approach that accounts for lags in the independent variables, we capture the temporal dynamics of these relationships. Our findings indicate that the financial crisis significantly impacted all regressions, notably increasing market volatility, as represented by the VIX index, and decreasing the valuation levels of key financial indicators, such as the S&P 500 and DJIA. This provides a comprehensive understanding of how crises and other factors affect market stability and performance over time. In contrast, while the COVID-19 crisis also significantly reduced the valuation of financial indicators, its impact on market volatility was less pronounced. This suggests that, although the health crisis negatively affected financial markets, it did not generate the same extreme volatility as the previous financial crisis. This difference can be attributed to the endogenous nature of the financial crisis compared to the health crisis, with the former particularly intensifying volatility for the VIX indicator (Longstaff, 2010). Huang & Chang (2022) assert that the significance of parameters and associated signs indicates that the impact tends to be greater in the case of the subprime crisis compared to the health crisis. This is because the subprime crisis affected a broad range of economic sectors, whereas the health crisis impacted non-essential sectors while increasing the participation of essential sectors and technology in the added value of the American economy (Huang & Chang, 2022). When examining other exogenous variables, such as U.S. GDP growth, we found interesting results. Contrary to expectations, we observed that GDP growth is positively associated with an increase in market volatility, as measured by the VIX index. This finding suggests a complex interaction between economic growth and risk perception in financial markets, which contradicts Prasad et al. (2022). Additionally, our analysis of consumer sentiment about the economy and the industrial production index revealed that both are inversely related to market volatility and positively related to the valuation of key financial indicators. This implies that higher consumer optimism and increased industrial production can contribute to greater stability and performance in financial markets. These variables are measured on a logarithmic scale (Figure 7).

Figure 7. Dynamic Regression Model for the Impact of the GFC and COVID-19 on Financial Indicators in the United States



Source: Prepared by the authors.
Note: *** p-values<0.01; ** p-values<0.05; * p-values<0.10.

Finally, when considering the relationship between the inventory-to-sales ratio and market indicators, we observe divergent effects. An increase in this ratio is associated with higher market volatility, as measured by the VIX index, and has a positive effect on the valuation of the S&P 500, but a negative impact on the DJIA (Prasad et al., 2022). Examining the lagged behavior of these variables, we find the expected negative relationship between GDP growth and the VIX, where an increase in GDP reduces market volatility (Prasad et al., 2022). However, the lagged effects of the industrial production index and consumer sentiment index are counterintuitive, showing that increases in these variables reduce volatility and positively impact the S&P 500 and DJIA valuations.

These findings highlight the complexity of financial markets and the need to consider multiple exogenous variables. Notably, the lagged inventory-to-sales ratio shows counterintuitive results: higher inventory levels decrease volatility instead of increasing it. This underscores the importance of considering a broad range of factors to gain deeper insights into market movements.

5.3. Risk-Adjusted Returns Analysis

This analysis aims to identify returns per unit of risk across the three financial indicators. To achieve this, we estimate an exponential GARCH model, including the mean of the volatility component, to relate the values associated with the mean of the volatility component to the return per unit of risk. The goal is to determine which periods related to crises had better returns compared to a risk-free asset (Agatón Lombera et al., 2024; Núñez-Mora et al., 2023; Pandey & Kumari, 2021).

Examining the VIX, it is evident that during the GFC, the volatility per unit of risk (r_{it}) was much higher than in the COVID-19 crisis. This result implies that during the financial crisis, higher levels of volatility were recorded each time risk levels increased, most likely due to the endogenous nature of the subprime mortgage effects (Table 8). Additionally, U.S. economic growth indirectly impacts higher levels of the volatility index, with this opposition being more evident in the context of the financial crisis. Similarly, the dummy variable selecting the periods of the respective crises has a positive effect on the growth of the volatility index (Núñez-Mora et al., 2023; Núñez Mora & Chávez Gudiño, 2010).

For the S&P 500 index, the return per unit of risk was higher during the financial crisis than the COVID-19 crisis, indicating superior returns on assets for the financial crisis. The dummy variable related to crises had a negative and significant effect during the Subprime Crisis, impacting the index valuation. Economic growth had a positive and significant effect on the index valuation in both crises. Similarly, for the Dow Jones Industrial Average, returns per unit of risk were higher during the GFC compared to COVID-19. The dummy variables for crisis periods and the growth rate of production showed that the Subprime Crisis had a greater negative impact on index valuations. However, economic growth had a greater positive impact on the index during COVID-19 (Table 8).

Table 8. GARCH-in-Mean Estimates for Calculating Returns per Unit of Risk.

	VIX Index		Log (S&P 500 Index)		Log (DJIA Index)	
	GFC	COVID - 19	GFC	COVID - 19	GFC	COVID - 19
Constant	9.35***	10.54***	6.58***	5.53***	7.41***	7.46***
	(1.95)	(0.47)	(0.01)	(0.09)	(0.07)	(0.01)
ω	0.51***	1.72**	-0.46***	-0.29***	-0.18***	-0.21***
	(0.15)	(0.73)	(0.00)	(0.02)	(0.01)	(0.00)

r_{it}	1.95***	1.82***	6.67***	5.34***	9.85***	9.43***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.08)	(1.15)
ϵ_{t-1}^2	0.17***	0.30***	0.44***	0.57***	0.26***	0.28***
	(0.02)	(0.03)	(0.00)	(0.04)	(0.04)	(0.02)
σ_{t-1}^2	0.83***	0.63***	0.91***	-0.22***	0.95***	0.95***
	(0.00)	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)
D_i	8.32***	3.27***	-0.08***	0.00	-0.04**	0.01
	(0.36)	(1.15)	(0.04)	(0.03)	(0.01)	(0.03)
X_i	-1.89***	-1.10***	0.01***	0.01***	0.00***	0.01***
	(0.11)	(0.23)	(0.00)	(0.00)	(0.00)	(0.00)
AIC	5.61	5.83	-1.88	-2.29	-2.53	-2.51
BIC	5.88	6.11	-1.58	-1.99	-2.23	-2.21
Likelihood	-248.01	-258.49	97.86	116.51	127.76	126.33

Source: Prepared by the authors.
Note: *** p-values<0.01; ** p-values<0.05; * p-values<0.10.

5.4. Discussion

The findings highlight crucial differences in how financial markets respond to systemic versus exogenous crises. During the Global Financial Crisis (GFC), endogenous shocks—such as the collapse of Lehman Brothers—produced more pronounced and persistent spikes in market volatility compared to the COVID-19 pandemic. This is reflected in significantly higher abnormal returns and superior risk-adjusted performance metrics during the GFC, suggesting that financial crises inherently generate greater instability than external shocks of similar scale. In contrast, equity markets displayed greater resilience amid the pandemic. While the GFC saw abrupt and severe declines followed by slow recoveries, positive developments during COVID-19, including the vaccination rollout, were associated with rapid reversals of negative returns. This asymmetry may indicate that contemporary markets better absorb non-financial crises, possibly due to the stabilizing influence of essential sectors and technology industries, as well as more targeted and effective policy interventions.

Moreover, the analysis uncovers complex, nonlinear relationships among macroeconomic indicators and financial variables. Contrary to conventional expectations, GDP growth exhibited a positive association with market volatility during both crises, suggesting that periods of economic expansion may coexist with heightened risk aversion in times of systemic stress.

Furthermore, indicators such as consumer sentiment and industrial production consistently acted as mitigating factors, correlating with lower volatility and stronger equity valuations. Interestingly, some variables demonstrated counterintuitive effects; for instance, the inventory-to-sales ratio influenced different indices divergently and exhibited lagged effects that contributed to volatility reduction, challenging traditional theoretical narratives.

These findings, alongside the enhanced explanatory power of advanced volatility models, emphasize that financial markets process heterogeneous crisis events through intricate mechanisms where behavioral and institutional factors significantly shape the impact of fundamental economic variables.

6. Conclusions

As noted at the outset, both the GFC and COVID-19 crises had profound impacts on financial markets, as reflected in the volatilities and returns of the VIX, S&P 500, and DJIA. This was observed when key events during these crises caused statistically significant changes in abnormal returns and volatility. As can be seen, the models used (GARCH) effectively captured this dynamic, providing information on market reactions to the main financial and health crises. It must be recognized that public policy responses and market expectations played a crucial role in shaping the observed financial results. These analyses underscore the importance of timely and effective public policy interventions to mitigate the adverse effects of such crises on financial markets.

The analysis contributes significantly to existing knowledge by providing comparative insights into the reactions of financial markets to major crises and the efficacy of different policy interventions. Future research could explore the long-term impacts of such crises on global financial stability and investigate the role of technological advancements in mitigating future economic shocks.

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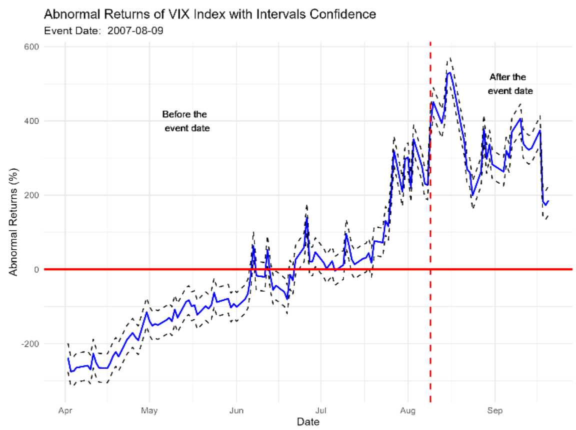
DOI: https://doi.org/10.21919/remef.v20i4.1235

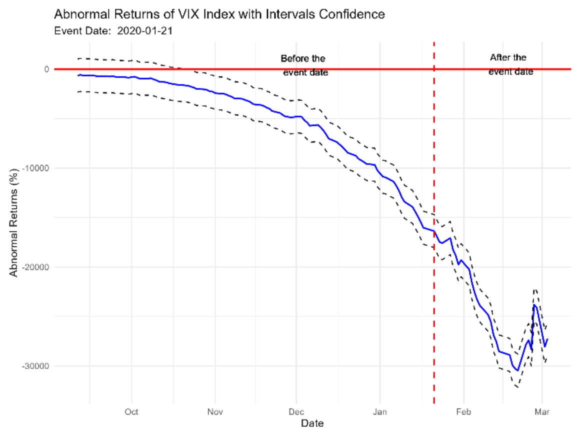
Appendix

Figure 1A. Calculation of Abnormal Returns for the Event Study of the VIX Index during the GFC and COVID-19

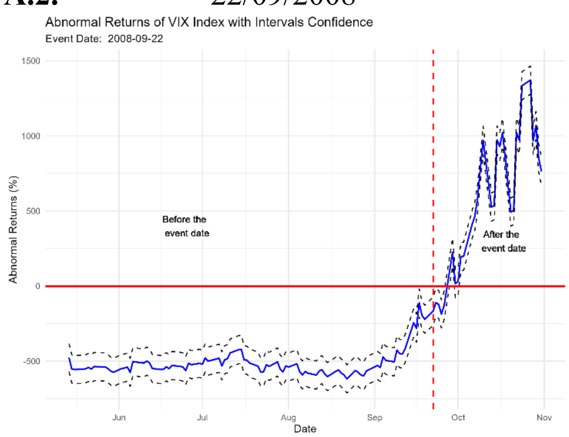
A.1. 09/08/2007



B.1. 21/01/2020



A.2. 22/09/2008



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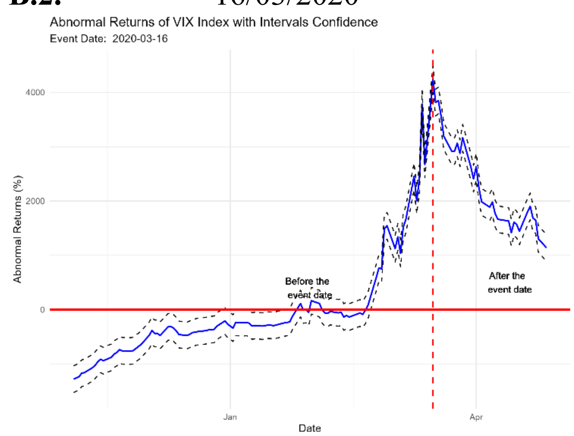
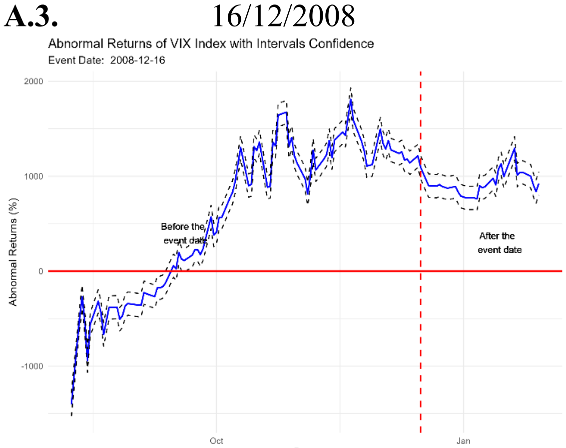
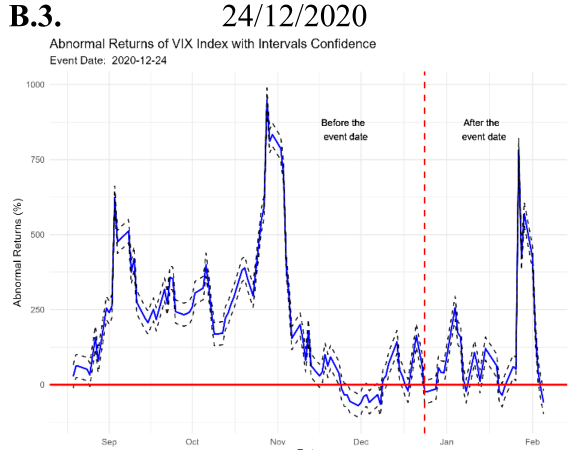


A.3. 16/12/2008



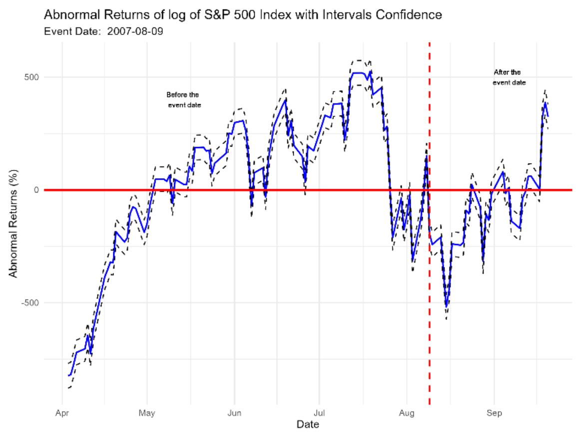
B.3. 24/12/2020



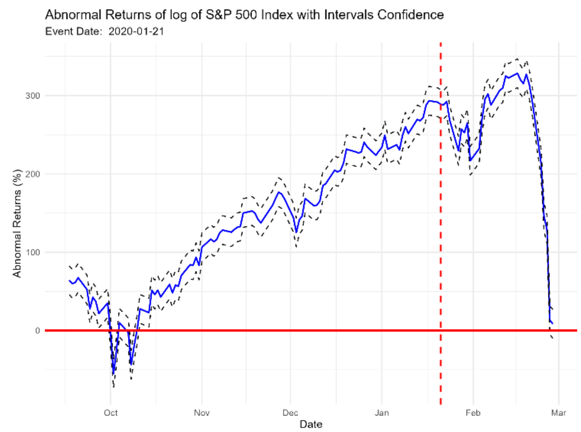
Source: Prepared by the authors.

Figure 2A. Calculation of Abnormal Returns for the Event Study of the S&P 500 Index Log during the GFC and COVID-19

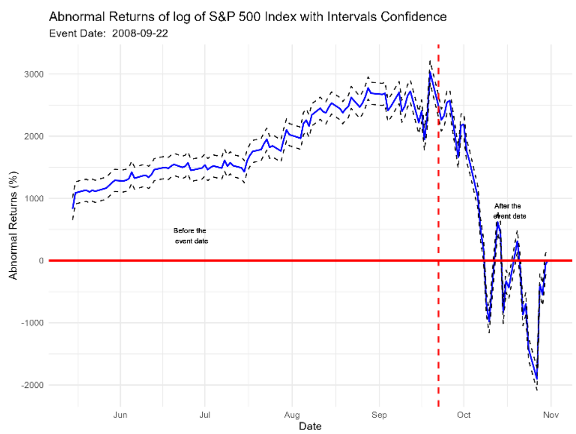
A.1. 09/08/2007



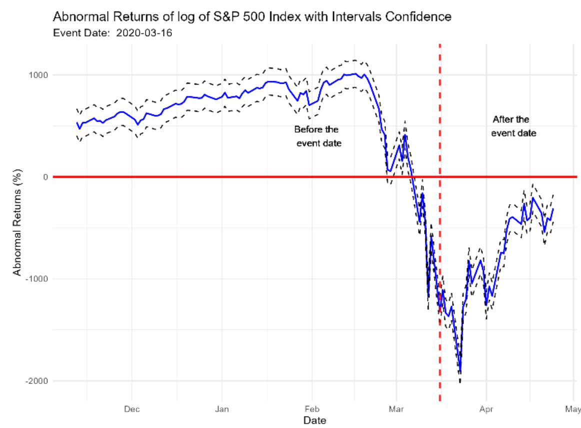
B.1. 21/01/2020



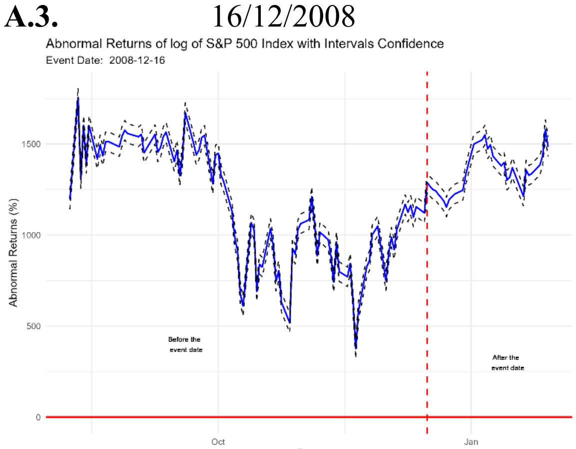
A.2. 22/09/2008



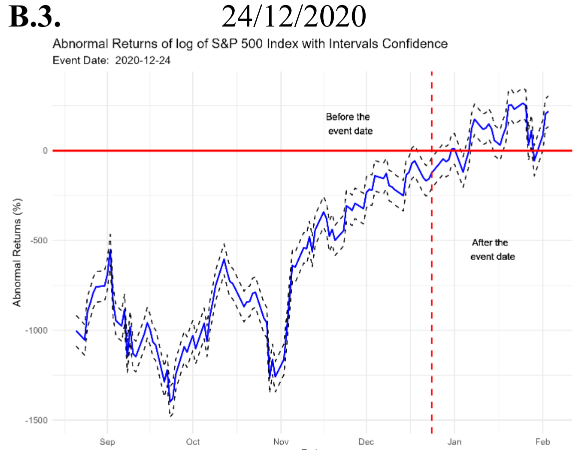
B.2. 16/03/2020



A.3. 16/12/2008



B.3. 24/12/2020



Source: Prepared by the authors.

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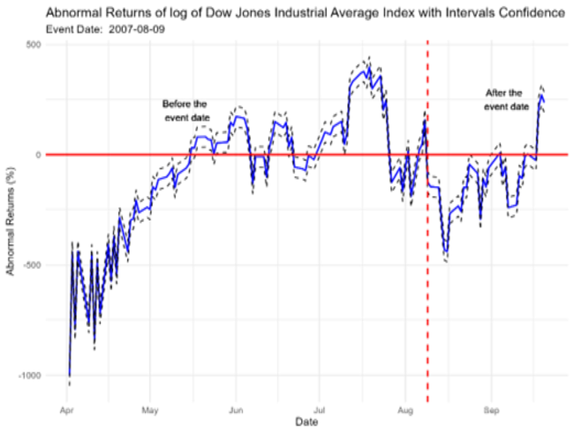
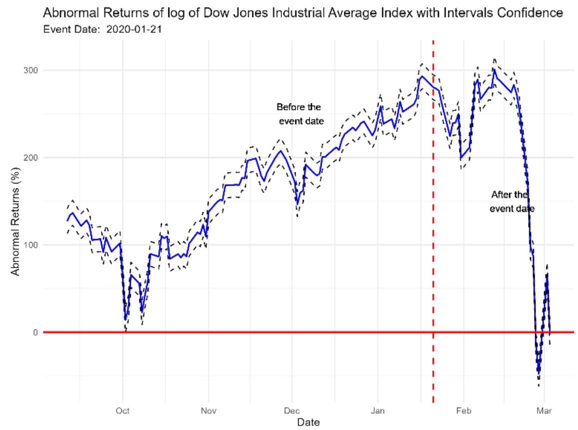
DOI: https://doi.org/10.21919/remef.v20i4.1235

Figure 3A. Calculation of Abnormal Returns for the Event Study of the DJIA Index Log during the GFC and COVID-19

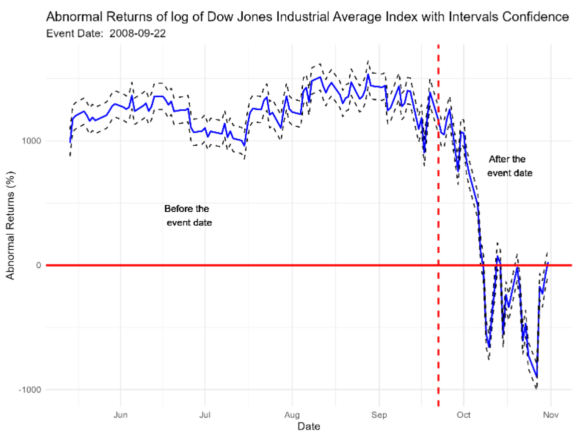
A.1. 09/08/2007



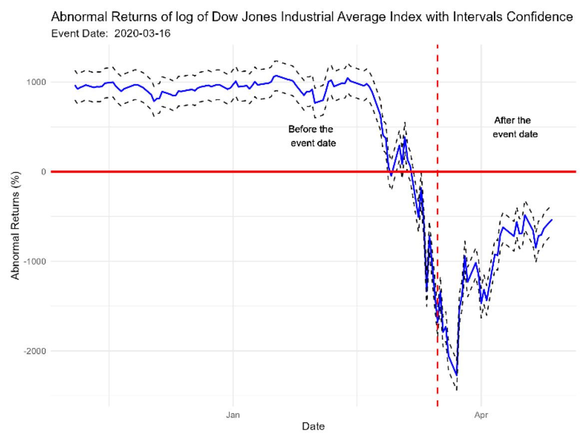
B.1. 21/01/2020



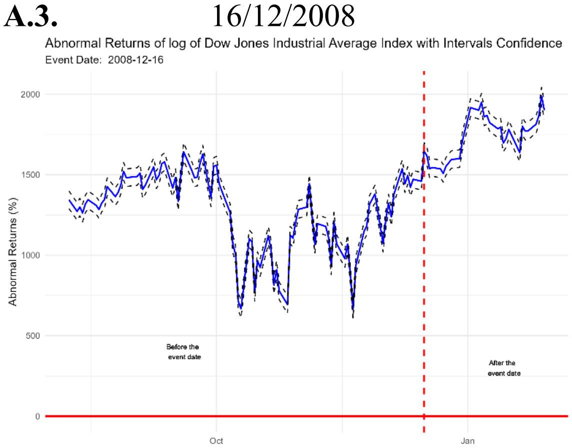
A.2. 22/09/2008



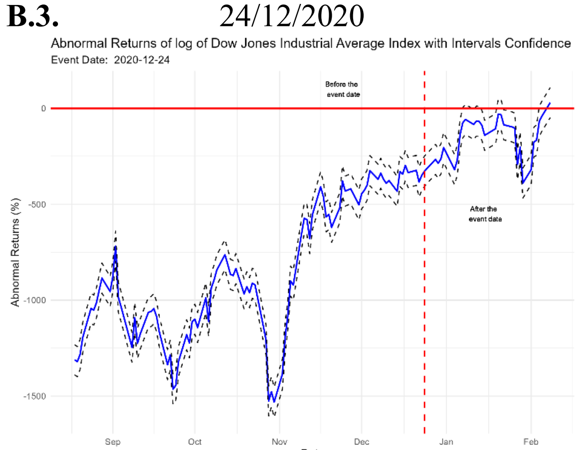
B.2. 16/03/2020



A.3. 16/12/2008



B.3. 24/12/2020



Source: Prepared by the authors.