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Unveiling COVID-19's impact on Financial Stability: A Comprehensive Study of Price Dynamics and Investor Behavior in G7 Markets

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ABSTRACT

The paper delves into the impact of the COVID-19 pandemic on foreign stock markets across several developed nations. It seeks to empirically validate the presence of contagion by employing an adjusted correlation test spanning 7 developing stock markets from February 01, 1992, to April 31, 2021. Employing the FIEGARCH (1.1), DCC-MGARCH (1,1), and Switching-Markov analysis models, the research uncovers compelling evidence of the pandemic's influence on most developed countries during the COVID-19 period. Notably, these markets appear significantly susceptible to the adverse effects brought about by the pandemic. Recognizing the substantial ramifications of financial downturns on monetary policy, risk assessment, asset valuation, and portfolio distribution, the findings hold paramount significance for policymakers, investors, and portfolio managers. This empirical investigation offers insights that could profoundly impact decision-making strategies in these domains, shedding light on crucial aspects for informed policy adjustments, investment decisions, and portfolio allocations amidst such critical market fluctuations.

Keywords: DCC-MGARCH, FIEGARCH, Switching-Markov Analysis, Investment Decisions, COVID-19 Pandemic, G7 Markets
JEL Classifications: G11, G41

1. INTRODUCTION

This paper presents a meticulous investigation into the profound impact of the COVID-19 pandemic on stock market behavior and investor conduct. Our analysis centers on the correlation between stock market returns and global market returns in major world economies, both before and after the pandemic outbreak.

The emergence of the COVID-19 pandemic has been universally acknowledged as a catastrophic event with unprecedented socio-economic consequences. The WHO Director-General's description of the virus as unparalleled, with unique features, underscores the gravity of the situation, thrusting us into uncharted territory.

Research by Baker et al. (2020); Huynh et al. (2021); Mishkin and White (2020); Salisu and Akanni (2020), among others, emphasizes the distinct nature of this pandemic. Analysts have warned about the multifaceted threats posed by the fallout of the coronavirus pandemic, encompassing challenges of demand, supply, and financial shocks, all of which have been unprecedented.

As the global spread of COVID-19 continues, policymakers and market participants worldwide are deeply concerned about its far-reaching economic implications. Notably, stock market activities have become a focal point in popular financial media and diverse policy discussions.

A growing body of recent research indicates that the escalating spread of COVID-19 has triggered amplified volatility and diminished returns in global stock markets. This consensus underscores the adverse effects of the pandemic on stock market sentiment and the consequential global financial implications.

For instance, Capelle-Blancard and Desroziers (2020) noted that, "Since the beginning of the crisis, stock prices seemed erratic. Initially disregarding the pandemic, panic ensued when Europe emerged as its epicenter. Currently, they exhibit behavior as if the containment of half the world's population will have no economic impact after all." The relationship between stock performance has been primarily driven by oscillations between greed and fear. If speculative bubbles, whether positive or negative, persist, the objective relationship between fundamentals and stock valuations may become suboptimal.

Our empirical analysis is guided by two key research inquiries. Firstly, we aim to discern the correlation between investor sentiment, as manifested in the Global Investment Return (TIR), and stock market behavior, measured by stock market returns, both before and after the COVID-19 period. Secondly, our study endeavors to explore the influence of COVID-19-induced uncertainty on global stock market behavior, accounting for the impact of investor sentiment (TIR).

The first research question seeks to unravel the potential relationship between investor behavior and stock market performance, notably before and after the COVID-19 era. Understanding the dynamics between pandemic-induced uncertainty and these variables is crucial. The COVID-19-induced fear among investors appears notably heightened in the equity segment, reminiscent of the market crashes in 1987 and the global financial crisis of 2008-2009.

Our hypothesis revolves around the notion that increased pandemic-induced uncertainty likely steered sentiments toward pessimism among investors. Recent studies suggest a shift in investors' focus towards information searches to resolve uncertainties concerning the COVID-19 crisis rather than fundamental data.

The second crucial aspect pertains to the lack of adequate empirical evidence on the COVID-19 impact on overall stock market behavior, encompassing returns, volatility, and market liquidity. Existing research primarily focuses on stock returns and volatility while largely disregarding market liquidity implications.

Our approach initially examines the correlation between Global Investment Return and Stock Market Return during the COVID-19 pandemic. Subsequently, it assesses the independent effects of pandemic uncertainty on investment return and stock market return.

This study focuses on G7 countries and a comprehensive measure of the global market. Empirical design incorporates the Dynamic Conditional Correlation (DCC-MGARCH), Fractionally Integrated EGARCH (FIEGARCH), and the Switching Markov-Model to capture COVID-19's effects on the stock market within G7 countries.

This meticulous empirical approach allows for a comprehensive examination of the pandemic's impact on sentiment and stock market behavior, fostering a deeper understanding of their potential interrelation. We examined the relationship between these variables across two distinct phases, assessing the pandemic's effects on stock market and global investment returns while isolating the influence of common dependence between exogenous market sentiment and investor sentiment using advanced analytical techniques.

Our findings reveal a positive correlation between Global Investment Return and Stock Market Return before the onset of COVID-19. However, this correlation diminishes afterward, underscoring the pandemic's effect on market and investor behavior. The results suggest a shift towards pessimistic investor sentiment following the spread of the pandemic.

In conclusion, this paper contributes substantially to the burgeoning research on the COVID-19 impact on market behavior, offering preliminary evidence on pandemic-induced uncertainty and stock market returns. It uniquely explores the impact of the pandemic on stock market returns while delving into the limited examination of pandemic-information search's effect on investor sentiment and subsequent stock market activity. Our empirical approach introduces novelty by employing DCC-MGARCH, FIEGARCH, and Switching-Markov analyses.

The subsequent sections of this paper are structured as follows: The first section reviews theoretical and empirical literature, the second presents the methodology, data, and variables, the third interprets the empirical results, and finally, the fourth section concludes the paper.

2. LITERATURE REVIEW

The global outbreak of the coronavirus (COVID-19) in early 2020 has inflicted profound economic repercussions on the global economy and financial markets worldwide (Contessi & De Pace, 2021) According to the OECD Economic Outlook, the pandemic has led to significant disruptions in economic activity, with widespread implications for employment, trade, and investment (OECD, 2020). Similarly, the World Bank's Global Economic Prospects report highlights the unprecedented challenges faced by economies across the globe, emphasizing the need for coordinated policy responses to mitigate the adverse effects of the crisis (World Bank, 2020). As aptly articulated by Shaikh and Huynh (2021), COVID-19 stands as an uncontained epidemic, poised to unfold its impact further. The disruptive effect of this pandemic shock and the subsequent international health crisis on financial markets has been extensively documented in recent scholarly works. Despite the notable market crash between January and May 2020, the asset price sell-off wasn't entirely attributable to this period. Baker et al. (2020) underscore the unparalleled volatility in the U.S. stock market during the first quarter of 2020, surpassing historical benchmarks such as the Great Depression, the Great Financial Crisis, and the Spanish Flu pandemic.

This section provides a concise review of recent literature exploring COVID-19's implications on the market. The unparalleled effect of the COVID-19 pandemic on the global financial system is characterized by a decline in liquidity, heightened volatility, diminished returns, and cross-market or cross-asset economic shock propagation (Al Guindy, 2021; Baker et al., 2020; Contessi and De Pace, 2021; Huynh et al., 2021; Paule-Vianez et al., 2021; Rubbaniy et al., 2021; Shaikh and Huynh, 2021; Xu et al., 2021; Zaremba et al., 2020; Zhang et al., 2020, among others). Despite a focused empirical inquiry into COVID-19's impact on stock market behavior, diverse methodologies have been employed. These range from establishing a Global COVID-19 fear index based on daily death and confirmed cases, feverish sentiment, pandemic anxiety indexes, the COVID-19+ positive sentiment index, the Equity Market Volatility Infectious Disease Tracker (EMV), pandemic intensity information searches, coronavirus-related news analyses, COVID-19 Twitter intensity, to investigating investor attention or pandemic attention through GSVI and exploring investor attention combined with pandemic-induced fear or uncertainty.

In contemporary literature, pandemic-induced fear sentiment, pandemic uncertainty, and pandemic attention are used interchangeably, measured through analogous internet search volume intensity methods. Cumulatively, a substantial body of recent literature (Al-Awadhi et al., 2020; Baker et al., 2020; Costola et al., 2021; Chundakkadan and Nedumparambil, 2021; Shaikh and Huynh, 2021; Smales, 2021; Szczygielski et al., 2022; Yu et al., 2021; Vasileiou, 2021; Zhang et al., 2021, among others) affirms the significant negative (positive) effect of the COVID-19 pandemic on stock returns (market volatility).

However, our comprehension of the impact of COVID-19-related uncertainty or fear on the stock market is encumbered by three potential issues. Firstly, prevailing sentiment effects in the market have been overlooked as existing literature largely focuses on pandemic search intensity or fear index to gauge investor sentiment. For example, Sun et al. (2021) and Zhang et al. (2021) highlight the detrimental influence of pandemic-induced fear on economic and investor sentiment. Furthermore, segments of investor attention directed towards COVID-19 exhibit an asymmetric impact on the equity market, where excessive attention tends to introduce noise (Wang et al., 2021). Building on the arguments of Sun et al. (2021) and Zhang et al. (2021), one might argue that pandemic-induced fear amplifies the prevailing pessimistic sentiment in the market. However, this fear's deterrent effect amid the existing pessimism, attributed to the market crash, could be significantly negative.

Secondly, the theoretical framework underpinning pandemic information searches as a measure of fear or uncertainty mirrors sentiment measures based on investor attention (e.g., FEARS index, Da et al., 2015). Studies by Da et al. (2015), Burggraf et al. (2021), and Goel and Dash (2021) suggest that investor sentiment can be directly gauged through internet search volume information, as evidenced by the Financial and Economics Attitudes Revealed by Search (FEARS) index. Smales (2021) suggests that rather than seeking information on potential stocks, retail investors explore information to alleviate household uncertainties during the COVID-19 crisis. Behavioral finance literature posits two competing theories on investor attention pricing in financial markets: limited attention bias (Kahneman, 1973) and the price pressure hypothesis (Barber and Odean, 2008). Given the vast investment universe and cognitive constraints, investors selectively focus on limited information. This selective attention results in temporary price pressure (Da et al., 2015). Prior literature has emphasized that investors' emotions explain market fluctuations and dictate their asset allocation strategies (Al Guingy, 2021; Garcia, 2013; Sun et al., 2021; Tetlock, 2007; Wang et al., 2021).

Niculescu et al. (2023) observed a discernible impact of COVID-19 on the decision-making processes of US retail investors. They reported a noteworthy 4.7% average increase in investments throughout 2020, with individuals directly affected by the pandemic showing a substantial 12% surge in their investments. Their findings underscored the application of psychological theories, emphasizing the diversification of investment choices during periods of crises.

Zhu et al. (2023) delved into the influence of social media sentiment on US stock market returns preceding, during, and following the COVID-19 outbreak. Their analysis, based on a dataset comprising 24 million tweets, revealed the diminished reliability of sentiment during the peak of the pandemic and the subsequent recovery phases. They emphasized the crucial role of machine learning in identifying pivotal topics for investors amidst disruptive periods.

Zhang et al. (2023) introduced Australia's inaugural sentiment index, highlighting its correlation with global and US trends. Their findings unveiled how sentiment amplifies short-term anomaly returns within the Australian stock market, while exerting less influence on long-term strategies.

Naeem et al. (2023) conducted an in-depth examination of COVID-19's impact on US Exchange-Traded Funds (ETFs). Their study underscored interconnections among these funds during the pandemic, emphasizing the risk role of USO, identifying distinct volatility phases, and acknowledging the influence of psychological indicators on market fluctuations. Their recommendations stressed the importance of diversification, cautious policy adjustments, and addressing concerns regarding stability, investor protection, and regulatory measures, shedding light on ETF behaviors and market dynamics during periods of extreme volatility.

Costola et al. (2023) scrutinized the impact of COVID-19 news on early financial markets, analyzing over 200,000 articles from MarketWatch.com, NYTimes.com, and Reuters.com between January and June 2020. Their findings highlighted a significant correlation between news sentiment and the S&P 500 market, showcasing varied effects stemming from different news categories on NYTimes.com.

Almeida and Gonçalves (2023) meticulously examined 166 top-ranked journal papers concerning cryptocurrency investor behavior. They unearthed trends such as herding behavior, the influence of social dynamics, and market-driven irrationality, while exploring how uncertainty and sociodemographic factors influence crypto investors. Their insights serve as a guide for future research and regulatory measures aimed at safeguarding investors in the cryptocurrency realm.

Bossman et al. (2023) investigated interactions among EU sectoral stocks, oil, volatility, geopolitical risk, and market sentiment during geopolitical unrest from January 2020 to October 2022. Their findings revealed asymmetric connections, suggesting the potential of EU stocks to hedge against geopolitical risks during bearish periods. However, they noted a lack of consistent hedging capability in oil. The study highlighted volatility and market sentiment as potential hedging tools for EU stocks, contributing to refined market regulation and portfolio management strategies.

Luo et al. (2023) analyzed emotions expressed on social media platforms during crises like COVID-19. Their research unveiled that negative sentiment amplifies information volume, depth, and influence compared to positive sentiment. The aim of their work was to provide insights into managing sentiment and devising effective information strategies during emergencies.

Catelli et al. (2023) employed NLP and Sentiment Analysis on 353,217 Italian tweets spanning from Jan 2021 to Feb 2022 to explore sentiments surrounding COVID-19 vaccinations. They noted an overall negative sentiment, particularly among Common users, highlighting varying attitudes during specific events, such as post-vaccination deaths, within this timeframe.

Amar et al. (2023) employed TYDL causality testing to investigate market interdependence across calm and stress periods. Their study proposed a portfolio management approach focused on minimizing causal intensity. Notably, they observed heightened interdependence and altered causal structures during significant events like COVID-19 and the Russian-Ukrainian conflict. These periods experienced varied portfolio performance, including negative ratios amidst crises, underlining the need for adaptable strategies in dynamic markets.

Kyriazis et al. (2023) delved into the influence of COVID-19-era Twitter sentiment on cryptocurrencies. Using novel Twitter-based metrics, they assessed sentiment's impact on major cryptocurrencies, unveiling diverse effects on returns and volatility. Particularly intriguing was the observation that lower-value cryptocurrencies exhibited less susceptibility to extreme sentiment but remained profitable due to investors' cohesive behavior.

Balcılar et al. (2023) investigated the increasing interconnection among 26 regional house prices in Türkiye during economic instability from 2010 to 2022, notably post-crisis, with Istanbul playing a pivotal role. This amplified connectivity aligned with economic volatility, encompassing currency devaluation and escalated borrowing costs. Furthermore, they uncovered a positive correlation between consumer sentiment and heightened connectivity post-crisis, revealing nuanced relationships within a volatile economic landscape.

Klöckner et al. (2023) explored diverse organizational responses to COVID-19, categorizing them into five distinct types. Their observations highlighted variations in response scope, collaboration, and strategic focus, particularly on potential or risk mitigation. Noteworthy was the positive stock market reception towards financial, digitalization, and risk management strategies, contributing valuable insights to the literature on effective crisis management and response strategies amid the pandemic.

Apergis et al. (2023) delved into COVID-19's impact on the CBOE Volatility Index (VIX) in the US financial market. Their categorization of VIX and COVID-19 cases into high and low conditions unveiled that escalating death rates heightened market fear. They emphasized how high COVID-19 cases influenced volatility during periods of uncertainty, contrasting with low cases that exhibited no discernible impact, underscoring the relevance of US policies in addressing the financial market ramifications of the pandemic.

Papadamou et al. (2023) scrutinized the influence of COVID-19-related Google searches on equity implied volatility. During the initial phase of the pandemic, intensified searches accelerated the flow of financial market information, consequently increasing implied volatility. Notably, in Europe, heightened COVID-related searches amplified the VIX's impact, while positive stock returns mitigated such searches, impacting market risk perception.

Hoang et al. (2023) delved into insider reactions to the early global COVID-19 cases, noting a surge in insider selling post-outbreak, especially in countries with weaker information systems and legal protections. They highlighted the impact of cultural disparities and government responses on insider behavior during health crises, emphasizing the pivotal role of transparent business systems in rebuilding investor trust.

Liu et al. (2023) devised an Investor Confidence Index (ICI) using social network data, revealing a cyclic influence on sentiment across a 5-day trading and 2-day holiday cycle. Their findings unveiled weekday market fluctuations and weekend stability, known as the holiday effect, elucidating the tie between investor sentiment and stock market dynamics.

Dash and Maitra (2022) correlated Google search data on pandemic uncertainty with stock market movements, noting that rising uncertainty aligned with negative investor sentiment during early COVID-19 times. They highlighted how this uncertainty corresponded with global stock market shifts, potentially leading to heightened volatility and illiquidity, prompting policymakers to prioritize financial stability measures.

Yuan et al. (2022) conducted an extensive analysis of COVID-19's financial contagion across 26 global stock markets, leveraging Google search data to scrutinize investor behavior's influence. Their findings underscored the substantial impact of investor actions on contagion complexity, elucidating diverse effects across market conditions, development levels, regions, and contagion directions.

Xu et al. (2022) delved into the multifaceted sentiments surrounding COVID-19 vaccines on Twitter, utilizing the VADER model. Their study revealed contrasting attitudes between China and other nations, shaped by fluctuating case numbers and public concerns. Furthermore, they explored biotechnology's role in shaping global perspectives, contributing insights to cultural identity and international relations theories.

Banerjee et al. (2022) investigated the interplay between COVID-19 news sentiment and cryptocurrency returns using transfer entropy analysis. They unveiled a unidirectional relationship from news sentiment to cryptocurrency performance, offering valuable insights for policymakers and market participants navigating the complexities of the cryptocurrency market during challenging periods.

Aharon et al. (2022) explored the nexus between media sentiment regarding COVID-19 and sovereign yield curve components across G-7 countries. They identified the US yield curve and media sentiment as significant risk transmitters, with Japan emerging as the primary receiver. Among European nations, France stood out as a noteworthy transmitter, offering policymakers insights into preparing for market crises.

Buchheim et al. (2022) investigated the impact of sentiments surrounding COVID-19 shutdowns on German firms. They noted that sentiments, rather than fundamentals, significantly influenced anticipated shutdown durations and overall outlooks for firms. Pessimistic firms, anticipating prolonged shutdowns, were more inclined toward substantial actions like layoffs or halting investments, contrasting with softer measures like remote work.

Ardiyono (2022) scrutinized the impact of the Covid-19 pandemic on ASEAN-5 firms, noting revenue declines leading to approximately a 1% reduction in employment for every 10% loss. The study unveiled varying labour adjustments based on pandemic severity and structural differences among firms.

Sun et al. (2021) examined the influence of Coronavirus-related news (CRNs) and economic announcements (ERAs) on medical stock portfolios across China, Hong Kong, Korea, Japan, and the US. Their findings indicated that both CRNs and ERAs positively impacted these markets' medical portfolios, indicating an optimistic sentiment toward the medical industry amidst the pandemic.

John and Li (2021) investigated the impact of COVID-19 news on stock and option markets, utilizing Google data as sentiment proxies across five news categories. Their findings highlighted the augmentation of jump volatility by COVID and Market sentiments, while Government relief efforts mitigated it. Banking and Lockdown sentiments exhibited delayed reductions in jump volatility within the S&P 500.

3. METHODOLOGY

In this study, we define contagion according to Forbes and Rigobon (2002) as a substantial surge in inter-market connections resulting from a shock in a specific country or a cluster of countries.

For our empirical analysis, we emulate the methodology set forth by Chiang et al. (2007). These scholars scrutinized the Asian crisis using a DCC-Garch (1,1) model and performed tests centered on adjusted correlation coefficients.

3.1. Dynamic Conditional Correlations' Asymmetric Model (DCC-GARCH [1.1]) Engle (2002)

We utilize Engle's DCC-MGARCH model (2002) to investigate the impact of the COVID-19 pandemic on both Total Investment Returns and Stock Market Returns. One key advantage of this model lies in its ability to detect changes in conditional correlations over time, enabling the identification of dynamic investor behavior in response to news and market innovations.

Moreover, the dynamic conditional correlations measured by this model are well-suited to explore potential contagion effects, particularly herding behavior, in emerging financial markets during crisis periods. This has been evidenced in prior studies such as Corsetti et al. (2005), Chiang et al. (2007), and Syllignakis and Kouretas (2011).

Another strength of the DCC-MGARCH model is its ability to estimate correlation coefficients of standardized residuals, directly accounting for heteroscedasticity (Chiang et al., 2007). This method adjusts for volatility, ensuring that time-varying correlations (DCC) remain unbiased by volatility fluctuations. Unlike the volatility-adjusted cross-market correlations found in Forbes and Rigobon (2002), the DCC-GARCH model continuously adapts correlation measurements to changing volatility, offering a more robust measure of correlation (Cho and Parhizgari, 2008).

The estimation of Engle's DCC-GARCH model involves two primary steps: Firstly, the estimation of the multivariate GARCH model; secondly, the estimation of conditional correlations that evolve over time. The multivariate DCC-GARCH model is defined as follows:

$$X^t = \mu_t + H_t^{1/2}\varepsilon_t \quad (1)$$

$$H_t = D_t R_t D_t \quad (2)$$

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \quad (3)$$

$$D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \sqrt{h_{NN,t}}\right) \quad (4)$$

Where $X_t = (X_{1t}, X_{2t}, \ldots X_{Nt})$ is the vector of the past observations, H_t is the multivariate conditional variance, $\mu_t = (\mu_{1t}, \mu_{2t}, \ldots \mu_{Nt})$ is the vector of conditional returns, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots \varepsilon_{Nt})$ is the vector of the standardized residuals, R_t is a N×N symmetric dynamic correlations matrix and D_t is a diagonal matrix of conditional standard deviations for return series, obtained from estimating a multivariate GARCH model with $\sqrt{h_{ii,t}}$, on the ith diagonal, i=1, 2.,... N.

The DCC specification is defined as follows:

$$R_t = Q^{-1/t} * Q * Q^{-1/t} \quad (5)$$

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1} \quad (6)$$

Where Q_t is a positive matrix, it defines the structure and dynamic $Q*\frac{1}{t}$ resizes the items in Q_t to ensure that $|qij| \leq 1$. $Q*\frac{1}{t}$ is the inverse matrix of the matrix Q_t. Q_t Is the conditional variance of standard errors.

And α and β are two scalar $\lambda_2 = \alpha$ And $\lambda_2 = \beta$ are parameters that govern the dynamics of conditional quasicorrelations.

λ_2 And λ_2 are nonnegative and satisfy $0 \leq \lambda 1 + \lambda 2 < 1$.

Therefore, for a pair of markets i and j their conditional correlation at time t can be defined as:

Where *qij* is the element on the ith line and jth column of the matrix Q_t. The parameters are estimated using quasi-maximum likelihood method (QMLE) introduced by Bollerslev et al. (1992).

**Contagion effect test with dynamic conditional correlation coefficient:

We use t-statistics to test the consistency of dynamic correlation coefficients between foreign Stock markets returns and Total investment return in the pre-Covid-19 and Covid-19 periods to judge the pandemic effect.

Hypothesis test:

We define null and alternative hypotheses as:

$$H_0 = \mu_\rho^{Covid-19} = \mu_\rho^{pre-Covid-19}, H_1 = \mu_\rho^{Covid-19} \neq \mu_\rho^{pre-Covid-19}$$

Where $\mu_\rho^{\text{Covid-19}}$ and $\mu_\rho^{\text{pre-Covid-19}}$ are the conditional correlation coefficient means of population in the pre-Covid-19 and Covid-19 periods.

If the sample sizes are $n^{\text{Covid-19}}$ and $n^{\text{pre-Covid-19}}$ the population variances $\sigma^{2\text{Covid-19}}$ and $\sigma^{2\text{pre-Covid-19}}$ are different. If the means of dynamic correlation coefficients estimated by DCC are $\rho_{ij}^{\text{Covid-19}}$ and $\rho_{ij}^{\text{pre-Covid-19}}$, and the variances are $S^{2\text{Covid-19}}$ and $S^{2\text{pre-Covid-19}}$, the t-statistic is calculated as:

$$t = \frac{\left(\rho_{ij}{}^{Covid-19} - \rho_{ij}{}^{pre-Covid-19}\right) - (\mu_\rho^{Covid-19} - \mu_\rho^{pre-Covid-19})}{\sqrt{\frac{S^{2Covid-19} + S^{2\,pre-Covid-19}}{n^{Covid-19} + n^{pre-Covid-19}}}} \quad (7)$$

If t-statistics is significantly greater than the critical value, H_0 is rejected supporting the existence of pandemic effect.

3.2. Correlation Test: Measurement of Pure Pandemic Effect

The correlation coefficient serves as a statistical measure indicating the relationship between two variables. It is accepted that two variables are correlated when they exhibit similar patterns of progression (Lescaroux and Mignon, 2008).

Consider two stochastic variables, denoted as ri and rj, representing returns in two distinct markets. To examine the relationship between these returns, we will employ the following straightforward linear model:

$$Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it} \quad (8)$$

$$E(\varepsilon_{it}) = 0, E(\varepsilon_{it}^2) < \infty, E(X_{j,t}, \varepsilon_{it}) = 0$$

In this context, Forbes and Rigobon (2002) propose an adjusted correlation coefficient defined as follows:

$$\frac{\rho}{\sqrt{1 + \delta[1 - (\rho)^2]}} \quad (9)$$

And $\delta = \frac{v^c(X_t)}{v^t(X_t)} = 1$; where "c" and "t" respectively denote the Covid-19 and the stability periods. Indeed, (δ) denotes the relative increase within V (xt) between the stable and the Covid-19 periods. Hence, in order to statistically test the increase of an adjusted correlation coefficient, we use the following two hypotheses:

$$\begin{cases} H_0 = \rho_1 = \rho_2 \\ H_1 = \rho_1 \neq \rho_2 \end{cases}$$

With
ρ_1: The Covid-19 period correlation coefficient.
ρ_2: The stable period correlation coefficient.

Still, to test the two hypotheses, we will use a Student test where the test statistics is defined as follows:

$$t = (\rho_1 - \rho_2)\sqrt{\frac{n_1 + n_2 - 4}{1 - (\rho_1 - \rho_2)^2}} \quad (10)$$

Where follows a Student (t) with (n1 + n2 – 4) degrees of freedom. Then, accepting H1 is about highlighting Correlation between two Variables which are the Total investment return and Stock market return, whereas the null hypothesis H_0 implies that the increase in the correlation coefficient reflects solely interdependence between the two variables.

3.3. Fractionally Integrated EGARCH

We estimate the Fractionally Integrated Exponential GARCH (FIEGARCH) model, introduced by Baillie et al. (1996), designed to capture long-memory innovations in EGARCH processes.

Before proceeding, it is important to note that although FIEGARCH models can be specified for arbitrary ARCH and GARCH orders, researchers often limit both to a single lag. Currently, our support is limited to these FIEGARCH (1,1) models.

The FIEGARCH model builds upon the EGARCH model by incorporating a long-run lag polynomial. The log conditional variance for this modified form of the EGARCH model is expressed as follows:

$$Log\left(\sigma_t^2\right) = \omega + \frac{\alpha(L)}{\beta(L)} \pi(L) g(Z_{t-1}) \quad (11)$$

The corresponding FIEGARCH (1, 1) is given by:

$$Log\left(\sigma_t^2\right) = (1-\beta)\omega + g\left(Z_{t-1}\right) + \sum_{k=1}^{\infty} \pi_k g\left(Z_{t-1-k}\right)$$

$$-\alpha g\left(Z_{t-2}\right) - \alpha \sum_{k=1}^{\infty} \pi_k g\left(Z_{t-2-k}\right) + \beta \log\left(\sigma_{t-1}^2\right) \quad (12)$$

Substituting using $Z_t = \epsilon_t/\sigma_t$ yields.

3.4. The Markov Switching Model

The Markov switching regression model broadens the simple exogenous probability framework by introducing a first-order Markov process for the regime probabilities. This model is part of the regime-switching models and assumes that unobserved states are dictated by an underlying stochastic process known as a Markov chain.

The Markov process involves a latent state denoted as S_t at time t, unseen by econometricians, taking values in k∈ {1,2,…,K}, where K signifies the total number of states. This latent variable S_t signifies the current system's state at time t, commonly referred to as a state or regime indicator.

This state indicator's dynamics are governed by a Markov process where the probability distribution of S_t given the entire path {S_{t-1}, S_{t-2},…, S_1} relies solely on the most recent state S_{t-1}. The transition probability, represented as P_r (S_t=j|S_{t-1}=i) or *Pij*, indicates the probability of transitioning from state i to state j in the next period.

These transition probabilities are organized in a K×K matrix called the transition matrix, P = [P_{ij}] K×K, where each row's elements sum to one. The diagonal elements of this matrix determine the expected state duration (1−P_{ij}) −1 for state i.

The vector of unconditional state probabilities, denoted as π≡P_r [S_0], remains time-invariant. The solution for π given l'K π=1 is expressed in Hamilton (1994, Chapter 22), involving the matrix P and π is given as a function of P.

The distribution of the initial state at t=0, represented by S_0, is shown as a K-vector:

$$\pi_0 \equiv [P_r\ (S_0=k)]K\times 1.$$

For an ergodic Markov process, the initial distribution can be set to the stationary distribution π. In cases where the Markov process isn't stationary, theory often guides the choice of π_0. For instance, in a change-point model, S_0 = 1 represents the process starting in the first regime.

4. EMPIRICAL EVIDENCE

The paper aims to empirically assess the Covid-19 pandemic's impact on several developed stock markets. It begins by analyzing the influence of the Covid-19 period on seven markets using FIEGARCH (1.1), MGARCH-DCC (1.1), and a Switching-Markov-Model. It then seeks to identify pronounced negative correlations by testing the statistical significance of heightened heteroscedasticity-adjusted correlation coefficients between calm and Covid-19 periods (Refer to Forbes and Rigobon, 2002).

4.1. Data

The paper delves into the global propagation of the Covid-19 financial crisis, focusing on stock market indices and total investment as key variables. The study utilizes monthly stock market data and monthly total investment returns measured by stock market indices for various tests across the seven examined markets (P_t, t). These indexes' monthly returns are computed as follows:

$$R_{i,t} = \frac{\begin{array}{l}\{MarketPriceClose(0m)+\\ DividendsPerShareByExDate\\ (QuarterlyPeriod(0m)/3\}\\ -MarketPriceclose(-1m)\end{array}}{Market\ Priceclose(-1m)} * 100 \quad (13)$$

With, P_t: Stock market's index i at day t
P_{t-1}: Stock market's index i at day t–1
$R_{i,t}$: Index's return of stock market i at day t

The second variable is the total investment return mean the stock performance ratio

$$TIR = \frac{Received\ products - Costs}{Investment\ amount} \quad (14)$$

The internal rate of return signifies the percentage return on all cash flows involved in an entity's monthly investment activities, as classified on the Statement of Cash Flow. It encompasses cash received or paid for all transactions deemed as investing activities.

TOTAL INVESTMENTS represent the entity's investments in various securities, directly or indirectly creating loans. This category includes treasury securities, Federal agency securities, State and municipal securities, Federal funds sold, Trading accounts securities, Securities purchased under resale agreements, Mortgage-backed securities, and other investments. These assets serve as interest-earning components for the company.

For insurance companies, TOTAL INVESTMENTS typically include fixed income securities, Equity securities, Real estate assets, Mortgage and Policy loans, and Other Investments. Meanwhile, for other financial companies, this category encompasses Loans, Real estate assets, Finance Receivables, and Other Investments.

The retained data consist of stock indices and Total investments, serving as the reference index for the various markets in the sample. These datasets are sourced from the internet and are denominated in US dollars to mitigate issues related to fluctuations in exchange rates.

The sample encompasses seven stock markets, categorized based on their economic positions. The group comprises:

G7: S&P/TSX, NIKKEI 225, CAC 40, DAX30, FTSE MIB, FTSE100, S&P500, representing Canada, Japan, France, Germany, Italy, the UK, and the USA, respectively.

The study period spans from February 01, 1992 to April 30, 2021, utilizing monthly data and totaling 352 observations for each market. This period is divided into two distinct sub-periods:
- Pre-Covid-19 period: Between February 01, 1992 and November 30, 2019
- Post-Covid-19 period: Between December 01, 2019 and April 30, 2021.

Analysis involves computing the monthly returns of both the Stock index and the Total of investment for each country. The first period comprises 335 observations, while the second period contains 17 observations.

4.2. Results and Interpretations

4.2.1. Descriptive statistics of the variables

Initially, we examine the descriptive statistics of the stock indexes' returns and the total investment return across the entire period (February 01, 1992-April 31, 2021), summarizing the means and standard deviations for the seven countries in our sample. These statistics prompt several observations:

For all series, both skewness and kurtosis statistics deviate from 0 and 3, respectively. Additionally, the Jarque-Bera statistic exhibits a probability (0.0000) below the 5% level, leading us to reject the assumption of a normal distribution for the series. This departure from normality suggests that the series possess characteristics significantly different from a Gaussian distribution. The kurtosis coefficients notably exceed three, indicating leptokurtic behavior across all variables and countries.

Furthermore, the non-zero skewness coefficients indicate asymmetry, potentially suggesting non-linearity, contrary to the expectations of linear Gaussian models. During the Covid-19 period, we observe a notable surge in standard deviations, signifying increased volatility. The Volatility analysis confirms an escalation in standard deviation between the pre-Covid-19 and Covid-19 periods. Higher standard deviations across all countries imply elevated price volatility and return instability.

Regarding skewness, most series display either leftward or rightward flatness. Notably, the returns of most developed countries exhibit skewness coefficients deviating either below or above zero, implying both leftward and rightward distributions, respectively. Moreover, significant kurtosis coefficients exceeding 3 are observed across all examined variables for each country.

Hence, the preliminary exploration of statistical properties within the series highlights considerations for applying various econometric tests. These findings, indicating departure from normal distribution, motivate the choice to employ an ARCH model later in the analysis. The subsequent step involves analyzing the distribution stationarity of all variables.

Conducting ADF and PP stationary tests across the daily series reveals that all employed series demonstrate stationarity. The ADF test, conducted with different specifications (constant, constant and trend; constant Ni or trend), yields ADF values below critical thresholds across all series for the 1%, 5%, and 10% levels. Similarly, the PP test exhibits t-test values lower than various critical values provided by Eviews, confirming stationarity. The probability of accepting the null hypothesis H0 for stationarity in both ADF and PP tests is zero across all series, leading to the conclusion that all series are stationary at levels.

4.2.2. Estimation of the asymmetric DCC-GARCH (1.1) model

4.2.2.1. Estimation of dynamic conditional correlations

The estimation of the DCC-GARCH (1.1) model facilitated an exploration of the Covid's impact on the relationship between the Stock market and Global investment in developed markets. These statistics revealed time-varying conditional correlations between the returns of the studied markets and investment returns in developed markets. Notably, these coefficients exhibited both positive and negative variations across all markets.

In contrast, these statistics unveiled that the conditional correlations between Stock market returns and Total investment returns in developed markets experienced a decline during the Covid-19 periods.

Further analysis using the DCC-GARCH (1.1) model underscored a significant visible impact of the Covid-19 pandemic on the conditional correlations between market behavior and investor behavior in developed markets. Consequently, it's evident that shocks influencing the overall stock market had a substantial ripple effect on stock prices in these developed markets.

4.2.2.2. The results and interpretation of the correlation coefficient

Table 1 displays the Correlation coefficients (DCC-MGARCH [1.1]) before the Covid-19 period between Stock market returns and Total investment returns of G7.

The table displays the estimated coefficients along with their standard errors, Z-statistics, and associated probabilities for the DCC-MGARCH (1.1) model before the COVID-19 period, illustrating the correlation between Stock market returns and Total investment returns across G7 countries:

For Canada, the α coefficient (0.036357) signifies a moderate positive correlation between Stock market and Total investment returns. Meanwhile, the β coefficient (0.000331) suggests a positive but comparatively smaller relationship between these returns.

In France, a similar pattern is observed with α (0.024220) indicating a moderate positive correlation, and a slightly larger β coefficient (0.000381) implying a stronger association between the returns.

For the United Kingdom, the α coefficient (0.019809) suggests a moderate positive correlation, while the β coefficient (0.000385) portrays a positive relationship, slightly stronger than that of France.

Table 1: Correlation coefficient (DCC-MGARCH (1.1) (Pre-Covid-19) between Stock market return and Total investment return of G7

Pre_COVID-19	Coefficient	Std.Error	Z-statistic	Prob.
CANADA				
α	0.036357	0.004445	8.178326	0.0000
β	0.000331	8.39E-05	3.938755	0.0001
ρ (1.2)	0.500293	0.054461	9.186280	0.0000
FRANCE				
α	0.024220	0.002400	10.09317	0.0000
β	0.000381	0.000116	3.296820	0.0010
ρ (1.2)	0.555021	0.046757	11.87025	0.0000
UNITED KINGDOM				
α	0.019809	0.002007	9.871527	0.0000
β	0.000385	7.80E-05	4.930149	0.0000
ρ (1.2)	0.442190	0.057182	7.733043	0.0000
GERMANY				
α	0.025520	0.002394	10.65825	0.0000
β	0.000631	0.000120	5.257367	0.0000
ρ (1.2)	0.540295	0.049826	10.84368	0.0000
ITALY				
α	0.019390	0.003167	6.121510	0.0000
β	0.000332	0.000133	2.493451	0.0127
ρ (1.2)	0.601847	0.048010	12.53595	0.0000
JAPAN				
α	0.011765	0.003131	3.757129	0.0002
β	3.49E-05	0.000130	0.269437	0.7876
ρ (1.2)	0.644355	0.441265	15.61516	0.0000
UNITED STATES				
α	0.028533	0.002935	9.720322	0.0000
β	0.000462	8.22E-05	5.620766	0.0000
ρ (1.2)	0.652865	0.038762	16.84300	0.0000

Regarding Germany, the α coefficient (0.025520) implies a moderate positive correlation, while the β coefficient (0.000631) indicates a stronger positive relationship, the highest among these countries.

In Italy, the α coefficient (0.019390) suggests a moderate positive correlation, and the β coefficient (0.000332) shows a smaller positive relationship.

For Japan, the α coefficient (0.011765) indicates a weaker positive correlation, while the β coefficient (3.49E-05) is notably small, suggesting a very weak relationship.

Finally, for the United States, a moderate positive correlation is indicated by the α coefficient (0.028533), and the β coefficient (0.000462) suggests a stronger positive relationship among these variables.

For all G7 countries, the ρ (1.2) coefficients highlight the dynamic nature of correlation over time. They all exhibit positive values, suggesting a strong contemporaneous relationship between Stock market and Total investment returns during the Pre-COVID-19 period. These results indicate varying degrees of association between these economic indicators, with Germany showing the strongest relationship and Japan the weakest among the countries analyzed.

The correlation coefficients (DCC-MGARCH [1.1]) between Stock market returns and Total investment returns for G7 countries are presented in Table 2, focusing on the Post-Covid-19 period.

Table 2: Correlation coefficient (DCC-MGARCH (1.1) (Post-Covid-19) between Stock market return and Total investment return of G7

Post_COVID-19	Coefficient	Std.Error	Z-Statistic	Prob.
CANADA				
α	0.163526	0.157779	1.036426	0.3000
β	−0.000432	0.002401	−0.0180132	0.8570
ρ (1.2)	0.681582	0.482808	1.411704	0.1580
FRANCE				
α	0.020422	0.016737	1.220176	0.2224
β	−0.000605	0.000866	−0.698911	0.4846
ρ (1.2)	0.006468	0.009570	0.675837	0.4991
UNITED KINGDOM				
α	0.025326	0.019072	1.327873	0.1842
β	−0.001699	0.001014	−1.675397	0.0939
ρ (1.2)	0.012774	0.012210	1.046158	0.2955
GERMANY				
α	0.034236	0.018633	1.837391	0.0662
β	−0.001490	0.001522	−0.979333	0.3274
ρ (1.2)	0.394838	0.596073	0.662398	0.5077
ITALY				
α	−0.012457	0.018421	−0.676272	0.4989
β	−0.001151	0.000908	−1.267546	0.2050
ρ (1.2)	0.000320	0.004593	0.069751	0.9444
JAPAN				
α	0.024090	0.013520	1.781838	0.0748
β	0.000284	3.08e-05	9.233152	0.0000
ρ (1.2)	−0.001254	0.002346	−0.534484	0.5930
UNITED STATES				
α	0.029545	1.559752	0.018942	0.9849
β	−0.001762	0.411647	−0.004281	0.9966
ρ (1.2)	0.290433	32.51810	0.008931	0.9929

For Canada, the results show a weak positive correlation (α = 0.163526) between Stock market and Total investment returns. However, the β coefficient (−0.000432) suggests a negligible relationship, indicating potential independence between the two variables.

France shows a slight positive correlation (α = 0.020422), hinting at a potential connection between Stock market and Total investment returns. However, the β coefficient (−0.000605) indicates a relatively weak association.

The United Kingdom exhibits a moderate positive correlation (α = 0.025326) is found, suggesting a potential link between Stock market and Total investment returns. The negative β coefficient (−0.001699) implies a contrasting effect, warranting further investigation.

Germany indicates a moderate positive correlation (α = 0.034236), but the negative β coefficient (−0.001490) suggests a potential inverse relationship between Stock market and Total investment returns.

Italy depicts a slightly negative correlation (α = −0.012457) is observed, indicating a potential weak inverse relationship between Stock market and Total investment returns. The β coefficient (−0.001151) supports this trend.

Japan shows a moderate positive correlation (α = 0.024090) is found, and the considerably positive β coefficient (0.000284) indicates that Stock market returns may have a notable influence on Total investment returns.

The United States indicates a positive correlation ($\alpha = 0.029545$) is present, but the β coefficient (-0.001762) does not provide conclusive evidence, suggesting a potentially negligible relationship between Stock market and Total investment returns.

These findings highlight the nuanced dynamics of the relationship between Stock market and Total investment returns in the Post-COVID-19 period for each G7 country.

The Dynamic Conditional Correlation (DCC) measures are well-recognized statistics, offering insights into correlation differences among observational rows and emphasizing the connection between these observations. Meanwhile, other correlation coefficients like Kendall's simply express the variance between concordance and discordance probabilities. These coefficients illustrate how one variable's high (or low) values are associated with high (or low) values of another variable. Moreover, rank correlation is preserved under strictly increasing transformations.

Our analysis of these coefficients confirms temporal variation and the presence of a consistent connection, even in non-linear contexts. Specifically, we examined the dynamic conditional correlation coefficients between stock market returns and total investment returns across G7 countries. Our findings highlight a strong correlation between stock market returns and total investment returns in most countries before the onset of the COVID-19 pandemic. However, during the peak of this crisis, particularly amidst significant financial turbulence, evidence of a negative correlation between these variables emerged, signifying the pandemic's profound impact on the financial stability of all markets.

The pronounced price fluctuations dominating global financial news underscore the need for deeper research to provide effective solutions that mitigate potential crashes. Such crashes can significantly deteriorate a country's economic, financial, and social stability.

Upon analyzing equal coefficient tests between stock market returns and total investment returns in the primary stock market, our results align with the DCCMGARCH model. The outcomes of the correlation tests are summarized in Tables 1 and 2, illustrating the relationship estimations between stock market returns and total investment returns during stable periods and the COVID-19 period.

Figure 1: Correlation coefficient (DCC-MGARCH (1.1) (Pre&Post-Covid-19) between Stock market return and Total investment return of G7

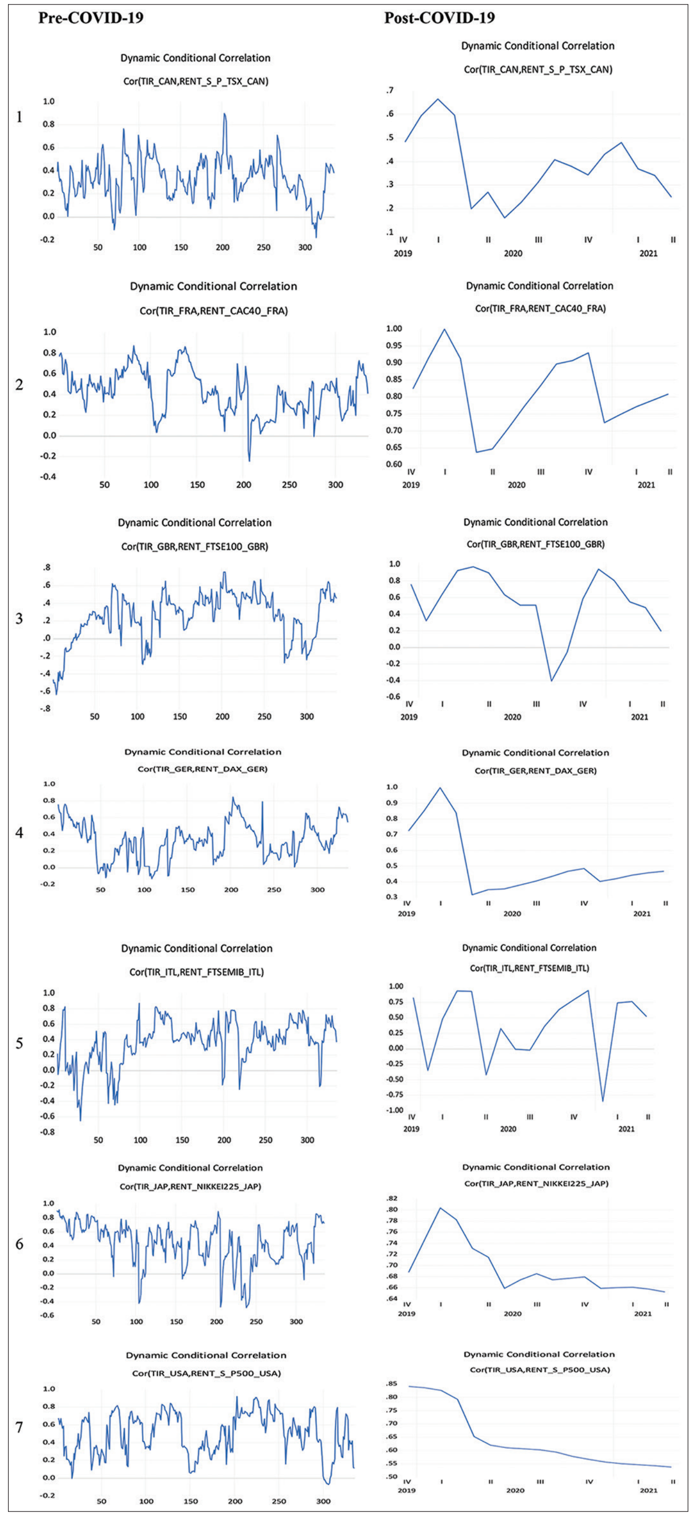

Figure 1 presents the Correlation Coefficient (DCC-MGARCH [1.1]) illustrating the correlation between Stock Market Return and Total Investment Return across G7 nations, both Pre- and Post-COVID-19. The outcomes depicted in Figure 1 highlight that correlations between stock market returns and Total investment returns in financial markets are notably strong during stable periods. This robust correlation can be interpreted in light of the positive and highly significant coefficients, supported by the t-statistics of the Dynamic Conditional Correlation. The statistical significance of the constant term in the mean equation was observed across all markets.

The correlation coefficients within the Group of 7 countries stand at (0.500293) for Canada, (0.555021) for France, (0.442190) for the United Kingdom, (0.540295) for Germany, (0.601847) for Italy, (0.644355) for Japan, and (0.652865) for the USA. These results strongly indicate financial stability in these markets. The significance of these coefficients is evident from the t-statistics resulting from the estimation of the DCC-MAGARCH model, significantly exceeding the critical value of 1.96, set at a 5% threshold.

Consequently, during stable periods, the t-statistics associated with the correlation coefficients are substantial, reaffirming the financial stability across all stock markets.

However, for the remaining G7 countries, the correlation coefficients lack statistical significance, demonstrating values below the critical threshold of 1.96. Specifically, these coefficients stand at (0.681582) for Canada, (0.006468) for France, (0.012774) for the United Kingdom, (0.394838) for Germany, (0.000320) for Italy, (−0.001254) for Japan, and (0.290433) for the USA. These results suggest a relative lack of substantial correlation, possibly indicating a divergence from geographical proximity as a source of contagion during the COVID-19 pandemic.

Considering these findings, we accept the null hypothesis for these markets, signifying that stock returns had a statistically insignificant impact on investment returns. This implies that these markets exhibit interdependence rather than a direct correlation between stock market returns and Total investment returns. Moreover, it is crucial to note that the choice of unstable or crisis periods influences correlation measures, as they rely on adjusted correlation coefficients of stock price returns.

These observations indicate a negative spillover effect on these markets. The notable decrease in correlation, observed in most countries, suggests their susceptibility to external shocks, leading to substantial variation in conditional correlation regimes, some of which are negative. This reflects the dynamic response of investors to news and innovations. Post-COVID-19, the Dynamic Conditional Correlation (DCC) values are notably lower compared to pre-COVID-19 levels.

The evolution of the conditional dynamic correlation between stock market returns and Total investment returns exhibits a noticeable decrease immediately after the onset of the COVID-19 pandemic. Particularly, there was a substantial decline during this financial event. However, this correlation was not consistently sustained, and there was no significant variation during the event.

Our empirical study highlights a robust correlation between stock market returns and Total investment returns, which notably increased during stable periods. Conversely, this correlation weakened significantly during and after the periods affected by COVID-19. This suggests that the crisis had a widespread impact across different markets, providing clear evidence of contagion.

The statistical significance of these periodic correlations is evident in the substantially larger t-statistics values, surpassing the critical value of 1.96, a 5% threshold. This leads to the rejection of the null hypothesis (H_0), indicating a negative effect of COVID-19. The decrease in average values of the Dynamic Conditional Correlation (DCC) implies that certain countries were notably influenced by the contagion effects of COVID-19 across all the G7 nations. This solidifies the evidence of a significant decrease in transactional conditional correlations of current yields.

The results suggest that there was a strong correlation between stock market returns and total investment returns in most countries before the onset of the COVID-19 pandemic. However, during the peak of the crisis, evidence of a negative correlation between these variables emerged, signifying the pandemic's profound impact on the financial stability of all markets.

The results also highlight the need for deeper research to provide effective solutions that mitigate potential crashes, as such crashes can significantly deteriorate a country's economic, financial, and social stability.

The findings indicate that correlations between stock market returns and total investment returns in financial markets are notably strong during stable periods, supported by positive and highly significant coefficients. However, during the COVID-19 period, the correlation weakened significantly, suggesting a widespread impact across different markets and clear evidence of contagion.

The decrease in average values of the Dynamic Conditional Correlation (DCC) implies that certain countries were notably influenced by the contagion effects of COVID-19 across all the G7 nations, solidifying the evidence of a significant decrease in transactional conditional correlations of current yields.

In summary, the analysis suggests that the COVID-19 pandemic had a profound impact on the financial stability of global markets, leading to a notable decrease in correlation between stock market returns and total investment returns, and providing clear evidence of contagion effects across different markets.

4.2.2.3. Estimation of fractionally integrated EGARCH: FIEGARCH (1.1)

Table 3 displays the FIEGARCH (1.1) model's relationship between Stock Market Return and Total Investment Return of G7 during the Pre-COVID-19 period.

The coefficients show the impact of each respective stock market index on the Total Investment Return for the pre-COVID-19 period.

In Canada (TIR_CAN), the coefficient of (0.791792) indicates a strong positive relationship between Stock Market Return and Total Investment Return. This coefficient, with its low standard error and high Z-statistic, strongly supports a significant correlation between these variables in the Canadian market before COVID-19.

France (TIR_FRA) showcases a coefficient of (0.772374), implying a positive relationship between Stock Market Return and Total Investment Return. Despite a relatively higher standard error and a Z-statistic slightly below the conventional threshold for significance, there's still statistical significance at a probability level of (0.0125), albeit less robust compared to Canada.

The United Kingdom (TIR_GBR) exhibits a coefficient of (0.013308), signifying a weak positive relationship between

Stock Market Return and Total Investment Return. However, this relationship is statistically significant given the low standard error and a high Z-statistic, indicating its presence before COVID-19.

Germany (TIR_GER) displays a coefficient of (0.487850), indicating a significant positive relationship between Stock Market Return and Total Investment Return. The low standard error and high Z-statistic validate this substantial correlation in the German market before the pandemic.

Italy (TIR_ITL) demonstrates a coefficient of (0.592776), suggesting a significant positive relationship between Stock Market Return and Total Investment Return in Italy before COVID-19. The low standard error and high Z-statistic affirm the robustness and statistical significance of this correlation.

Japan (TIR_JAP) showcases a substantial coefficient of (0.903191), indicating a strong positive relationship between Stock Market Return and Total Investment Return. The low standard error and high Z-statistic affirm the strong statistical significance of this correlation in Japan before the COVID-19 period.

The United States (TIR_USA) presents a coefficient of (0.230664), suggesting a significant but relatively weaker positive relationship between Stock Market Return and Total Investment Return compared to other countries. Despite this, the relationship is statistically significant given the low standard error and high Z-statistic before the COVID-19 period.

In summary, before the COVID-19 period, most G7 countries demonstrated statistically significant positive correlations between Stock Market Return and Total Investment Return, suggesting varying degrees of positive relationships between these variables across different economies. The Z-Statistic values indicate the significance of these relationships, with low P = 0.0000 indicating high significance for all coefficients and constants.

Table 4 showcases the FIEGARCH (1.1) model's correlation between Stock Market Return and Total Investment Return of G7 during the Post-COVID-19 period.

Canada (TIR_CAN) exhibits a coefficient of (−0.031537), showcasing a negligible relationship between Stock Market Return and Total Investment Return. The high standard error and a Z-statistic close to zero indicate a lack of statistical significance in this correlation during the Post-COVID-19 period.

France (TIR_FRA) displays a coefficient of (1.273647). However, the considerably high standard error and a Z-statistic close to zero suggest an absence of statistical significance, implying an insignificant relationship between Stock Market Return and Total Investment Return in France during this period.

Table 3: FIEGARCH (1.1) (Pre-COVID-19) between stock market return and Total investment return of G7

Variable (Pre-COVID-19)	Coefficient	Std.Error	Z-statistic	Prob.
TIR_CAN=f (Rent_S&P_TSX_CAN)	0.791792	0.194973	4.061024	0.0000
C	0.027266	0.003323	8.205314	0.0000
TIR_FRA=f (Rent_CAC40_FRA)	0.772374	0.309386	2.496472	0.0125
C	0.018829	0.001926	9.773804	0.0000
TIR_GBR=f (Rent_FTSE100_GBR)	0.013308	0.001506	8.835664	0.0000
C	2.012446	0.106381	18.91735	0.0000
TIR_GER=f (Rent_Dax_GER)	0.487850	0.152566	3.197631	0.0000
C	0.018364	0.001487	12.34821	0.0000
TIR_ITL=f (Remt_FTSEMIB_ITL)	0.592776	0.151309	3.917638	0.0001
C	0.018163	0.003275	5.545855	0.0000
TIR_JAP=f (Rent_NIKKE 225_JAP)	0.903191	0.067879	13.30586	0.0000
C	0.010453	0.001779	5.874164	0.0000
TIR_USA=f (Rent_S&P_500_USA)	0.230664	0.080214	2.875598	0.0000
C	0.020499	0.002505	8.182975	0.0000

Table 4: FIEGARCH (1.1) (Post-COVID-19) between Stock market return and Total investment return of G7

Variable (Post-COVID-19)	Coefficient	Std.Error	Z-Statistic	Prob
TIR_CAN=f (Rent_S&P_TSX_CAN)	−0.031537	10.35247	−0.003046	0.9976
C	0.024282	0.021092	1.151249	0.2496
TIR_FRA=f (Rent_CAC40_FRA)	1.273647	8.7549930	0.145478	0.8843
C	0.026823	0.011515	2.329410	0.0198
TIR_GBR=f (Rent_FTSE100_GBR)	−0.112295	6.582923	−0.017059	0.9864
C	0.057869	0.012703	4.555702	0.0000
TIR_GER=f (Rent_Dax_GER)	0.844203	3.834059	0.220185	0.8257
C	0.063693	0.005950	10.70520	0.0000
TIR_ITL=f (Remt_FTSEMIB_ITL)	−0.003823	0.007581	−0.504303	0.6140
C	14.82181	1.520193	9.749953	0.0000
TIR_JAP=f (Rent_NIKKE 225_JAP)	1.153239	3.576780	0.322424	0.7471
C	0.33344	0.014322	2.328141	0.0199
TIR_USA=f (Rent_S&P_500_USA)	0.452330	3.696158	0.122378	0.9026
C	0.038895	0.014229	2.733545	0.0063

The United Kingdom (TIR_GBR) demonstrates a negative coefficient of (−0.112295), but with a high standard error and a Z-statistic close to zero, implying an almost negligible correlation between Stock Market Return and Total Investment Return in the UK during the Post-COVID-19 period.

Germany (TIR_GER) presents a coefficient of (0.844203), indicating a positive relationship. However, the high standard error and a Z-statistic close to zero suggest a lack of statistical significance in this relationship between Stock Market Return and Total Investment Return during this period.

Italy (TIR_ITL) exhibits a coefficient of (−0.003823), suggesting a negligible relationship between Stock Market Return and Total Investment Return. The high standard error and a Z-statistic close to zero indicate an insignificant correlation during the Post-COVID-19 period.

Japan (TIR_JAP) showcases a coefficient of (1.153239), implying a positive relationship. However, similar to the other countries, the high standard error and low Z-statistic imply an insignificant correlation between Stock Market Return and Total Investment Return in Japan during this period.

The United States (TIR_USA) displays a coefficient of (0.452330). Yet, the high standard error and a Z-statistic close to zero signify an insignificant relationship between Stock Market Return and Total Investment Return in the US during the Post-COVID-19 period.

In summary, during the Post-COVID-19 period, the coefficients across G7 countries generally exhibit relationships between Stock Market Return and Total Investment Return that lack statistical significance due to high standard errors and Z-statistics close to zero. This indicates a weak or negligible correlation between these variables across these countries during this specific period.

4.2.2.4. Estimation of switching-markov model

Table 5 presents the Switching-Markov-Model analysis conducted for the Pre-COVID-19 period, focusing on the relationship between Stock Market Return and Total Investment Return across G7 countries.

The coefficients in "Regime 1" indicate the strength and significance of these relationships:

Several countries, like Canada and the United States, demonstrate coefficients above 2, signifying strong positive relationships between Stock Market Return and Total Investment Return. These relationships are statistically significant, as indicated by their high z-Statistics and low standard errors.

Other countries, such as France, the United Kingdom, and Japan, also show notable coefficients above 2, suggesting strong correlations between these variables. However, despite relatively higher standard errors, the z-Statistics support the significance of these relationships.

Meanwhile, Germany and Italy display coefficients below 1, implying slightly weaker associations. However, even with their lower coefficients, the z-Statistics suggest these relationships are statistically significant.

Overall, this analysis before the COVID-19 period reveals varying strengths of positive relationships between Stock Market Return and Total Investment Return across different countries, with some demonstrating stronger and more significant correlations than others.

Table 6 exhibits the Switching-Markov-Model outcomes post-COVID-19, exploring the relationship between Stock Market Return and Total Investment Return within the G7 countries.

For Canada (TIR_CAN) and France (TIR_FRA), the coefficients indicate insignificant relationships, suggesting a lack of statistical significance and a negligible correlation between the variables post-COVID-19.

The United Kingdom (TIR_GBR) shows a slightly negative coefficient, approaching significance but not conclusively. Germany (TIR_GER) demonstrates a slightly positive but statistically insignificant relationship.

Italy (TIR_ITL) exhibits a negative relationship, albeit statistically insignificant. Japan (TIR_JAP) also presents a negligible relationship between Stock Market Return and Total Investment Return post-COVID-19.

The United States (TIR_USA) portrays a notably high coefficient, yet the relationship lacks statistical significance, suggesting no clear correlation during this period.

Across these G7 countries, the relationships between Stock Market Return and Total Investment Return appear weak and statistically insignificant during the post-COVID-19 period, suggesting a lack of clear correlation between these variables.

Table 5: Switching-Markov-Model (Pre-COVID-19) between Stock market return and Total investment return of G7

Switching-Markov-Model (Pre-COVID-19)	Regime 1			
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
TIR_CAN/RENT_S_P_TSX_CAN	2.024973	0.311705	6.496437	0.0000
TIR_FRA/RENT_CAC40_FRA	2.787338	1.000937	2.784730	0.0054
TIR_GBR/RENT_FTSE100_GBR	2.342765	0.334920	6.994994	0.0000
TIR_GER/RENT_DAX_GER	0.305952	0.060657	5.043968	0.0000
TIR_ITL/RENT_FTSEMIB_ITL	0.598649	0.249376	2.400589	0.0164
TIR_JAP/RENT_NIKKEI225_JAP	2.562751	0.259553	9.873723	0.0000
TIR_USA/RENT_S_P500_USA	3.235158	0344403	9.393522	0.0000

Table 6: Switching-Markov-Model (Post-COVID-19) between Stock market return and Total investment return of G7

Switching-Markov-Model (Pre-COVID-19)	Regime 2			
	Coefficient	Std. Error	z-Statistic	Prob.
TIR_CAN/RENT_S_P_TSX_CAN	0.264463	0.482595	0.548002	0.5837
TIR_FRA/RENT_CAC40_FRA	−0.184225	1.268601	−0.145219	0.8845
TIR_GBR/RENT_FTSE100_GBR	−0.887742	0.467713	−1.898049	0.0577
TIR_GER/RENT_DAX_GER	0.241952	0.421185	0.574456	0.5657
TIR_ITL/RENT_FTSEMIB_ITL	−1.260275	1.107133	−1.138324	0.2550
TIR_JAP/RENT_NIKKEI225_JAP	−0.278393	0.406597	−0.684690	0.4935
TIR_USA/RENT_S_P500_USA	7.640529	10.75257	0.710577	0.4773

Figure 2: Filtered regime probabilities (G7)

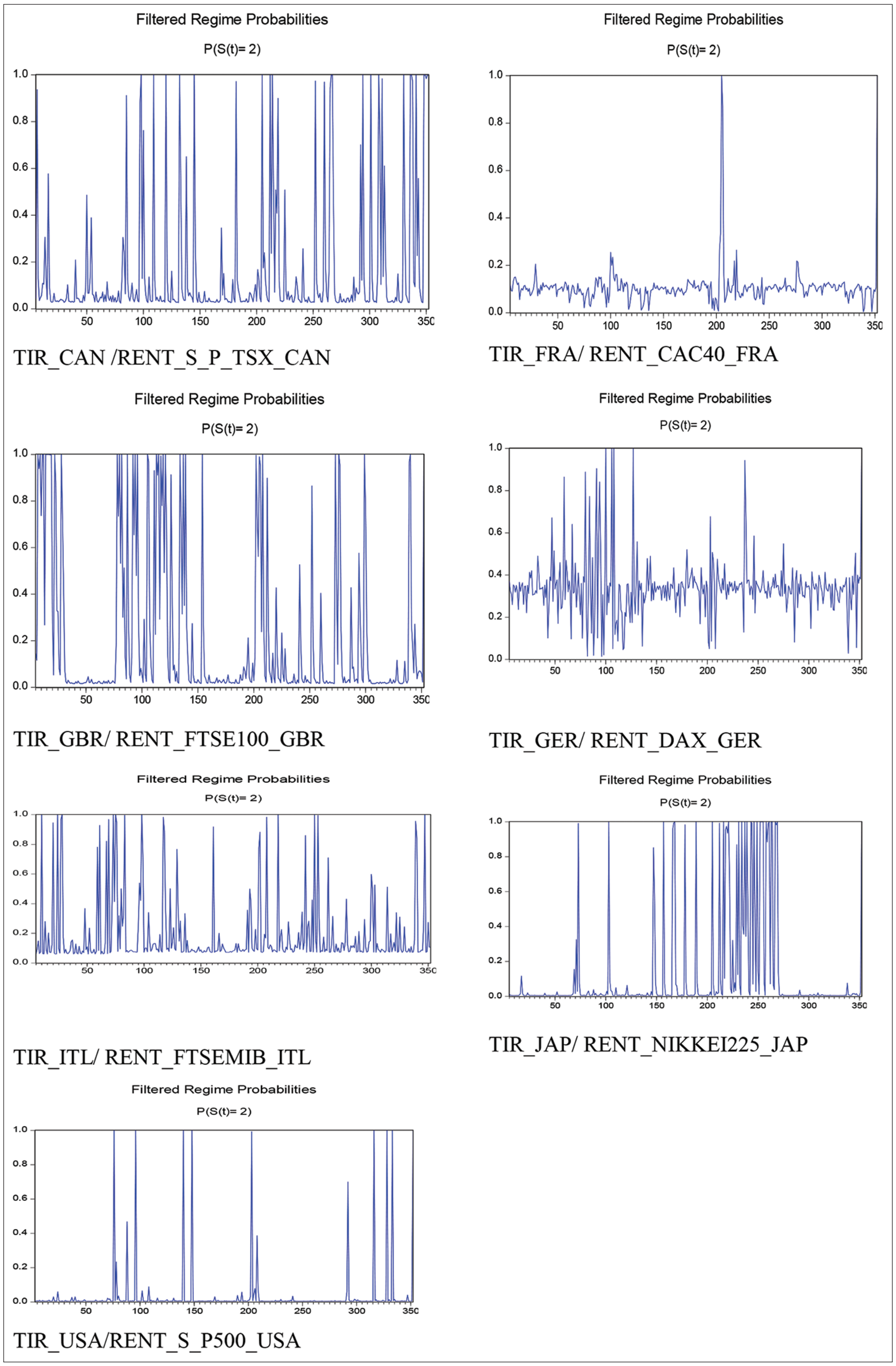

Figure 2 showcases the Filtered Regime Probabilities for G7:

After employing the DCC MGARCH Model, our findings affirm the adverse impact of the Covid-19 pandemic on financial markets.

Our analysis of the dynamic conditional correlations (DCC-MGARCH [1.1]) between monthly stock market returns and total investment returns reveals intriguing insights. Across the performance series studied, we observe both high and low correlations, a manifestation of the persistence phenomenon mentioned earlier.

The correlation coefficient evolution, visualized in graphics, illustrates significant decreasing trends during the COVID-19 pandemic across most studied series. This simultaneous decrease indicates their convergence to levels seen at the start of 2020-2021, following a pronounced decline from early 2021. The pandemic's onset in late 2019, intensifying in early 2021, caused this notable effect.

These factors suggest high volatility in stock market indexes. Examining correlations and conditional variances highlights asymmetry in their behavior. Volatility tends to surge after a decline or lower correlation. Surprisingly, for certain indexes, correlations rise amidst relatively volatile markets.

Our study struggles to validate the hypothesis of non-temporal variation in Pearson correlations. This aligns with Nelson's work, emphasizing the struggle to explain performance and volatility evolution adequately.

We explore alternative dependence measures - FIEGARCH and Switching-Markov - encompassing non-linear agreement measures beyond linear correlation. Using these measures reconfirms the outcomes observed with the DCC-MGARCH Model.

Pre-COVID-19, correlation coefficients for the G7 countries stood at (21.05201) for Canada, (10.91213) for France, (10.70292) for the UK, (10.50329) for Germany, (0.592776) for Italy, (13.91880) for Japan, and (19.70929) for the USA. These outcomes highlight financial stability, supported by significant t-statistics from the FIEGARCH-Model estimations, far exceeding the critical value of 1.96 at a 5% threshold.

Post-COVID-19, correlation coefficients for the same group show varied trends: (-0.031537) for Canada, (1.273647) for France, (−0.112295) for the UK, (0.844203) for Germany, (−0.003823) for Italy, (1.153239) for Japan, and (0.452330) for the USA. Notably, these figures lack significance with the t-statistics from the FIEGARCH-Model, falling below the critical value.

The Switching-Markov-Model results validate a transition in regimes, signaling a transformation in the nature of the relationship between Stock Market and Total Investment Return, elucidated in Figure 2.

5. CONCLUSION

This paper delves into the relationship between Global investment returns and the stock market returns across G7 countries. Our exploration extends to understanding the correlation between stock markets and investments, shedding light on the irrational behavior of investors in financial markets. Leveraging a multivariate dynamics model, we estimated conditional GARCH dynamic correlations using monthly data spanning from January 1992 to April 2021. Our aim was to explore potential correlation channels, utilizing dynamic conditional correlations between the two variables across the seven countries.

Employing the DCC-MGARCH model enabled us to simultaneously evaluate conditional correlation coefficients and their determinants over time. This model proved instrumental in identifying contagion channels and examining correlation coefficients' behavior during specific periods of financial turmoil. Notably, these coefficients exhibited statistical significance, indicating the profound influence of market behavior on investor actions. The statistically significant increase in conditional correlations over time highlighted a group of investors trading in the same direction, significant at a 5% level of significance.

The impact of the COVID-19 pandemic on correlation coefficients was discerned through significantly lower coefficients compared to previous financial crises. This discrepancy underscores evidence of herding behavior during the pandemic, especially evident in the analysis of dynamic correlation coefficients, particularly around the period spanning 2020-2021.

Our findings, validated through Fractionally Integrated EGARCH (FIEGARCH) and the Equality of Coefficients test via the Switching-Markov Model, aimed to study the dynamic conditional correlation between Global investment returns and Stock market returns across international markets concerning volatility.

We observed varied correlation periods before the COVID-19 era: intervals with strong correlations signifying a robust market-investor relationship, and intervals with low correlations indicating the impact of the pandemic. These outcomes align with existing literature, highlighting excess volatility beyond the realm of efficient financial market theory.

The analysis of correlation coefficients across different tests provided substantial evidence of correlation effects due to herding behavior, notably during financial crises, underscoring the need for further exploration into these dynamics.

As we move forward, future research endeavors could delve deeper into understanding the behavioral drivers behind these observed correlations, especially during periods of crisis like the COVID-19 pandemic. Exploring the psychological aspects influencing investor decisions and how these impact market correlations could provide invaluable insights. Additionally, investigating the role of information dissemination, sentiment analysis, and the advent of technological advancements in trading platforms on market correlations might unravel new dimensions. Further, extending this study to encompass emerging markets or other global economic clusters could offer a more comprehensive view of correlation dynamics in varying financial environments. Finally, examining the efficacy of regulatory measures or policy interventions in mitigating excessive market volatility during crises stands as a potential area ripe for exploration.

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