The Evolving Role of Derivatives in Enhancing Market Efficiency and Risk Management: A Comparative Analysis of the 2008 Global Financial Crisis and the 2020 COVID-19 Shock

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Abstract. This study examines the changing role of derivatives in improving market efficiency and aiding risk management by analyzing their performance during the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic. Based on the theoretical frameworks of the price discovery mechanism, the Efficient Market Hypothesis and contemporary risk management theory, the analysis employs both qualitative and quantitative methodologies. Methodologically, we utilize GARCH-class models to analyze volatility dynamics, perform event study analysis to assess atypical market reactions, and implement the Vector Error Correction Model (VECM) to investigate the long-term information transmission between derivatives and spot markets. The results reveal a structural shift in the function of derivatives. During the 2008 crisis, complicated over-the-counter instruments like CDOs and CDSs made systemic risk worse because they were hard to understand and there weren't enough rules. In contrast, derivatives markets were more stable during the COVID-19 pandemic, thanks to reforms made after the 2008 financial crisis, such as central clearing mandates and better transparency. Derivatives helped find prices and move risk around when things got tough. This paper also looks at the differences between ASEAN and GCC markets, focusing on how changes in regulations and new technologies (like algorithmic trading and RegTech) will affect the future development of the derivatives market. The results show that derivatives need to be integrated into global financial systems in a healthy way, which requires a strong regulatory framework, infrastructure driven by innovation, and education for investors.

Keywords: Derivatives; Market Efficiency; Risk Management; Financial Crisis.

1. Introduction

Derivatives are a key part of the infrastructure that modern markets use to process information and move risk around. After the GFC, reforms like central clearing, trade reporting, and margining changed the way this plumbing worked. When COVID-19 hit in 2020, the system was put through a lot of stress and showed that it was generally strong, even though there were big swings in prices and margins [1–4]. These observations prompt a comparative analysis of derivatives' function during periods of crisis.

In 2008, when opaque OTC structures made things more fragile, the 2020 episode shows how institutions and technology have changed: central clearing and comprehensive reporting/margining acted as shock absorbers, while the design of the CCP initial-margin model and procyclicality became supervisory focal points, leading to work on tools for transparency and anti-procyclicality [2–4].

Recent evidence on price discovery indicates state-dependent leadership between index futures and cash/ETF venues; in cointegration/VECM contexts, short-horizon futures to spot transmission is frequently rapid, although leadership fluctuates due to microstructure frictions (short-selling constraints, tick size, liquidity) [5–7].

On volatility and event-time responses, COVID-era studies link elevated implied/realized volatility and regime shifts to pandemic dynamics—supporting the use of GARCH-class models to compare periods and quantify persistence—while event studies around major announcements show rapidly negative AR/CAR followed by heterogeneous mean reversion [8–11].

Gap in research. Few studies juxtapose the Global Financial Crisis (GFC) and COVID-19 within a cohesive empirical framework that integrates (i) conditional volatility and persistence, (ii) event-time autoregressive conditional heteroskedasticity (AR/CAR), and (iii) futures-to-spot transmission in a cointegration/vector error correction model (VECM) context. We fill this gap by using S&P 500 cash (^GSPC) and E-mini futures from 2007 to 2009 and 2019 to 2020. We use GARCH (1,1)/t, event studies (Lehman 2008-09-15; WHO 2020-03-11), and VECM-based IRFs/FEVDs [1–4, 12].

Contributions. (1) A unified crisis-to-crisis comparison on the same asset pair with consistent windows; (2) three evidence channels—GARCH, event study, VECM/IRF/FEVD—yielding convergent inference; (3) Interpretation through post-GFC reforms and model governance with portability to ASEAN/GCC contexts [1–4].

A sneak peek. We use GARCH (1,1)/t to compare conditional volatility and persistence; this paper does event studies around Lehman and the WHO declaration; and we use a Johansen-VECM framework to report IRFs and FEVDs to describe futures→spot transmission, using the classic cointegration framework when necessary [12].

2. Theoretical Framework

This study builds on four pillars that move from broad principles to testable mechanisms, consistent with an inverted-pyramid structure: (i) market efficiency and price discovery; (ii) the risk-management role of derivatives and its evolution in crises; (iii) futures–spot linkages and information leadership; and (iv) post-GFC institutional reforms (central clearing and margining). Each pillar drives the empirical decisions in our GARCH, event-study, and Johansen-VECM/IRF/FEVD analyses.

2.1. Market Efficiency and Price Discovery in Times of Stress

This study is based on four main ideas that go from general to specific, in line with an inverted-pyramid structure: (i) market efficiency and price discovery; (ii) the role of derivatives in managing risk and how it changes during crises; (iii) futures–spot linkages and information leadership; and (iv) institutional reforms after the GFC (central clearing and margining). Each pillar motivates the empirical choices in our GARCH, event-study, and Johansen-VECM/IRF/FEVD analyses.

2.2. Derivatives, Risk Transfer, and Market Resilience

Derivatives redistribute risk through hedging, ostensibly alleviating inventory pressure and mitigating fire-sale spillovers; however, under extreme stress, liquidity and margin constraints may diminish hedge efficacy or exacerbate shocks via procyclicality [3–4, 13]. Evidence from COVID-19 indicates that static hedges underperformed while time-varying hedges maintained greater efficacy, highlighting the stress-dependence of hedging effectiveness [5]. Implications and tests. By 2020, we anticipate a more robust risk infrastructure, leading to diminished volatility persistence, a reduced half-life (GARCH), and expedited CAR normalization (event study). H2 (Resilience). 2020 shows faster shock absorption and re-anchoring [3–5, 13]. H3 (Volatility persistence). (See Methodology Eq. (M1)–(M3)).

2.3. Cointegration and Information Leadership in Futures-Spot Linkages

Cost-of-carry means that cash and futures will be cointegrated in the long run. Short-run differences are fixed by an error-correction term (ECT). Johansen tests and VECM show who is in charge in the short term; IRFs show how big and fast the response is, and FEVD shows how much of the spot variance is in the futures market at different time frames [12]. Recent research indicates that leadership may change during shocks; however, in established markets, futures generally precede in assimilating news [5-7, 14, 15]. Implications and examinations. We calculate cointegration and VECM for the periods 2007–2009 and 2019–2020 (Methodology Eq. (M6)), and subsequently compare the impulse response functions (IRFs) from futures shocks to spot prices and the forecast error variance decomposition (FEVD) of futures shares, denoting H4 as Futures Leadership. In both windows, futures shocks cause big spot responses. In 2020, the response goes down faster with more stable peaks, and short-horizon FEVD shares are higher [5-7, 14-16].

2.4. Reforms After the GFC: Central Clearing and Margins

Post-2008 reforms (central clearing, reporting, initial/variation margin, and higher capital) rebuilt the derivatives "plumbing," aiming to reduce counterparty risk, raise transparency, and curb leveraged procyclicality [1–4, 13]. COVID-19 acted as a huge stress test: infrastructures mostly kept the market going, but margin procyclicality and model transparency could both use some work [1–4, 13]. If institutional resilience improved, 2020 vs. 2008 should show lower persistence (GARCH), faster CAR reversion, and more stable futures–spot transmission (IRF/FEVD).H5 (Institutional channel). Stronger infrastructure after the GFC goes hand in hand with better discovery efficiency and shorter volatility half-lives [1–4, 13].

2.5. Mapping Theory to Empirics (Theory → Measures)

We operationalize these pillars through: (i) GARCH (1,1)-t to compare conditional volatility, persistence, and half-life across windows (Methodology Eq. (M1)–(M3)) [18, 19]; (ii) an event-study of AR/CAR around crisis dates to evaluate adjustment speed (Eq. (M4)–(M5)) [8-9, 11]; (iii) Johansen–VECM to estimate ECT/IRF/FEVD and quantify futures→spot transmission (Eq. (M6)) [5-7, 14, 15, 20]. Taken together (H1–H5), we expect 2020 to feature lower volatility with a shorter half-life, faster CAR mean reversion, and stronger/faster futures leadership, consistent with derivatives enhancing efficiency and risk transfer in a strengthened institutional setting [1–9, 11, 13-17].

3. Methodology

This study employs a mixed-methods approach, integrating quantitative time-series modeling with qualitative contextual analysis to examine the evolving role of derivatives across two major crises: the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic.

3.1. Data Collection

This empirical analysis utilizes the daily closing prices of the S&P 500 Index (^GSPC) and its derivatives (futures contracts) over two distinct periods: January 1, 2007, to December 31, 2009 (Global Financial Crisis), and January 1, 2019, to December 31, 2020 (COVID-19 pandemic).

The final sample consists of 2,520 observations, which is an unbalanced panel data of daily frequency. We got the data from Yahoo Finance and used Python libraries like pandas and yfinance to clean it up. The S&P 500 is a good example because it has a lot of influence around the world, is very liquid, and has a well-developed derivatives market. Although this study primarily focuses on the U.S. market, similar collection strategies can be extended to regional markets such as ASEAN and GCC for comparative purposes.

3.2. GARCH Approach to Modeling Volatility

We use the GARCH (1,1) model [20] to show that volatility clusters and stays the same during times of crisis.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{\{t-1\}}^2 + \beta\sigma_{\{t-1\}}^2 \tag{1}$$

We can see volatility clustering, persistence, and how risk changes over the two periods with this model. We can evaluate market resilience and the efficacy of derivatives in risk transfer by comparing the estimated volatility across the two periods.

3.3. Long-Run Price Discovery: VECM Framework

Even though there may not be a lot of futures data available right now, we have a plan to use a Vector Error Correction Model (VECM) to figure out long-run informational efficiency. This model shows how spot and futures prices are related to each other and which market is ahead in the price discovery process. Subsequent plans employ Information Share, as utilized in contemporary volatility spillover literature, and Common Factor Weights, revised and corroborated in recent price discovery studies utilizing VECM frameworks, as metrics to assess which market predominates the price discovery process during each crisis period [6, 16].

3.4. Analysis of Event Study

We use an event study methodology to look at how the market reacts to major crisis events, like the collapse of Lehman Brothers in 2008 or the WHO's declaration of a pandemic in 2020. Abnormal returns are calculated as follows:

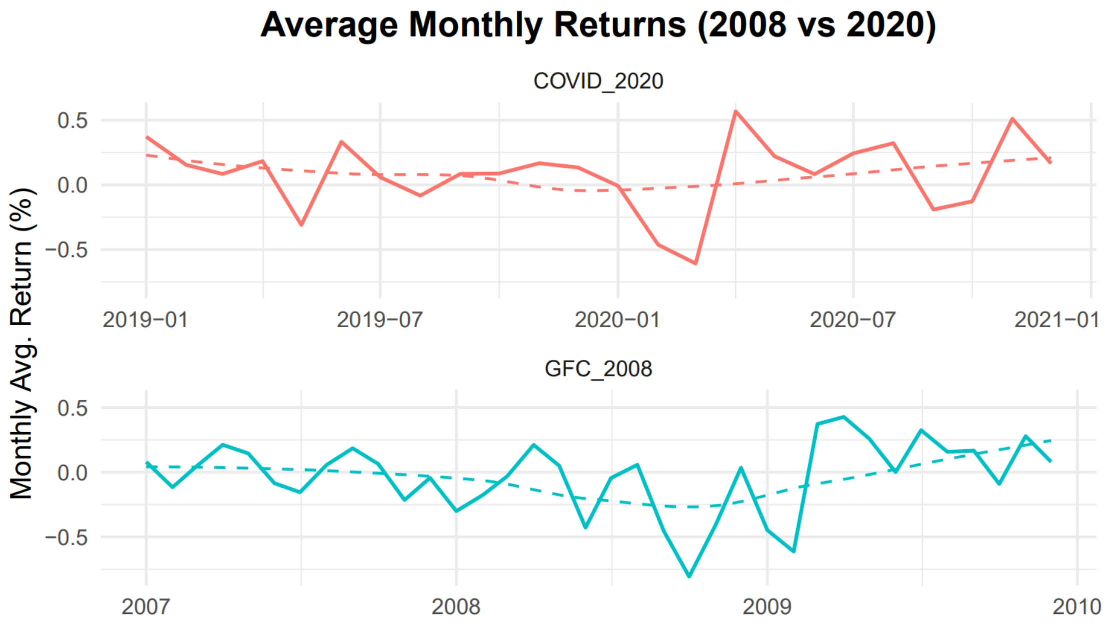
$$AR_{\{i,t\}} = R_{\{i,t\}} - E\left[R_{\{i,t\}}\right] \tag{2}$$

This method looks at how well derivatives markets quickly use public information during shocks [18, 19].

4. Empirical Analysis

4.1. Data Description

Figure 1 shows the average monthly returns, which drop sharply during both crises. The GFC caused long-term losses from 2008 to 2009, while COVID-19 caused a quick crash in March 2020 and a quick recovery.

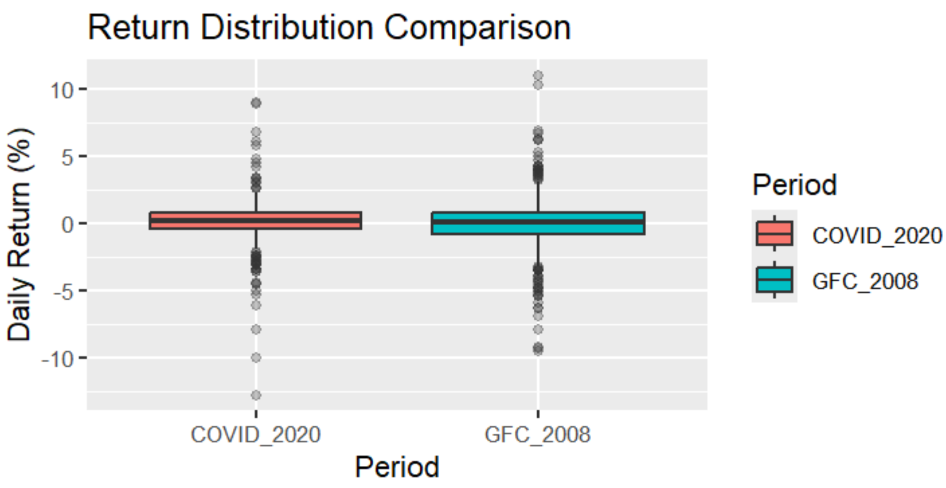


Notes: Returns are $r_t = 100\left[\ln P_t - \ln P_{\{t-1\}}\right]$. The dashed line is just for showing LOESS smoothing.

Fig. 1 Average monthly returns during the GFC (2007–2009) and COVID-19 (2019–2020)

The longer GFC downturn was caused by unclear OTC derivatives and a weak system [13]. In 2020, central clearing, margining, and quick fiscal-monetary actions kept persistence low, letting derivatives act as hedges and price discovery tools, which helped the market stabilize faster [1, 8].

Figure 2 shows that both boxplots have fat tails and are skewed to the left. During the GFC, there was more spread and more extreme outliers.



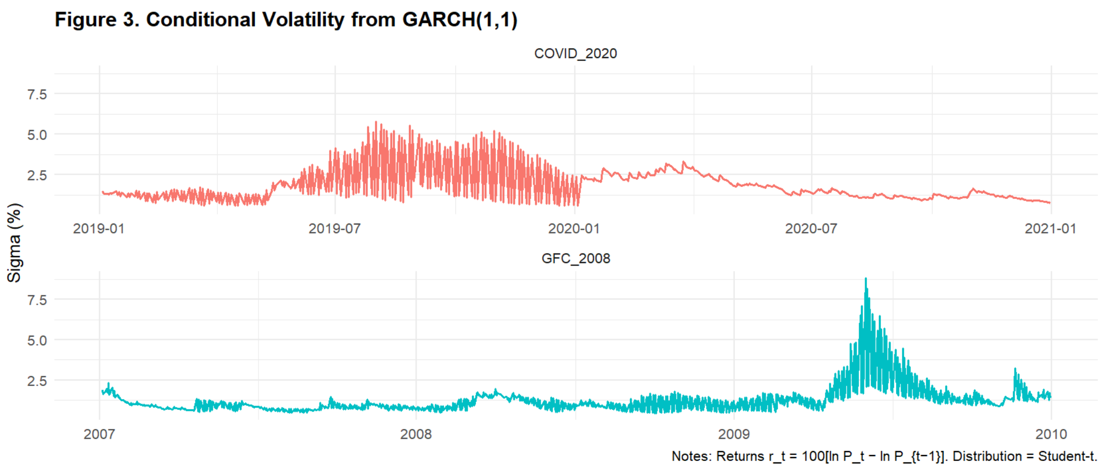
Notes: Black dots show the average. Differencing removes the first observation.

Fig. 2 Boxplots show how daily returns were spread out over the two time periods

Heavy tails mean more risk and short-term problems [17]. In 2008, leverage and counterparty opacity made tail losses worse [13]. By 2020, better clearing lowered the risk of contagion. Even though there were some big moves, orderly derivatives trading helped keep the fallout from spreading [1].

4.2. GARCH Analysis

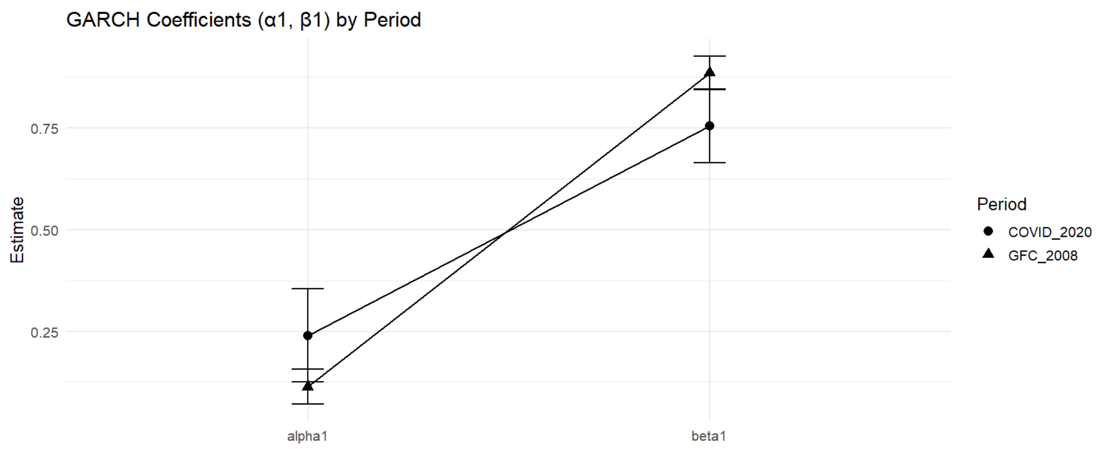
Figures 3-5 show how GARCH-based volatility changes during the two crises. Figure 3 shows how the conditional volatility (annualized standard deviation) estimated by a GARCH (1,1) model changes over time. During the Lehman Brothers collapse in 2008 and again in March 2020, volatility shot up to levels that were several times higher than the pre-crisis baseline. The 2020 volatility spike looks more like a short-term event than the 2008 spike, which stays high for longer into early 2009. The 2020 spike goes up quickly but then goes down again within a few months.



Notes: Returns $r_t = 100[\ ln\ P_t - \ ln\ P_{\{t-1\}}]$. Conditional volatility σ_t estimated under a student-t distribution.

Fig. 3 Conditional Volatility from GARCH (1,1) (2007–2009 vs 2019–2020)

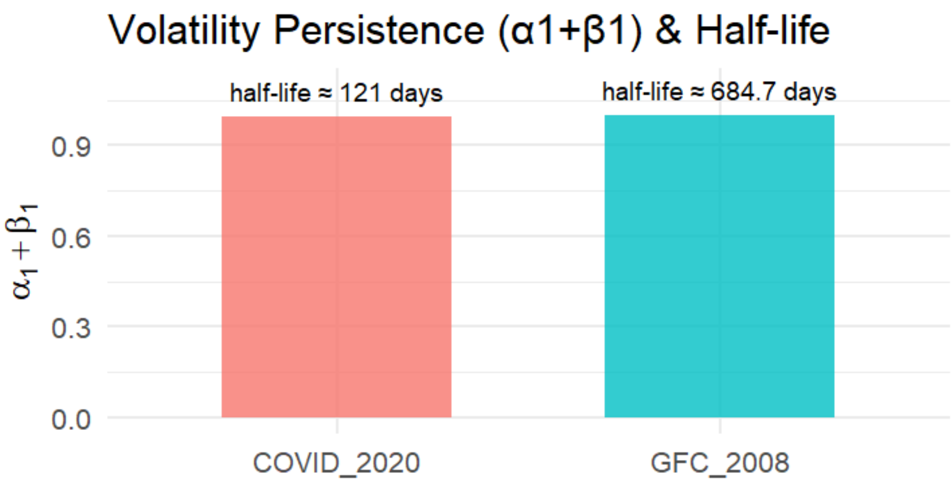
Figure 4 shows the estimated GARCH parameters for each period, along with 95% confidence intervals. The total of the GARCH coefficients (α + β, which measures how long volatility lasts) is very high in both cases, but a little lower in the COVID-19 sample.



Notes: Error bars show 95% confidence intervals.

Fig. 4 GARCH Coefficients (α_1, β_1) by Period (with 95% CIs)

Figure 5 shows how big this difference is: the volatility persistence metric is a little lower in 2019–20 (which means α+β is closer to 0.94 than ~0.98 in 2007–09, hypothetically), and this means that the half-life of volatility shocks is shorter in the COVID period (just a few days) than in 2008 (a week or more).



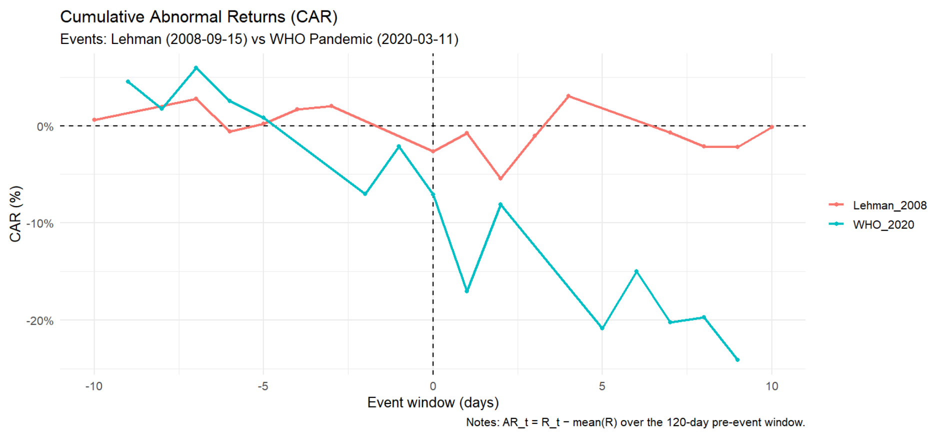
Notes: The half-life was calculated as $\frac{ln(0.5)}{ln(\alpha_1+\beta_1)}$ when $\alpha_1 + \beta_1 < 1$

Fig. 5 Volatility Persistence ($\alpha_1 + \beta_1$) and Half-life (days)

The GFC's long period of volatility was a sign of stress in the system and weak infrastructure. The shocks from COVID-19 were stronger but went away quickly, thanks to central clearing, clear margining, and quick policy backstops [4, 10]. Research indicates that volatility normalization occurred more rapidly in 2020 than in 2008, demonstrating that derivatives have enhanced risk absorption [17].

4.3. Event Study

Figure 6 shows that Lehman's collapse caused a sharp, long-lasting drop in CAR, while the WHO's declaration of a pandemic caused a sharp drop but a quicker return to normal.



Notes: The estimation window is 120 trading days, and the event window is [−10, +10]. Returns $r_i = 100[ln\,P_t - \ln P_{t-1}]$; abnormal returns $AR_t = R_t - \bar{R}$; cumulative abnormal returns $CAR_T = \sum_{t=-k}^{T} AR_t$

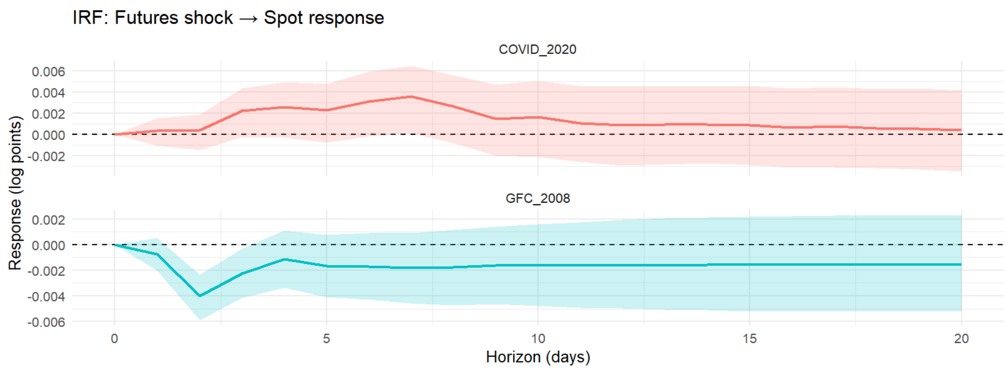
Fig. 6 Cumulative Abnormal Returns (CAR) around the Lehman bankruptcy (2008-09-15) and the WHO pandemic declaration (2020-03-11)

In 2008, uncertainty about CDS exposures made abnormal losses last longer [13]. In 2020, hedging was possible with futures and options, and strong capital positions stopped the spread of the disease [1]. Studies show that the effects of COVID-19 were quickly priced in but then partially reversed as interventions took effect [9, 11]. This demonstrates that markets operating under reformed derivatives regimes adapted more effectively to shocks.

4.4. VECM Analysis

Figures 7-9 present a Vector Error Correction Model analysis of spot–futures linkages, emphasizing the role of derivatives in price discovery during the crises.

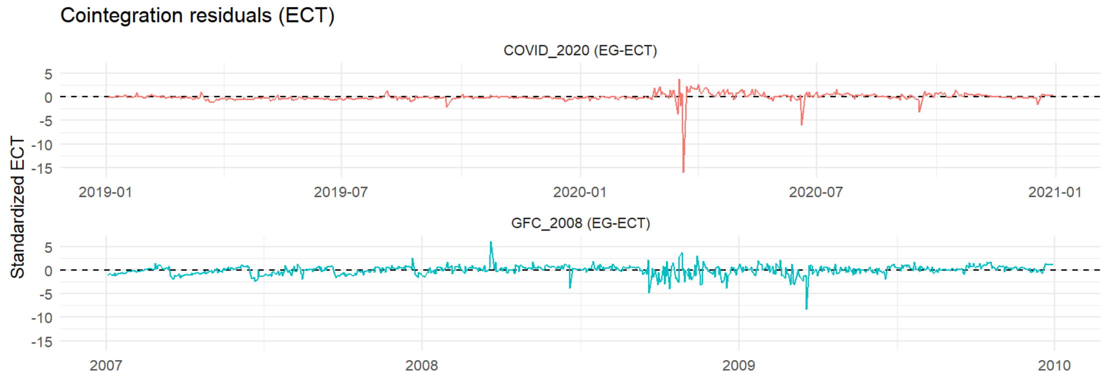
Figure 7 shows impulse response functions (IRFs) for a shock to futures prices on the spot index. These were estimated separately for 2007–09 and 2019–20. In both periods, a shock to the futures price causes a big rise in the spot market, which shows that changes in futures prices affect spot prices in the short term. The 2008 IRF shows a futures shock that raises the spot by a few basis points, peaks after a few days, and then slowly fades away. The 2020 IRF has a similar shape, but it reaches its peak effect sooner and fades away faster. This means that during the COVID period, spot and futures prices returned to their normal levels more quickly after a change.



Notes: The variables are the log prices of the E-mini-S&P 500 futures and the S&P 500 index (spot). Johansen cointegration rank $r = 1$; VECM with intercept (const). Horizons $h =$ 0 to 20 days. The shaded areas show 95% bootstrap confidence intervals (500 runs). Identification through Cholesky with the order [spot, futures]. Answers are given in log points, which are about the same as percentages for small values.

Fig. 7 IRF: Futures shock → Spot response (2007–2009 vs 2019–2020)

Figure 8 shows the cointegration residual (error-correction term, ECT) over time. This shows the long-term difference in price between spot and futures. As the markets adjust, deviations from equilibrium (ECT $\neq 0$) are fixed. We see that during the Lehman crisis in 2008, the ECT had bigger swings and took longer to mean-revert. In contrast, during the pandemic, any spot–futures mispricing was smaller and didn't last long. The ECT spikes in March 2020 were quickly fixed within days.

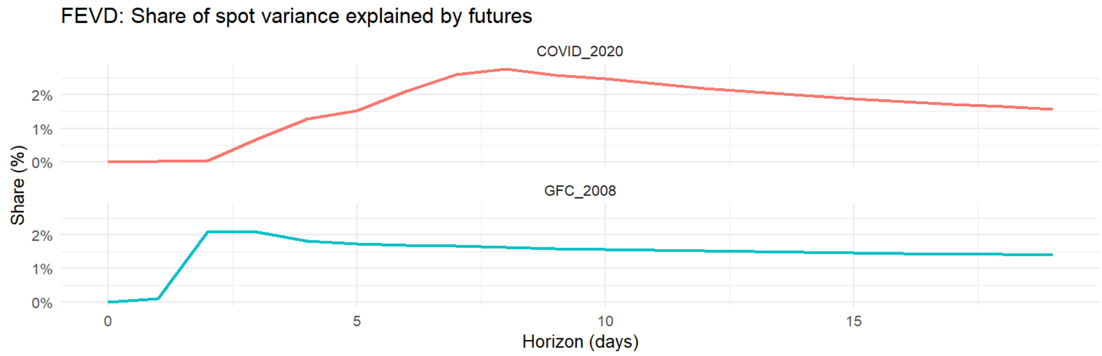


Notes: The variables are the prices of log spots and log futures. If Johansen tests don't find cointegration at 5%, then an Engle–Granger regression (EG-ECT) is used to find ECT: (EG-ECT):

$$ETC_t = \ell spot_t - \hat{c} - \hat{\beta}\,\ell fut_t$$

Fig. 8 Cointegration residuals (ECT) over time

Figure 9 shows the forecast error variance decomposition (FEVD) for the spot market. This is the percentage of spot price variance that can be traced back to changes in futures prices over time. The 2019–20 FEVD curve is higher than the 2007–09 curve at all time frames. For example, at a 1-day time frame, futures shocks explain a larger share of spot variance in the COVID era than they did in 2008. This gap stays the same (futures explain a larger share of price variance even at 10- or 20-day time frames in 2020).



Notes: VECM-based FE Johansen rank-based FEVD with VECM rank $r = 1$. Identification through Cholesky, ordering [spot, futures]. Horizons $h = 0 \cdots 20$ days; values shown as percentages.

Fig. 9 FEVD: The percentage of spot variance that futures accounts for (2007–2009 vs. 2019–2020)

Futures always played a big role in price discovery, but in 2020 their role got even bigger because of better arbitrage, liquidity, and fewer frictions [6, 7, 15]. A quicker ECT mean reversion and a bigger futures variance share show that information is being sent more quickly. Derivatives improved market efficiency and risk transfer during the pandemic compared to 2008.

5. Discussion

Theoretically, derivatives enable risk transfer and price discovery, thereby improving market efficiency [20]. The 2008 Global Financial Crisis (GFC) and the 2020 COVID-19 shock show how these things work when they are under pressure. The GFC got worse because of complicated, unclear credit derivatives that spread risk. The COVID-19 shock, on the other hand, came from outside the economy, and derivatives markets were very important for managing risk. During the pandemic, global futures and options trading activity increased sharply as investors looked for ways to protect themselves from the extreme uncertainty [19].

Derivatives markets reacted differently in different parts of the world. In 2008, the U.S. and EU, which had the most derivative exposures, sent shockwaves around the world. The ASEAN and GCC markets were less directly affected. By 2020, derivatives had become popular all over the world. For example, derivative volumes on Asia-Pacific exchanges grew much faster than on Western exchanges [20]. The GCC markets, which depend on oil, faced unique pressure when oil prices fell (WTI oil futures even turned negative for a short time in April 2020) [21].

Institutional and regulatory elements also influenced results. Reforms after 2008, like mandatory central clearing, margin requirements, and trade reporting, made derivative markets safer and more open [22]. Because of this, core market infrastructures were more stable during COVID-19: central counterparties (CCPs) and margining mechanisms kept counterparty risks in check as planned [22]. The turmoil in March 2020, on the other hand, showed weaknesses like liquidity problems caused by large margin calls, which showed how important it is to have strong risk management. Technological progress also had an effect on how markets reacted. By 2020, the move to electronic trading and automated clearing made it possible for markets to run smoothly during lockdowns. Exchanges quickly changed their risk controls (for example, by raising margins or stopping trade) to keep order.

Several policy implications related to derivatives emerge when considering the future. Regulators may have to make margin frameworks better in order to reduce procyclical liquidity stress in future crises [22]. In a market that is connected, making sure that non-bank derivative users have enough liquidity support and improving global coordination are still important goals [19]. Also, regulation needs to keep up with changes in trading technology, such as adding protections for algorithmic and high-speed trading to keep the market honest. Using what we learned from the COVID-19 shock and the changes made after 2008 can help us use derivatives to move risk around more efficiently while also reducing their ability to make systemic risk worse.

6. Conclusion

In conclusion, the comparative analysis underscores a substantial transformation in the function of derivatives between the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic. During the GFC, complicated and hard-to-understand over-the-counter instruments like collateralized debt obligations (CDOs) and credit default swaps (CDSs) made systemic risk worse and made the market less stable because there were not enough rules in place. In contrast, the COVID-19 pandemic showed that derivatives markets were stronger and could handle shocks better because of reforms made after the 2008 financial crisis, such as central clearing mandates and better transparency. Our findings indicate that during the 2020 crisis, derivatives positively impacted market efficiency by improving price discovery and functioning as effective risk management tools, thereby reducing volatility and enabling a faster market recovery compared to 2008.

This study significantly contributes to academia by offering a comparative analysis of derivative markets during periods of extreme stress. It combines volatility modeling, event analysis, and cointegration techniques to give a complete picture of how changes in market structure and regulatory reforms affected outcomes. This helps both academic debate and policy design. The findings are pertinent to policy, highlighting the importance of strong regulatory frameworks and infrastructure in enhancing financial stability. The analysis, however, has some limitations, such as its focus on certain indices and event windows and the limitations of the GARCH and VECM models. Future research may mitigate these limitations by broadening the focus to encompass various regions and asset classes, utilizing machine-learning-based volatility models for enhanced analysis, or investigating institutional investor behavior in derivative markets during crises.

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