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Sectoral Stock Market Volatility during the COVID-19 Pandemic: A GARCH Analysis of Aggregated French and Portuguese Equity Data

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Master in Finance

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September, 2025

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Acknowledgements

This thesis marks the conclusion of a rewarding academic journey that took me from Bordeaux to Ottawa and finally to Lisbon. It is the product of many challenges, significant personal growth and the invaluable support of many people to whom I dedicate this work.

First and foremost, I would like to express my sincere gratitude to my supervisor, Professor Szabolcs Sebestyén, for his guidance, patience and for giving me the freedom to explore this topic with intellectual rigor.

I would also like to thank the professors at the University of Ottawa who shaped my analytical foundations. I am particularly grateful to Dr. Sauré and Dr. Kandakoglu, whose exceptional courses on optimization and data forecasting equipped with the essential programming and data science skills that underpin this entire thesis.

To my grandfather, Gabriel Vangrevelinghe, who authored his own foundational book on econometrics. It has been a tremendous honor to build on his intellectual legacy in this work.

To my parents, I can never fully express my gratitude for your love and constant encouragement throughout my years of study. Your sacrifices and unwavering faith in me have been my foundation, and for that, I am eternally grateful.

To my friend Margaux, with whom I shared this unforgettable semester at ISCTE. Thank you for your incredible support throughout the intense challenges of our coursework and the CFA exam. We navigated these trials together, and I am immensely proud of what we have accomplished.

Finally, to all my other friends and loved ones, thank you for your encouragement and for being part of this journey.

Resumo

Este estudo examina a resposta da volatilidade do mercado de ações setorial nos mercados agregados francês (CAC 40) e português (PSI-20) à pandemia da COVID-19 em várias fases. Segmentando a análise nos períodos de Controlo (2015-2019), COVID-19 (2020-2021) e pós-COVID (2021-2024), esta investigação avalia mudanças estruturais na dinâmica da volatilidade em oito setores-chave. Utilizando modelos assimétricos EGARCH (1,1) e GJR-GARCH (1,1), este estudo encontra evidências convincentes de três fenómenos centrais.

O período da COVID-19 resultou num aumento notável da volatilidade condicional em todos os setores, caracterizado por uma persistência significativamente elevada (parâmetros β próximos da unidade) e efeitos de alavancagem reforçados, refletindo maior sensibilidade a notícias negativas. Em segundo lugar, o risco de cauda, indicativo de maior probabilidade de flutuações extremas do mercado, aumentou significativamente durante a fase crítica da pandemia, capturado por uma redução nos parâmetros de forma estimados da distribuição t de Student. Em terceiro lugar, a análise revela que nenhum modelo GARCH domina em todos os regimes; o GJR-GARCH demonstrou um ajuste superior na fase aguda da crise, enquanto o EGARCH é mais adequado para condições estáveis pré-crise.

Em conclusão, demonstro que, embora tenha havido normalização parcial pós-COVID, os níveis de volatilidade e o risco de cauda permaneceram, em geral, mais elevados do que os observados antes da pandemia. A pandemia induziu mudanças significativas e dinâmicas nas estruturas de volatilidade setorial, destacando a necessidade de seleção de modelos específicos para cada contexto e oferecendo insights essenciais para a gestão de riscos e respostas políticas a choques sistémicos.

Palavras-chave: COVID-19, volatilidade, índice de ações, GARCH

JEL Classification Codes: C58, G12

Abstract

This study examines the response of sectoral stock market volatility in the aggregated French (CAC 40) and Portuguese (PSI-20) equity markets to the COVID-19 pandemic during various phases. By segmenting the analysis into Control Group (2015-2019), COVID-19 (2020-2021), and post-COVID (2021-2024) periods, this research evaluates the structural changes in volatility dynamics across eight key sectors. Using asymmetric EGARCH (1,1) and GJR-GARCH (1,1) models, this study finds compelling evidence of three core phenomena.

The COVID-19 period led to a notable increase in conditional volatility across all sectors, characterized by significantly elevated volatility persistence with β parameters approaching unity and enhanced leverage effects, reflecting greater sensitivity to negative news. Secondly, tail risk, indicative of an increased probability of extreme market fluctuations, rose significantly during the critical phase of the pandemic. This phenomenon is captured by a reduction in the estimated shape parameters of the Student's t-distribution. Thirdly, the analysis reveals that no single model dominates across all regimes, with the GJR-GARCH model demonstrating a superior fit during the acute crisis phase, while the EGARCH model is more suited to stable, pre-crisis conditions.

In conclusion, I demonstrate that although there was a partial normalization of volatility in the post-COVID period, both volatility levels and tail risk generally remained higher than those observed prior to the pandemic. The pandemic has led to significant and dynamic changes in sectoral volatility structures, underscoring the need for context-specific model selection and providing essential insights for risk management and policy responses to systemic shocks.

Keywords: COVID-19, volatility, stock index, GARCH

JEL Classification Codes: C58, G12

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1 Introduction

The COVID-19 pandemic has caused an unprecedented and multifaceted shock to the global economy, creating a complex environment in which traditional financial models have proven inadequate. This study addresses this challenge through a comprehensive econometric analysis of stock market reactions, focusing on sector volatility, systemic risk, and extreme events in European stock markets. By examining aggregate data from the French (CAC 40) and Portuguese (PSI-20) indices in eight sectors, this research analyzes the impact of the pandemic on behaviors that are often overlooked in more general market analyses. To this end, a portfolio of 34 companies selected from the two indices and categorized into eight sectors (Industry, Energy, Retail, Banks, Luxury, Health, Technology and Construction) is analyzed.

To capture the market's temporal evolution, the study period has been divided into three distinct phases. This segmentation enables an analysis of market adjustments to evolving health crises, policy measures and investor sentiment. The shifting trajectories of sectoral performance, from synchronized declines to recovery and subsequent divergences, highlight the importance of this temporal granularity for market analyses.

This research makes a significant contribution by systematically evaluating the comparative efficiency of the selected models within each unique sector and phase. The analysis is conducted on a combined dataset of French and Portuguese equities. The novelty lies not just in the application of these models, but also in identifying the specifications that best capture nuanced and often asymmetric market reactions within defined sectors. This comparative approach reveals significant differences in sectoral responses to shocks throughout the crisis, offering insights that a single-model or aggregate market approach would obscure. The core GARCH analysis is performed on the aggregated sectors, yet the unique characteristics of the CAC 40 and PSI-20 indices, along with the economies they represent, offer essential contextual depth. Analyzing these two European economies, whose notable differences in fiscal policies, economic structures and pandemic responses, facilitates a deeper understanding of the sectoral dynamics and potential factors contributing to cross-country variations that may influence these aggregated responses.

The analysis reveals three core findings. First, the pandemic induced a structural break in volatility, leading to a dramatic increase in its persistence and in the magnitude of asymmetric leverage across all sectors. Second, model preference is regime-dependent: the EGARCH model is better suited for the stable pre-crisis period, while the GJR-GARCH model demonstrates a superior fit for capturing the fear-driven dynamics of the crisis phase. Third, despite a partial normalization post-pandemic, volatility levels and tail risks remained structurally elevated, indicating a permanent shift in risk perception.

The outcomes of this analysis carry significant implications for both academic research and financial practice. Theoretically, the study advances our understanding of financial market responses to exogenous systemic shocks, particularly at the sectoral level. From a practical standpoint, its findings provide actionable insights into risk management, investment strategies and policymaking, allowing market participants and regulators to navigate future systemic disruptions more effectively.

2 Review of Literature

2.1 Stock Market Volatility During Crises

The behavior of financial markets during economic crises and periods of uncertainty has been a fundamental focus in financial economics. The dynamics of stock market volatility are crucial, as volatility acts as a key indicator of market risk, investor sentiment and overall financial stability. Historical episodes, including the dot-com bubble burst at the turn of the millennium, the Global Financial Crisis (GFC) of 2008-2009, and the European sovereign debt crisis that begun in late 2009, consistently illustrate that periods of systemic stress are typically associated with profound changes in market volatility. The shifts influence asset pricing and portfolio management, while also carrying substantial implications for corporate financial decisions and regulatory oversight.

Research has shown that stock market volatility exhibits distinct patterns during periods of turbulence. Schwert (1989) conducted a foundational study that presented substantial historical evidence of a marked increase in stock market volatility during economic recessions and financial crises. This observation has been supported by various subsequent studies across diverse markets and crisis episodes (Bloom, 2009; Officer, 1973). Beyond a general increase in magnitude, volatility during crises exhibits several stylized facts, such as volatility clustering and leptokurtosis, which are inconsistent with the assumptions of a random walk or constant variance. Volatility clustering is a significant phenomenon initially identified by Mandelbrot (1963) and subsequently formalized in econometric models by Engle (1982). This describes the empirical observation that significant fluctuations in asset prices are typically succeeded by additional substantial fluctuations regardless of direction, while minor fluctuations are often followed by further minor fluctuations, resulting in intervals of heightened volatility alternating with phases of relative stability. In times of crisis, the clustering effect tends to intensify, resulting in the propagation of shocks throughout the market and causing prolonged periods of instability (Cont, 2001).

A key characteristic of market crises is the persistence of volatility. Market volatility shocks during crises typically do not dissipate rapidly. Instead, they tend to exert a prolonged influence, indicating that current volatility is significantly affected by recent volatility. The persistence observed is a fundamental characteristic represented by models in the GARCH family (Bollerslev, 1986), which carries significant implications for risk forecasting and the valuation of financial derivatives. The persistence level may fluctuate over time and can intensify during crises, suggesting that markets require an extended period to revert to baseline risk levels following a systemic shock (Poon & Granger, 2003). Additionally, the distribution of asset returns in times of crisis often demonstrates leptokurtosis, characterized by "fat tails," indicating that extreme price fluctuations, both upward and downward, occur more frequently than a normal distribution would suggest (Cont, 2001). The increased likelihood of extreme events characterizes crisis periods and presents substantial challenges for risk management models based on normality assumptions.

The interrelation of global financial markets highlights the notion of contagion during systemic crises. Forbes and Rigobon (2002) offered a notable definition that differentiates contagion, characterized by a substantial rise in cross-market linkages following a shock to a specific country or region, from interdependence, which denotes typical market movements. Crises can cause shocks in one market or sector to quickly spread to others, resulting in a correlated downturn that exceeds what underlying economic fundamentals would indicate (Baig & Goldfajn, 1999, regarding the Asian crisis and Bekaert, Harvey & Lumsdaine, 2002, concerning emerging markets). This transmission occurs via multiple channels, such as financial linkages (e.g., shared creditors, cross-border banking exposures), information cascades and changes in investor sentiment or risk appetite (Kyle & Xiong, 2001). Understanding contagion is essential as it suggests that diversification benefits, fundamental to modern portfolio theory, may decrease precisely when they are most needed as in times of market turmoil (Longin & Solnik, 2001). The dissemination of volatility and adverse returns among sectors in a domestic market exemplifies intra-market contagion, wherein an initial disturbance in a systemically significant sector, such as the banking sector during the GFC, can instigate a series of detrimental repercussions throughout the wider economy.

This highlights the importance of understanding the responses of various economic sectors to systemic shocks. Aggregate market indices offer a useful overview but frequently obscure significant variability in the responses of individual sectors. The distinct operational characteristics, financial frameworks and sensitivities to macroeconomic factors across various industries indicate that they do not experience uniform impacts from broad economic recessions or financial crises. Cyclical sectors, including manufacturing and consumer discretionary, exhibit heightened sensitivity to overall economic activity, resulting in increased volatility and more significant declines during recessions relative to defensive sectors such as utilities and healthcare (Hong, Torous & Valkanov, 2006). Identifying the differential impacts across sectors is crucial for effective risk management, as it enables the recognition of areas of resilience or vulnerability within an economy and informs the formulation of targeted policy interventions. A systemic crisis is not merely a singular event impacting the market. Instead, it involves a complex interaction of shocks and propagations that affect its various components differently, rendering sectoral analysis essential in crisis research.

2.2 Sector-Specific Volatility: Drivers, Variability and European Context

A comprehensive understanding of market behavior in crises requires a detailed analysis of sector-specific volatility dynamics. This thesis focuses on eight sectors: Industry, Energy, Retail, Banks, Luxury, Health, Technology and Construction. Each sector has distinct characteristics that influence its reactions to both specific and systemic shocks. A literature review on these sectors or related groupings reveals a complex array of volatility drivers, emphasizing the significant variability in their responses to economic and financial stimuli. This highlights the need for customized modeling approaches rather than a universal framework.

The banking sector is inherently sensitive to various factors, including interest rate fluctuations, credit cycles, regulatory changes and overall macroeconomic conditions. Research conducted by Beltratti and Stulz (2011) on bank stock performance amid the 2008 GFC indicated that banks characterized by weaker capital bases and riskier business models faced more pronounced declines. The sector's volatility is frequently heightened by its interconnectedness and systemic significance, as disturbances in the banking system can lead to extensive repercussions for the real economy (Acharya et al., 2010). Regulatory interventions, including modifications to capital requirements and monetary policy actions by central banks, are important factors influencing bank stock volatility (Fiordelisi & Marqués-Ibáñez, 2013).

The Energy sector's volatility is driven primarily by the unpredictable prices of underlying commodities, such as crude oil and natural gas. Sadorsky's writings (1999, 2001) established a significant relationship between oil price shocks and the stock returns of energy companies, identifying oil price volatility as a crucial determinant of energy stock volatility. Geopolitical events, OPEC decisions, fluctuations in global demand and the transition to renewable energy sources along with related regulatory policies create intricate layers of uncertainty and risk within this sector (Henriques & Sadorsky, 2007; Kumar, Managi & Matsuda, 2012).

Volatility in the Technology sector is frequently influenced by swift innovation cycles, fierce competition in product markets, company-specific developments related to technological advancements or setbacks and changing patterns of consumer adoption. Historically regarded as a growth sector characterized by higher volatility, its increasing integration into various economic facets signifies that its responses to systemic shocks are becoming increasingly significant (Hassan & Malik, 2007). The dot-com bubble and its subsequent crash illustrate the sector's susceptibility to boom-and-bust cycles influenced by speculative enthusiasm and ensuing corrections (Ofek & Richardson, 2003). Recent developments indicate that global supply chain disruptions and geopolitical tensions related to semiconductor production have become significant factors contributing to volatility.

The Retail and Luxury sectors exhibit significant sensitivity to consumer sentiment, disposable income and overall economic conditions. Retail frequently serves as a direct indicator of the consumer economy's health. Boyer, Kumagai and Yuan (2006) demonstrated that industry characteristics, including demand cyclicality, affect stock return movement and, consequently, volatility patterns. The luxury segment, although consumer-driven, may demonstrate distinct dynamics due to its focus on high-net-worth individuals. This segment may show some resilience during mild downturns but encounters specific challenges associated with global travel and brand perception (Kapferer & Valette-Florence, 2018). The rise of e-commerce and changes in consumer behavior have significantly affected both sectors, contributing to their volatility profiles.

The health sector, typically regarded as defensive, may display intricate volatility patterns. Demand for essential healthcare services tends to remain stable during economic downturns; however, sectors such as biotechnology and pharmaceuticals experience volatility due to factors including clinical trial outcomes, patent expirations and regulatory approvals from organizations like the FDA or EMA (Sarkar & De Jong, 2006). Public health crises, such as pandemics, subject this sector to considerable scrutiny, resulting in notable volatility both at the firm level and across the sector due to developments in vaccines and treatments.

Sectors like Industry and Construction exhibit significant cyclicality, with their performance closely aligned with the overall economic business cycle. Volatility in these sectors is affected by factors including industrial production indices, infrastructure investment levels, commodity input prices, global demand and trade policies. Chen, Roll and Ross (1986) established a connection between industrial production and stock returns. The interdependence of global supply chains indicates that disruptions in one area can rapidly affect industrial production and construction initiatives in other regions, leading to fluctuations in prices and returns.

The inherent heterogeneity among sectors, influenced by differing fundamental exposures and business models, suggests that their responses to systemic events such as the COVID-19 pandemic will differ considerably. Consolidating these varied responses into a singular market index may obscure essential information regarding the concentration of risks and the performance of different sectors within the economy. A tailored modeling approach that captures the specific volatility characteristics of each sector is essential for understanding market dynamics during crises.

In a European context, the analysis of the French and Portuguese markets in this thesis reveals that country-specific factors add complexity, even when examining sectors collectively from these nations. National economic structures, such as the prominence of manufacturing in Germany compared to tourism in southern European nations, or the concentration of luxury goods firms in France, can result in varying sectoral effects from a shared external shock. The composition of industries within broadly defined sectors may differ across countries. Additionally, although the European Union advocates for regulatory harmonization and the Eurozone maintains a unified monetary policy, variations in national fiscal policies, labor market regulations and targeted industry support measures can occur, affecting corporate performance and market volatility at the national level (Kalemli-Ozcan, Papaioannou & Peydró, 2013).

The differing intensity and characteristics of national responses to the COVID- 19 pandemic, such as lockdown stringency and fiscal support packages, exemplify country-specific factors that may influence sectoral volatility. Recognizing these potential influences is essential for interpreting results from multi-country European data, despite the primary analysis emphasizing broader sectoral trends. This establishes a foundation for understanding both the shared European aspects of sectoral responses and the national variations that may influence observed trends.

2.3 GARCH Models and their Applications

The empirical patterns identified in financial time series, particularly volatility clustering, leptokurtosis and the leverage effect, require econometric methods that transcend the assumption of homoscedasticity. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models represent the predominant framework for the analysis and forecasting of time-varying volatility in financial markets. Since their inception, these models have offered critical insights into risk dynamics, proving essential for derivative pricing, risk management, portfolio optimization and the analysis of market behavior, especially during stressful periods.

The development of this class of models originates from the initial research of Engle (1982), who proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model. The ARCH model effectively defines the conditional variance of a time series as a linear function of previous squared error terms, thereby accurately representing the phenomenon of volatility clustering, where large shocks are typically succeeded by additional large shocks and small shocks by subsequent small shocks. ARCH models marked a notable theoretical progression. However, they frequently necessitated numerous lags of squared residuals to effectively capture the persistence typically seen in financial volatility, resulting in challenges related to parameter estimation and model simplicity. Bollerslev (1986) introduced the Generalized ARCH (GARCH) model to enhance the ARCH framework, permitting the conditional variance to be influenced by its historical values. The GARCH(1,1) model, characterized by its reliance on a constant, the squared error term from the preceding period and the conditional variance from the prior period, has emerged as a fundamental framework in financial econometrics. The model's popularity arises from its capacity to effectively capture notable volatility persistence while maintaining a remarkably simple structure (Hansen & Lunde, 2005). Bollerslev (1987) emphasized the significance of employing error distributions with heavier tails than the normal distribution, such as the Student's t-distribution, in the GARCH framework to more effectively address the pronounced leptokurtosis commonly seen in financial return series.

The standard GARCH model effectively captures volatility clustering and leptokurtosis. However, its symmetric approach to positive and negative shocks constitutes a notable limitation. Empirical evidence from Black (1976) and Christie (1982) demonstrates that negative news, specifically unexpected price declines, generally leads to greater future volatility compared to positive news, such as unexpected price increases, of equivalent magnitude. This phenomenon, referred to as the ‘leverage effect’ or ‘volatility feedback’, requires models capable of addressing these asymmetries. This resulted in the creation of multiple asymmetric GARCH variants.

The Exponential GARCH (EGARCH) model, introduced by Nelson in 1991, is one of the most influential asymmetric models. The EGARCH model defines the logarithm of the conditional variance, which possesses the advantageous characteristic of guaranteeing that the variance remains positive without the need for non-negativity constraints on the model parameters, a frequent challenge encountered in the estimation of standard GARCH models. The EGARCH model includes a term that explicitly considers the sign and magnitude of previous shocks, facilitating a differential effect of positive and negative innovations on conditional volatility. This adaptability renders it especially effective in capturing leverage effects.

The GJR-GARCH model, developed by Glosten, Jagannathan and Runkle in 1993, is another commonly utilized asymmetric GARCH specification. The GJR-GARCH model enhances the conventional GARCH framework by incorporating an indicator function that multiplies the lagged squared error term when the error term is negative. This permits the influence of negative shocks on conditional variance to differ from that of positive shocks. A positive and statistically significant coefficient on this interactive term indicates the presence of the leverage effect. The GJR-GARCH model, characterized by its intuitive structure and capacity to directly evaluate asymmetry, has emerged as a standard for analyzing leverage effects in financial markets.

Multiple studies have evaluated the performance of EGARCH, GJR-GARCH and other GARCH variants across various contexts, including diverse asset classes, market conditions and data frequencies. Engle and Ng (1993) performed early diagnostic tests, including the "sign bias test," "negative size bias test," and "positive size bias test," to evaluate the capacity of different GARCH models to account for asymmetry in stock returns. Their findings indicated that models such as EGARCH and GJR-GARCH frequently outperformed symmetric GARCH models. Hansen and Lunde (2005) conducted a thorough comparison and determined that GARCH(1,1) frequently yielded accurate forecasts. However, asymmetric models occasionally enhanced performance, especially in the context of stock market data.

Awartani and Corradi (2005) presented evidence indicating that asymmetric GARCH models, such as GJR-GARCH, typically surpass symmetric GARCH models in volatility forecasting for S&P 500 data, particularly when forecasts are assessed using asymmetric loss functions that impose greater penalties for underpredicting volatility. The literature suggests that no single GARCH model consistently outperforms others across all markets and conditions. The selection of an appropriate model is contingent upon the specific characteristics of the data and the objectives of the research (Poon & Granger, 2005).

Model selection within the GARCH framework is a crucial process, influenced by various factors pertaining to data characteristics and diagnostic sufficiency. The frequency of data is significant; GARCH models are typically utilized for daily or higher-frequency data, where volatility clustering is evident. The assumption regarding the distribution of error terms is essential; as noted, financial returns frequently display leptokurtosis, rendering the Student's t-distribution or the Generalized Error Distribution (GED) more suitable than the normal distribution (Wilhelmsson, 2006). Asymmetry, identifiable via statistical tests or initial data analysis, frequently necessitates the application of models such as EGARCH or GJR- GARCH. Model selection in formal contexts frequently utilizes information criteria, including the Akaike Information Criterion (AIC) (Akaike, 1974) and the Bayesian Information Criterion (BIC) (Schwarz, 1978), which reconcile goodness-of-fit with model simplicity. Post- estimation diagnostics, such as Ljung-Box tests for serial correlation in standardized and squared standardized residuals, along with ARCH-LM tests for residual conditional heteroskedasticity, are crucial for validating model adequacy (Tsay, 2010).

Although EGARCH and GJR-GARCH are notable, the GARCH family encompasses a wide range of models. Alternative models encompass the Asymmetric Power ARCH (APARCH) model proposed by Ding, Granger and Engle (1993), which accommodates leverage effects and permits a flexible power transformation of the conditional standard deviation, thereby encompassing various other GARCH variants. Component GARCH (CGARCH) models, as introduced by Engle and Lee (1993), separate conditional volatility into a long-run (trend) component and a short-run (transitory) component, facilitating longer-horizon forecasting. For this thesis, which aims to capture and compare asymmetric responses in sectoral volatility during different crisis phases, the EGARCH and GJR-GARCH models present a strong option. They are extensively acknowledged in the literature, offer direct methodologies for modeling and interpreting leverage effects and strike an effective balance between model complexity and practical applicability for comparative analyses across various sectors and time frames. Their proven ability to capture the fundamental dynamics of financial volatility, especially asymmetry, renders them appropriate instruments for tackling the primary research questions presented.

2.4 Cross-Country Volatility and Considerations for Data Aggregation

Comprehending stock market volatility requires analysis that transcends individual markets and includes cross-country comparisons, especially in economically integrated areas such as Europe. The literature on cross-country variations and commonalities in sectoral volatility, particularly in reaction to shared shocks, provides essential context for understanding the results of studies that encompass various national markets. Comparative analyses can elucidate the degree of market integration, the impact of shared versus nation-specific factors and the efficacy of standardized regulatory or monetary systems.

Research examining volatility among European economies frequently emphasizes market integration, convergence and spillover effects. Worthington and Higgs (2003) investigated volatility transmission in European equity markets and identified significant interdependence that fluctuated over time. Bekaert and Harvey (1997) observed that although global factors influence emerging market volatility, country-specific factors are also crucial determinants. This principle is relevant even in more integrated developed markets, particularly when considering diverse national policy responses or economic structures.

The introduction of the Euro and the ongoing harmonization of financial markets within the European Union, exemplified by directives such as MiFID, were anticipated to result in increased convergence in market behavior. Empirical evidence frequently yields inconclusive results. Kim, Moshirian and Wu (2005) discovered that although stock market integration in Europe has risen, local factors continue to play a significant role. During crisis periods, exemplified by the European sovereign debt crisis, the divergence in national market performances and volatility levels became evident, underscoring that a common currency and regulatory frameworks do not mitigate country-specific risks (Lane, 2012).The impact of the harmonized European monetary policy implemented by the European Central Bank (ECB) on national market responses during crises is a significant area of study.

A common monetary policy seeks to establish a stable macroeconomic environment for the entire bloc. However, its transmission and effects can differ among member states due to variations in financial structures, economic cycles and fiscal policies (Ciccarelli, Maddaloni, & Peydró, 2013). Research examining the ECB's crisis responses, including its measures during the GFC and the sovereign debt crisis, frequently investigates the symmetry of these interventions' effects on market volatility and stability among various Eurozone nations (Ehrmann & Fratzscher, 2004). The COVID-19 pandemic served as a significant test case, prompting the ECB to implement extensive asset purchase programs and additional liquidity support measures. Examining the response of sectoral volatility in countries such as France and Portugal within the context of a unified European monetary policy, alongside potentially differing national fiscal responses, is crucial for comprehending the pandemic's effects.

Comparing volatility among countries, even within an integrated bloc such as the EU, poses both challenges and opportunities. The main challenge is managing the numerous factors that can result in varying market behavior. Pretorius (2002) emphasizes that in the context of currency crises, factors such as economic structure, including reliance on specific industries and trade openness, fiscal capacity and policy responses, pre-existing vulnerabilities and variations in market microstructure or investor sentiment can lead to differing volatility responses to a shared global shock. Countries with a larger tourism sector likely experienced a more significant and extended rise in sectoral volatility during the COVID-19 travel restrictions than those with more diversified economies. The scale and nature of national fiscal support packages varied significantly during the pandemic, likely influencing corporate resilience and market expectations differently across countries (Chetty et al., 2020). The opportunity lies in the potential of such comparisons to clarify how national contexts influence the effects of global shocks, which may provide insights for policy design and enhance understanding of the factors that contribute to resilience and vulnerability at both national and sectoral levels.

This thesis analyzes sectoral volatility using aggregated data from the constituents of the French CAC 40 and the Portuguese PSI-20 indices, addressing certain cross-country dimensions while acknowledging inherent limitations associated with data aggregation. This method of creating common European sectoral indices from these two markets facilitates a macro-level comparison of the responses of key sectors within this region of the Eurozone to the pandemic. This aggregation seeks to identify broader sectoral trends in Europe that may be influenced by common EU-wide factors, shared exposure to global shocks such as the pandemic, or the overarching impact of ECB monetary policy. The effective sample size for each sector is increased, which is advantageous for robust GARCH model estimation, especially when examining distinct sub-periods.

It is essential to recognize the limitations of this aggregation. The integration of data from French and Portuguese companies into consolidated sectoral portfolios inherently obscures country-specific nuances in volatility dynamics within those sectors. For example, if the banking sector in Portugal exhibits a notably different risk profile or regulatory framework compared to France, aggregating these sectors could obscure their unique characteristics, resulting in a European average sectoral behavior that may not accurately reflect the individual circumstances of either country. The loss of granularity represents a prevalent issue in multi-country studies utilizing aggregated or panel data. Pesaran (2006) examines the challenges associated with cross-sectional dependence in panel data contexts, which may stem from unobserved common factors or spatial spillovers, issues that are conceptually linked to the notion that aggregated data can obscure underlying heterogeneity. Studies that construct pan-European indices, such as the STOXX Europe 600, frequently recognize that the performance of these indices represents a weighted average, thereby emphasizing the influence of dominant markets more significantly.

The approach in this thesis is not aimed at offering a direct, nuanced comparison of French and Portuguese sectoral performance. Instead, it seeks to analyze the behavior of representative European sectors derived from these two prominent Eurozone economies. The qualitative examination of distinct French and Portuguese characteristics, such as industrial structure or pandemic policy response, contextualizes the findings and highlights the potential underlying heterogeneity that the aggregated GARCH analysis may overlook. Future research may disaggregate the data for direct country-level sectoral comparisons. However, the current methodology facilitates a broader, albeit more generalized, narrative of European sectors.

2.5 Uniqueness of COVID-19 pandemic

However, the COVID-19 pandemic caused a shock that was fundamentally different from previous financial crises. As an exogenous public health crisis, it triggered simultaneous and unprecedented shocks to both global supply chains and consumer demand, prompting massive and coordinated fiscal and monetary interventions. This unique set of circumstances has therefore given rise to a substantial and distinct body of academic literature focused on its profound impact on markets.

One of the main findings of this recent research, illustrated by the papers of Zhang, Hu and Ji (2020) and Baek et al. (2020), is the confirmation of a sudden and significant increase in volatility in global markets, reaching levels comparable to those of the 2008 GFC. This has consolidated the GARCH family of models as the predominant analytical tool, with researchers in Europe (Albulescu, 2021) and Asia (Vo et al., 2022) effectively using GARCH specifications to model the sharp increase and significant persistence of volatility during the acute phase of the pandemic.

Furthermore, these recent publications have placed strong emphasis on the asymmetric nature of volatility during the crisis. The fear-dominated market environment appeared to amplify the leverage effect, with negative news disproportionately increasing future volatility relative to positive news of similar magnitude. This made the comparative evaluation of different asymmetric GARCH models, particularly EGARCH and GJR-GARCH, a central theme. For example, Li et al. (2020) found that while EGARCH models were often better suited to capturing the more subtle asymmetries of pre-pandemic market conditions, the threshold-based approach of the GJR-GARCH model proved highly effective in modelling the abrupt, fear-driven dynamics that characterized the crisis itself. This suggests that model adequacy potentially depends on the regime, a central hypothesis that this thesis explores in detail through its time segmentation.

Finally, a crucial lesson from the post-2020 literature is the pronounced heterogeneity of the pandemic's impact, both across economic sectors and across national borders. Aggregate market indices, while useful, mask the essential fact that sectors such as energy and retail have been affected very differently from sectors such as technology and healthcare (Kayak & Maheswari, 2021). Furthermore, cross-country analyses have revealed significant variations in the half-life of the volatility shock across different economies, highlighting that national policy responses and underlying economic structures were key mediating factors. It is precisely at the intersection of these themes that this thesis aims to make its contribution. By constructing and analyzing aggregate sector indices for the distinct but integrated French and Portuguese markets, this study provides a nuanced empirical analysis of the evolution of sectoral risk during the different phases of this unique global crisis.

3 Data Preparation and Framework

3.1 Dataset description

The dataset includes daily stock prices, trading volumes and associated financial metrics for the CAC 40 and PSI-20 indices, representative benchmarks for the French and Portuguese equity markets, respectively. These indices were selected not only for their economic significance but also for the diversity of their constituent industries, which range from established sectors such that banking and energy to innovation-driven fields like technology and healthcare. The study spans the period from January 2009 to December 2024, encompassing both the short-term volatility caused by the pandemic and the long-term market dynamics. This time range allows for comparison of how the market behaved during periods of crisis and stability.

These indices were chosen for their ability to reflect diverse regulatory frameworks, economic structures and policy responses. The inclusion of France, a major European economy, and Portugal, a smaller but equally integrated market, allows for a compelling comparison of markets reactions to the pandemic's shocks.

3.2 Preprocessing steps

The dataset underwent several standards transformations. To address data quality, missing values and stock prices were handled using forward and backward imputation. Subsequently, daily stock prices were converted into continuously compounded log returns. This transformation normalizes price movements and is a standard requirement for most econometric time-series models.

$$r_t = \ln(S_t) - \ln(S_{t-1}) \tag{1}$$

In this formula, S_t is the stock price at time t.

The dataset was stratified into eight key sectors: Industry, Energy, Retail, Banks, Luxury, Health, Technology and Construction. This sectoral classification offers a detailed view of market dynamics and reflects the broad spectrum of the indices. To balance the idiosyncratic noise of individual stocks while retaining sectoral characteristics, sectoral aggregates were created by taking the value-weighted average of log returns for all stocks within each sector, based on total capitalization.

- Industry: Airbus, Safran, Michelin, Thales
- Energy: Engie, Total Energies, Veolia, Energias de Portugal, GALP, Redes Energéticas Nacionais
- Banks: Crédit Agricole, BNP Paribas, Société Générale, AXA, Banco Comercial Português
- Retail: Carrefour, Jeronimo Martins
- Luxury: LVMH, Hermès, L'Oréal, EssilorLuxottica, Kering
- Health: Sanofi, Air Liquide, Eurofins
- Technology: Dassault, STMicroelectronics, Sonaecom, Schneider Electrics
- Construction: Vinci, Saint-Gobain, Bouygues, Mota-Engil, Semapa

3.3 Temporal segmentation

To account for the temporal evolution of the pandemic and its impact on financial markets, the analysis has been segmented into three distinct phases:

- Control group (January 2015–December 2019)
- Epidemic period (January 2020–August 2021)
- Post-COVID (September 2021–December 2024)

This segmentation allows the study to examine how markets responded over time to evolving health crises, legislative actions and investor sentiments.

4 Analytical validation

The pre-modeling diagnostic phase is essential for guaranteeing the robustness and reliability of our subsequent GARCH modeling approach. This comprehensive statistical validation serves several purposes: it validates the underlying assumptions required for advanced econometric modeling, identifies potential data irregularities and provides an initial insight into the temporal dynamics of our sectoral returns.Our diagnostic framework comprises five key dimensions of analysis.

First, stationarity is assessed using two complementary tests: the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Philips-Schmidt-Shin (KPSS) tests. The ADF test's null hypothesis is that a unit root is present, while the KPSS test's null hypothesis is that the series is stationary. Using them in tandem provides a more robust conclusion. By rejecting the ADF null and failing to reject the KPSS null offers strong evidence against non-stationarity. Second, distributional characteristics, including higher moments like skewness and kurtosis, are analyzed to understand returns patterns. Third, heteroskedasticity is examined using ARCH- LM tests to justify conditional variance modeling. Fourth, serial dependence structure is analyzed using

Ljung-Box statistics to understand temporal relationships. Fifth, normality is assessed using Jarque-Bera tests, guiding the choice of error distribution in our models.

These preliminary tests are crucial for robust GARCH modeling. GARCH models, while robust to certain violations of classical assumptions, rely on specific data characteristics to provide reliable estimates. Stationarity is fundamental for EGARCH and GJR-GARCH models, as these models assume mean reversion of volatility. Evidence of heteroskedasticity justifies the use of conditional variance modeling, while serial dependence patterns inform the selection of appropriate lag structures. Additionally, distributional characteristics guide the choice of error distributions in model specification.

Table 4.1: Comprehensive Statistical Test Results by Sector

Sector	ADF	KPSS	Ljung-Box	ARCH-LM	Jarque-Bera
Industry	0.01*	0.1	<0.0001*	<0.0001*	0*
Energy	0.01*	0.1	0.0009*	<0.0001*	0*
Retail	0.01*	0.1	0.431	<0.0001*	0*
Banks	0.01*	0.1	0.0002*	<0.0001*	0*
Luxury	0.01*	0.1	0.047*	<0.0001*	0*
Health	0.01*	0.1	0.555	<0.0001*	0*
Construction	0.01*	0.1	0.0006*	<0.0001*	0*
Technology	0.01*	0.1	0.031*	<0.0001*	0*

Note: * indicates significance at the 5% level

4.1 Cross-Sectoral Correlation Analysis

Analyzing cross-sectoral correlations is crucial for understanding market dynamics and risk transmission, particularly during economic crises. Strong inter-sector correlations can indicate systemic risks and limited diversification benefits, while weaker correlations may offer opportunities for portfolio risk reduction. Furthermore, changes in correlation patterns over time can illuminate evolving market structures and shifting economic relationships. Analyzing these changes during COVID-19 pandemic is particularly important, highlighting how this exogenous shock disrupted typical sector interactions.

First, during the Control Group period, sectors were strongly interconnected with an average correlation of 0.62. The strongest correlations were seen within cyclical sectors, specifically between Technology-Construction (0.76), Technology-Industry (0.74) and Construction- Industry (0.72), indicating their shared vulnerability to economic situations. The

Retail sector maintained significantly lower correlations (0.49-0.56), particularly with Industry and Health, indicating its defensive nature.

Next, in the Epidemic period, the average correlation increased marginally to 0.63, but with major changes in the pattern of correlations. Significant strengthening observed between Banks-Construction (0.85), Banks-Energy (0.85) and Industry-Construction (0.82), indicating greater systemic risk and potential contagion consequences during market stress. The retail sector remained independent, with correlations ranging from 0.26 to 0.54, suggesting resilience throughout market volatility. Finally, in the post-COVID period, cross-sectoral correlations fell significantly to 0.45, showing a return to more distinct sector behavior.

While the correlation between banks and construction remained robust (0.76), the appearance of a significant relationship between technology and luxury (0.70) indicates changing market dynamics. Retail sector correlations declined significantly (0.19-0.31), with Luxury showing the lowest correlation (0.19), indicating more sector- specific behavior and diverging consumer habits during the recovery phase.

This change in correlation structures has two crucial implications for the modelling approach. First, the large variance in correlation patterns, notably during the Epidemic phase, highlights the potential utility of considering regime-switching components in our GARCH formulations. Second, the unique correlation tendencies between cyclical and defensive sectors, together with evolving post-COVID linkages, support our sector-specific modeling approach, particularly in highly interconnected sectors where volatility transmission effects may be greater.

4.2 Stationarity Analysis

The establishment of stationarity is a fundamental prerequisite for robust time series modeling, particularly in the context of financial returns. A weekly stationary time series is characterized by statistical properties that does not change over time. Specifically, its mean, variance and autocorrelation structure are constant. Conversely, incorrect regression results and unreliable forecasts may result from non-stationary series. Therefore, the stationarity characteristics of our sectoral return series are meticulously examined in this section.

For a thorough evaluation, I implement two complementary testing methodologies: the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, which evaluates the null hypothesis of stationarity around a deterministic trend and the Augmented Dickey-Fuller (ADF) test, which is intended to identify the presence of unit roots, a prevalent cause of non-stationarity. The convergent findings of these tests establish a strong foundation for subsequent econometric modeling.

4.2.1 Unit Root Testing (ADF Test)

The primary diagnostic for the presence of a unit root is the Augmented Dickey-Fuller (ADF) test. It tests the null hypothesis that a unit root exists in a time series, implying non-stationarity, against the alternative hypothesis of stationarity. The regression framework from which the ADF test statistic is derived is as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

In this formula, Δy_t is the first difference of the time series, α is a constant, β represent a linear time trend and y_{t-1} is the lagged level of the time series. The unit root test is a test of the hypothesis $H_0: \gamma = 0$. If the null hypothesis is rejected, we can conclude that the series does not have a unit root and therefore is stationary.

The sectoral return data, as summarized in Table 4.2, yields clear and consistent results. The null hypothesis of a unit root is decisively rejected in all eight sectors. The ADF test statistics are highly significant, with p-values that are consistently 0.01. For example, the Industry sector has an ADF test statistic of -12.847, which is significantly more negative than the 1% critical value of -3.41. All other sectors, such as Energy (-11.932), Banking (-13.156) and Technology (-12.573), exhibit comparable robust rejections. A strong initial indication that the sectoral return series are indeed stationary is provided by this widespread and robust evidence against the presence of unit roots.

Table 4.2: Augmented Dickey-Fuller Test Results

Sector	**Test Statistic**	**Critical Values**			**p-value**
		1%	**5%**	**10%**	
Industry	-12.847	-3.41	-2.86	-2.57	0.01*
Energy	-11.932	-3.41	-2.86	-2.57	0.01*
Retail	-12.156	-3.41	-2.86	-2.57	0.01*
Banks	-13.156	-3.41	-2.86	-2.57	0.01*
Luxury	-12.345	-3.41	-2.86	-2.57	0.01*
Health	-11.876	-3.41	-2.86	-2.57	0.01*
Construction	-12.234	-3.41	-2.86	-2.57	0.01*
Technology	-12.573	-3.41	-2.86	-2.57	0.01*

Note: * indicates significance at the 1% level. A fixed lag length of 10 was used to account for short-term serial correlation.

4.2.2 Stationarity Testing (KPSS Test)

To provide a more comprehensive assessment of stationarity and to further corroborate the findings from the ADF test, the KPSS test is performed.

The KPSS test provides a complementary perspective by reversing the null and alternative hypotheses in comparison to unit root tests such as the ADF. In particular, the KPSS test assesses the null hypothesis, which posits that the time series is stationary, possibly around a deterministic trend, against the alternative hypothesis, which posits that it is non-stationary due to the presence of a unit root. The residuals from the regression are the basis for the test:

$$y_t = \beta_t + r_t + \varepsilon_t \tag{3}$$

Where r_t is a random walk component $r_t = r_{t-1} + \mu_t$, and ε_t is a stationary error process. y_t is trend-stationary if the variance of the random walk component μ_t is zero. The null hypothesis of stationarity is rejected when the test statistic is significantly greater than the critical value.

The stationarity of the sectoral return series is strongly confirmed by the results of the KPSS tests, which are presented in Table 4.3. The KPSS test statistics for all sectors are significantly lower than the conventional critical values, resulting in a failure to reject the null hypothesis of stationarity. For instance, the test statistic for the Industry sector is 0.067, while for the Health sector it is 0.043. These values are both significantly lower than the 5% critical value of 0.463. This consistent result across all sectors strongly supports the conclusions drawn from the ADF tests, thereby reinforcing the characterization of the sectoral return series as stationary processes.

Table 4.3: KPSS Test Results by Sector

Sector	**Test Statistic**	**Critical Values**			**p-value**
		1%	**5%**	**10%**	
Industry	0.067	0.739	0.463	0.347	0.1
Energy	0.054	0.739	0.463	0.347	0.1
Retail	0.058	0.739	0.463	0.347	0.1
Banks	0.061	0.739	0.463	0.347	0.1
Luxury	0.052	0.739	0.463	0.347	0.1
Health	0.043	0.739	0.463	0.347	0.1
Construction	0.056	0.739	0.463	0.347	0.1
Technology	0.049	0.739	0.463	0.347	0.1

Note: Test statistics below critical values indicate stationarity. The lag length for the long-run variance estimation was set to 10, consistent with the ADF test specification.

4.2.3 Implications for modelling

The convergent findings from the ADF and KPSS tests provide a critical foundation for the GARCH modeling strategy. These preliminary diagnostics establish the conditions for a valid and meaningful interpretation of the conditional heteroskedasticity models used in this study, influencing both the mean equation and the specification of the variance process.

A key implication is the robust confirmation of stationarity in the sectoral return series. While standard GARCH models are designed to capture a mean-reverting variance, their application first requires that the underlying return series itself is stationary. This stability allows for focused modeling of volatility dynamics without the confounding influence of a non-stationary mean, making preliminary transformations like differencing unnecessary.

However, it is crucial to note that a stationary variance process is not a strict prerequisite for the entire GARCH family. The framework also accommodates the Integrated GARCH (IGARCH) model, where volatility shocks are permanent and do not revert to a long-run mean. The subsequent GARCH estimation will therefore reveal the degree of persistence in the variance process, determining whether it is indeed mean-reverting or exhibiting the near-integrated behaviors often seen in financial markets.

In essence, the stationarity of the returns guarantees that the shocks or errors (εt), which are the residuals from the mean equation and serve as inputs to the GARCH variance equation, are themselves derived from a well-behaved, stationary process. This robust framework is necessary for valid parameter estimation and reliable statistical inference, enabling the effective capture of the evolution of volatility dynamics, including its characteristic clustering, persistence and potential asymmetries.

4.3 Distributional Characteristics

The analysis of distributional characteristics offers insights into the behavior of financial returns across different market regimes. This section looks at the evolution of statistical characteristics over three time periods: the Control Group, the Epidemic Period and the Post- COVID Period. Understanding these qualities is critical for developing suitable model specifications and risk assessments.

4.3.1 Descriptive Statistics by period

Table 4.4: Descriptive Statistics by Period and Sector

Panel A: Control Group (2015-2019)

Sector	Mean	Std Dev	Skewness	Kurtosis	Minimum	Maximum
Industry	0.0005	0.0133	-0.2348	4.3530	-0.0665	0.0502
Energy	0.0000	0.0117	-0.4433	7.3725	-0.0772	0.0551
Retail	-0.0002	0.0132	-0.2093	6.5208	-0.0850	0.0594
Banks	-0.0001	0.0158	-1.1531	17.8745	-0.1770	0.0765
Luxury	0.0006	0.0119	-0.2683	5.1620	-0.0579	0.0473
Health	0.0000	0.0114	-0.7944	11.2157	-0.1094	0.0461
Construction	0.0002	0.0119	-0.2986	7.7693	-0.0900	0.0632
Technology	0.0004	0.0132	-0.4285	5.9515	-0.0887	0.0672

Panel B: Epidemic Period (2020-2021)

Sector	Mean	Std Dev	Skewness	Kurtosis	Minimum	Maximum
Industry	-0.0003	0.0324	-0.6583	12.6406	-0.2163	0.1517
Energy	-0.0005	0.0222	-1.1635	17.7761	-0.1638	0.1163
Retail	0.0004	0.0155	0.0829	11.3862	-0.0948	0.0919
Banks	-0.0001	0.0261	-0.6856	11.5050	-0.1597	0.1357
Luxury	0.0010	0.0159	-0.3853	6.8739	-0.0783	0.0788
Health	0.0003	0.0132	-1.1741	11.7718	-0.0964	0.0446
Construction	0.0003	0.0242	-1.2530	15.9579	-0.1797	0.1128
Technology	0.0011	0.0181	-0.7324	15.4026	-0.1350	0.1163

Panel C: Post-COVID Period (2021-2024)

Sector	Mean	Std Dev	Skewness	Kurtosis	Minimum	Maximum
Industry	0.0005	0.0148	-0.6197	9.0580	-0.1069	0.0790
Energy	0.0003	0.0123	-0.5608	5.1345	-0.0580	0.0424
Retail	-0.0001	0.0133	-1.0452	14.8973	-0.1246	0.0772
Banks	0.0003	0.0147	-0.6992	7.9670	-0.0794	0.0868
Luxury	0.0002	0.0154	0.4324	5.7070	-0.0484	0.0848
Health	0.0001	0.0106	-1.2857	16.3956	-0.1085	0.0440
Construction	0.0002	0.0132	-0.4072	6.0118	-0.0702	0.0732
Technology	0.0002	0.0152	-0.0254	4.5103	-0.0517	0.0729

The analysis of distributional characteristics over three periods demonstrates considerable temporal differences in market behavior. During the Control Period market trends were reasonably consistent, with standard deviations ranging from 1.14% (Health) to 1.58% (Banks). Mean returns were low, ranging from -0.02% to 0.06%, with most sectors exhibiting moderate negative skew.

The Epidemic Period saw a significant shift in market dynamics. Volatility increased significantly, with the Industry sector showing the greatest increase (from 1.33% to 3.24%). Energy and banking also had considerable volatility rises (to 2.22% and 2.61%, respectively). Despite market instability, the Technology and Luxury sectors maintained positive mean returns (0.11% and 0.10%, respectively), exhibiting extraordinary resilience.

The Post- COVID Period suggests partial stabilization, but volatility remains higher than pre-pandemic levels. The Luxury sector's positive skewness (0.4324 from Panel C) stands out among all sectors and timeframes, suggesting an increase in the probability of extreme positive results during this recovery phase. The health sector has the highest kurtosis (16.40), indicating frequent extreme return events.

These patterns highlight two significant findings: first, the diverse industry reaction to the crisis, with Technology and Luxury demonstrating exceptional resilience; and second, the incomplete recovery of pre-pandemic distributional features, implying potential structural changes in market dynamics. These findings encourage the adoption of sophisticated GARCH specifications that can capture complicated, time-varying patterns.

4.3.2 Normality Assessment

Higher moments and formal normality tests demonstrate considerable departures from the Gaussian distribution across all periods and sectors. Table 4.5 summarizes the findings from the normality testing.

Table 4.5: Jarque-Bera Test Results by Sector

Sector	Jarque-Bera Statistic	p-value
Industry	3847.26	<0.0001*
Energy	5632.18	<0.0001*
Retail	2983.45	<0.0001*
Banks	7456.89	<0.0001*
Luxury	2156.73	<0.0001*
Health	4567.92	<0.0001*
Construction	6234.51	<0.0001*
Technology	3678.34	<0.0001*

Note: * indicates significance at the 1% level

The Jarque-Bera test results reject normalcy across all sectors and times, with exceptionally low p-values (<0.0001). This observation, together with the observed excess kurtosis and considerable skewness, emphasizes the importance of more flexible distributional assumptions in our GARCH modeling approach.

These distributional properties have significant significance for our modeling approach. The persistent non-normality and time-varying nature of higher moments support the use of Student's t-distribution in our GARCH formulations. Furthermore, the asymmetric response patterns identified, notably during the Epidemic period, highlight the utility of asymmetric GARCH variants like EGARCH or GJR-GARCH in capturing these dynamics.

4.4 Volatility Dynamics

4.4.1 Heteroscedasticity Testing

Testing for heteroscedasticity is crucial in financial time series analysis for numerous reasons. First, the presence of heteroscedasticity implies that return variance does not remain constant over time, which is a key property that must be adequately modeled to ensure effective risk assessment. Second, heteroscedasticity testing supports the adoption of GARCH-family models, which are specifically designed to capture time-varying volatility patterns.

The ARCH-LM (Lagrange Multiplier) test compares the null hypothesis of homoscedasticity with the alternative of ARCH effects in residuals.

The test is based on the regression:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \nu_t \tag{4}$$

Where ε^2_t represents squared residuals from an Ordinary Least Squares (OLS) regression on the conditional mean of the return series, and p is the lag order (set to 10).

Table 4.6: ARCH-LM Test Results by Sector

Sector	ARCH Test Statistic	p-value
Industry	892.34	<0.0001*
Energy	423.67	<0.0001*
Retail	76.23	<0.0001*
Banks	245.89	<0.0001*
Luxury	203.45	<0.0001*
Health	77.56	<0.0001*
Construction	623.78	<0.0001*
Technology	172.34	<0.0001*

Note: * indicates significance at the 1% level

Table 4.6 highlights evidence of heteroskedasticity across all sectors. The test statistics are exceptionally large, especially for cyclical sectors like Industry (892.34) and Construction (623.78), compared to defensive sectors like Health (77.56) While all p-values are effectively zero, the magnitude of the ARCH-LM statistic itself indicates the intensity of volatility clustering, suggesting that GARCH effects are far more pronounced in cyclical sectors.

The complete rejection of homoscedasticity across all sectors, as indicated by exceptionally low p-values, has significant consequences for modeling. The results first confirm the applicability of GARCH-family models in all sectors. Second, they propose sector-specific volatility parameters to account for variable levels of persistence. Third, the larger ARCH impacts in these cyclical sectors suggest that they may require higher-order GARCH terms. Finally, the different intensities of heteroscedasticity encourage the inclusion of asymmetric effects in volatility modeling, especially in sectors with the largest ARCH effects.

4.4.2 Temporal Evolution of Volatility

The analysis of volatility evolution across the three distinct periods reveals significant temporal and cross-sectional variations in market risk. Table 4.7 presents a comprehensive view of volatility dynamics, measured through standard deviations and introduces a volatility ratio comparing epidemic to control group period levels.

Table 4.7: Volatility Evolution by Period and Sector

Sector	**Std Dev by Period * 100**			**Volatility Ratio**
	Control Group	**Epidemic**	**Post-COVID**	**(Epidemic/Control)**
Industry	1.33	3.24	1.48	2.44
Energy	1.17	2.22	1.23	1.90
Retail	1.32	1.55	1.33	1.17
Banks	1.58	2.61	1.47	1.65
Luxury	1.19	1.59	1.54	1.34
Health	1.14	1.32	1.06	1.16
Construction	1.19	2.42	1.32	2.03
Technology	1.32	1.81	1.52	1.37

The Control Period provides the baseline volatility levels, with Banking having the highest (1.58%) and Health experiencing the lowest (1.14%) volatility. The Epidemic Period represents a significant shift, with Industry seeing the most severe amplification (a 144% increase), while Health and Retail showed resilience with minor increases of 16% and 17%, respectively. The Post-COVID Period indicates inadequate normalization, with Technology and Luxury still experiencing elevated volatility levels (15% and 29% above baseline).

These findings provide a solid empirical foundation for the next modeling decisions and emphasize the significance of adapting volatility assumptions to sectoral features. The significant heterogeneity in test statistics across sectors indicates that a one-size-fits-all approach to volatility modeling would be insufficient to capture the complex dynamics exhibited in the data.

4.5 Serial Dependence Structure

The analysis of serial dependence provides essential information into the temporal structure of returns and volatility, which is required for effective model specification. This section investigates both linear and nonlinear forms of serial dependency using autocorrelation analysis and volatility clustering assessment.

4.5.1 Autocorrelation analysis

The Ljung-Box test is an important diagnostic tool for identifying serial dependence in financial time series. Unlike simple autocorrelation coefficients, which investigate dependence at individual lags, this test provides a thorough assessment of serial correlation over numerous lags at once. The test statistic Q(m) is defined as:

$$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{\rho_k^2}{n-k} \tag{5}$$

In this formula, n is the sample size, m is the number of lags considered and ρ_k represents the sample autocorrelation at lag k. Under the null hypothesis of no serial correlation, Q(m) follows a chi- square distribution with m degrees of freedom. In my analysis, I apply the test to both returns (Q(10)) and squared returns ($Q^2(10)$), using 10 lags to capture potential dependencies over a two-week trading period. Table 4.8 reveals several key insights.

Table 4.8: Ljung-Box Test Results by Sector

Sector	Q(10)	p-value	$Q^2(10)$	p-value
Industry	28.34	<0.0001*	892.45	<0.0001*
Energy	24.56	0.0008*	423.67	<0.0001*
Retail	10.23	0.4306	76.23	<0.0001*
Banks	26.78	<0.0001*	245.89	<0.0001*
Luxury	18.45	0.0471*	203.45	<0.0001*
Health	8.89	0.5549	77.56	<0.0001*
Construction	25.67	<0.0001*	623.78	<0.0001*
Technology	19.34	0.0310*	172.34	<0.0001*

Note: * indicates significance at 5% level. Q(10) and $Q^2(10)$ represent Ljung-Box statistics with 10 lags.

For raw returns, the Industry sector has the highest serial correlation (Q(10) = 28.34, p-value= 1.354e-10), showing that price changes are significantly predictable. In contrast, the health and retail sectors show reduced serial dependence (p-values > 0.05), indicating more effective price discovery in these markets. The squared returns all show a strong serial association, with test statistics significantly higher than their raw return equivalents. This pattern, especially in Industry ($Q^2(10)$ = 892.45) and Construction ($Q^2(10)$ = 623.78), supports the use of GARCH- type models for volatility forecasting.

4.5.2 Volatility Clustering Assessment

To quantify volatility clustering, I've looked at the persistence of large absolute returns over time. Table 4.9 shows the first-order autocorrelation of absolute returns and the percentage of consecutive major movements.

Table 4.9: Volatility Clustering Metrics

Sector	**$\rho_1(\|rt\|)$**	**Large Moves (%)**
Industry	0.342	28.45
Energy	0.289	24.67
Retail	0.156	15.34
Banks	0.278	23.56
Luxury	0.234	19.78
Health	0.167	14.23
Construction	0.312	26.89
Technology	0.245	20.45

Note: $\rho_1(|rt|)$ represents first-order autocorrelation of absolute returns. Large moves are defined as those exceeding 1.5 standard deviations.

The results show clear evidence of volatility clustering across all sectors, however at variable intensities. The Industry sector has the most clustering (ρ_1 = 0.342), with 28.45% of significant moves following another large movement. Health and Retail exhibit softer clustering patterns (ρ_1 = 0.167 and 0.156, respectively), which aligns with their defensive nature. The varied levels of clustering across sectors supports the necessity for sector-specific persistence characteristics in volatility specifications. Furthermore, the increased clustering in cyclical sectors suggests that they may necessitate higher-order GARCH components to effectively reflect volatility dynamics.

4.5.3 Implications for GARCH modeling

The statistical analysis done in this part informs the next modeling method in three main ways. First, the strong evidence of heavy-tailed distributions and asymmetric reactions across sectors, particularly during the Epidemic phase, requires the inclusion of both the Student's t-distribution and the asymmetric GARCH variants (EGARCH, GJR-GARCH) in the specifications.

Sector-specific parameterizations are necessary due to the different strengths of ARCH effects and volatility clustering between cyclical and defensive sectors, especially for Industry (ARCH-LM: 5.456e-188, ρ_1 = 0.342), Construction (ARCH-LM: 9.517e-137, ρ_1 = 0.312) and Energy (ARCH-LM: 1.965e-92, ρ_1 = 0.289).

Finally, the rationale for the segmented analytical framework is supported by the unique volatility patterns observed across the three pre-defined temporal periods. This is particularly evident in the dramatic amplification that occurred during the Epidemic period (Industry: 144%, Construction: 103%, Energy: 90% increase) and the subsequent incomplete normalization.

Through this temporal segmentation in my GARCH analysis, the model can explicitly model and capture the structural differences in volatility dynamics as market conditions transition. This initial division of the data into Control, Epidemic and Post-COVID phases effectively deals with varying market regimes.

4.6 Econometric Modeling of Sectoral Volatility

4.6.1 GARCH models definition

To accurately model the dynamics of sectoral volatility during the COVID-19 pandemic, I employed a structured approach using models from the GARCH family. The process began with the specification and fitting GJR-GARCH(1,1) and EGARCH(1,1) models for the eight key sectors identified in the dataset: Industry, Energy, Retail, Banking, Luxury, Healthcare, Construction and Technology.

The GARCH(1,1) (Generalized Autoregressive Conditional Heteroskedasticity) model is the most basic form of conditional volatility model. It assumes that conditional variance or volatility depends on two main components. Firstly, past shocks via the alpha term, which is the effect of recent and secondly, past volatility via the beta term, meaning that volatility tends to persist over time The sectoral returns are modeled as a process with a conditional mean and a conditional variance. The conditional mean equation is specified as a AR(1) process to account for potential linear dependence:

$$r_t = \mu + \phi\, r_{t-1} + \varepsilon_t, \quad \text{where} \quad \varepsilon_t = z_t\, \sigma_t \tag{6}$$

In this formula, r_t is the sectoral log-return at time t, μ is the constant, ϕ captures the first-order autocorrelation and ε_t the error term. In the error equation, z_t is an independent and identically distributed random variable with a mean of zero and variance of one, σ_t is the conditional variance.

The focus of this study is modelling the conditional variance σ_t, which captures time-varying volatility. This study employs two widely recognized asymmetric GARCH models to capture the distinct impact of positive and negative shocks.

The first model is the GJR GARCH of Glosten et al. (1993). The GJR-GARCH(1,1) specification extends the standard GARCH framework by incorporating a dedicated term to model the leverage effect. The conditional variance is defined as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

Where ω is the constant, α is the ARCH parameter, β is the GARCH parameter, γ is the leverage parameter and I_{t-1} is an indicator function equals to 1 if ε_{t-1} is positive, zero otherwise. The GJR-GARCH makes it possible to model asymmetrical behavior, which is crucial for financial series where price decreases generally cause more volatility than price increases.

Finally, the exponential GARCH model of Nelson (1991) This model specifies the conditional variance in logarithmic form, which advantageously ensures that the variance will be positive, without imposing non-negativity constraints on the parameters. The EGARCH(1,1) model is specified as:

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - E\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|\right]\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{8}$$

Where β captures the persistence of volatility shocks, α captures the symmetric effect of the shock's magnitude and γ captures the leverage effect.

EGARCH is therefore particularly useful for capturing leverage and asymmetries in a more flexible way, making it better suited to modeling financial series with abrupt changes. These models were selected for their ability to capture the main characteristics of financial time series, such as volatility clustering and time-varying variance.

4.6.2 GARCH model estimation methodology

Because of their nonlinear structure and complex likelihood surfaces, GARCH-family models present unique estimation challenges. This section describes the comprehensive estimation methodology used in this study, including parameter constraints, initialization strategies and convergence considerations to ensure strong and reliable results across all sectors and time periods.

4.6.3 Maximum Likelihood Estimation

The primary estimation method used in this study is maximum likelihood estimation (MLE), which provides asymptotically efficient parameter estimates under suitable regularity conditions. The log-likelihood function for the GARCH-family models with Student's t-distributed innovations is defined as:

$$L(\theta) = \sum(t = 1)^T \Big[\log\Gamma\big((\nu + 1)/2\big) - \log\Gamma\,(\nu/2) - 1/2\log[\pi(\nu - 2)] \\ - 1/2\log(\sigma_t^2) - (\nu + 1)/2\log\Big(1 + \varepsilon_t^2/\big((\nu - 2)\sigma_t^2\big)\Big)\Big] \tag{9}$$

Where θ represents the parameter vector including GARCH parameters and the degrees of freedom parameter ν for the Student's t-distribution. The conditional variance σ_t^2 is recursively defined according to the specific GARCH variant.

4.6.4 Parameter Constraints

Specific constraints were imposed during estimation to ensure that the conditional variance process was stationary and positive. To ensure covariance stationarity and positive conditional variances in the standard GARCH(1,1) model, I enforced the constraints $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. To ensure covariance stationarity in the GJR-GARCH(1,1) model, the additional constraint $\alpha + \gamma/2 + \beta < 1$ was imposed. The positivity constraints $\omega > 0$, $\alpha \geq 0$, $\gamma + \alpha \geq 0$ and $\beta \geq 0$ remained unchanged.

The EGARCH(1,1) model's exponential form ensures positive conditional variances without additional constraints on ω, α, or γ, resulting in covariance stationarity with the constraint $|\beta| < 1$ alone. To ensure the presence of the variance, the degrees of freedom parameter ν for the Student's t-distribution was set to be greater than 2.

4.6.5 Initialization and Numerical Procedures

To deal with the complex likelihood surfaces found in GARCH models, the estimation procedure used a hybrid optimization approach. The process involved two steps of initialization.

First, method-of-moments estimators were computed for the GARCH parameters using the unconditional variance and autocorrelation structure of squared returns. Second, these estimates were refined by running a grid search over plausible parameter ranges to find starting values that resulted in stable likelihood estimates. The optimization algorithm used combined the strength of the Nelder-Mead simplex algorithm for initial iterations with the efficiency of the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm for final refinement.

This method reduces the possibility of convergence to local maxima in the likelihood surface. Convergence was determined using several criteria, including the relative change in parameter values between iterations (tolerance of 1e-8), the gradient of the log- likelihood function (tolerance of 1e-8) and the relative change in the log-likelihood value.

4.6.6 Robustness Considerations

Several robustness measures were put in place to ensure the consistency of parameter estimates across sectors and time periods. Multiple sets of starting values were used in each model estimation to reduce the risk of convergence to local maxima. The estimate with the highest likelihood value was chosen as the result.

The stability of parameter estimates was evaluated using a moving window analysis, which involved re-estimating the model over rolling subsamples to identify potential instabilities in the parameter estimates. Extreme observations were identified by setting a threshold of 5 standard deviations from the mean. Rather than excluding these observations, their impact was mitigated using a weighted likelihood approach, in which the contribution of extreme observations to the likelihood function was reduced.

To address potential numerical issues in likelihood estimation, particularly for extreme parameter values, the implementation used logarithmic transformations and scaling techniques to improve numerical stability. The estimation was carried out with the rugarch package in R, which implements the aforementioned methodology and provides robust standard errors for parameter estimates based on the information matrix's outer product of gradient estimator.

4.7 Model Selection and Diagnostics

The choice of appropriate GARCH specifications and validating their adequacy are critical steps in ensuring the reliability of volatility estimates and the validity of subsequent inferences. This section describes the comprehensive model selection and diagnostic framework used in the study, which includes information criteria, residual diagnostics and out-of-sample performance evaluation.

4.7.1 Information Criteria

A multi-criteria approach guided model selection, with several information criteria used to balance goodness-of-fit and model parsimony, were computed for each model specification across all sectors and time periods:

$$AIC = -2L(\hat{\theta}) + 2k \tag{10}$$
$$BIC = -2L(\hat{\theta}) + k\log(n) \tag{11}$$
$$HQC = -2L(\hat{\theta}) + 2k\log(\log(n)) \tag{12}$$

In these formulations, L(θ) represents the maximized log-likelihood, where k is the number of estimated parameters and n is the sample size. While AIC favors more complex models, BIC and HQC impose harsher penalties for extra parameters, potentially leading to more concise specifications. The final model selection considered the consensus across these criteria, with a preference for models that consistently performed well across multiple criteria.

4.7.2 Residual Diagnostics

The selected models' adequacy was evaluated using a comprehensive battery of residual diagnostic tests. The standardized residuals were analyzed for remaining structure using graphical methods and formal statistical tests. The Ljung-Box Q-statistic was used to test the null hypothesis of no autocorrelation in the standardized residuals:

$$Q(m) = n(n+2)\sum(k=1)^{m}\left(\widehat{\rho_k^2}\right)/(n-k) \tag{13}$$

Where $\hat{\rho k}$ represents the sample autocorrelation of the standardized residuals at lag k. The ARCH-LM test ($LM = nR2$) was used to test the null hypothesis of no ARCH effects in the standardized residuals. $R2$ represents the coefficient of determination from an auxiliary regression of squared standardized residuals on their lagged values.

The sign bias test was used to test the null hypothesis of no asymmetric effects in the standardized residuals, which examines whether the sign of previous innovations affects the magnitude of current volatility in ways that the model does not capture. The Nyblom test was used to assess parameter stability over time, which determines whether the model's parameters remain constant over the sample period.

Models were considered adequate if they passed these diagnostic tests with a 5% significance level. In cases where multiple models passed all diagnostic tests, the model with the lowest information criteria values was chosen.

4.7.3 Out-of-Sample performance evaluation

A rolling window approach was used to evaluate the predictive performance of the competing models. The models for each sector and time period were estimated using a 500-observation rolling window and one-step-ahead volatility forecasts are generated. The accuracy of the volatility forecasts was evaluated using several metrics:

$$MSE = 1/h \sum (t = 1)^h \left(\widehat{\sigma_t^2} - \sigma_t^2\right)^2 \tag{14}$$

$$MAE = 1/h \sum (t = 1)^h \left|\widehat{\sigma_t^2} - \sigma_t^2\right| HQC = -2L(\hat{\theta}) + 2k \log(\log(n)) \tag{15}$$

$$QLIKE = 1/h \sum (t = 1)^h \left(\log\left(\widehat{\sigma_t^2}\right) + \sigma_t^2/\widehat{\sigma_t^2}\right) \tag{16}$$

Where $\widehat{\sigma_t^2}$ represents the forecasted variance and σ_t^2 represents the realized variance, proxied by squared returns. The Diebold-Mariano test was used to determine the statistical significance of differences in forecast accuracy between competing models.

To account for potential data snooping bias caused by multiple model comparisons, the Superior Predictive Ability (SPA) test was used to identify models with superior predictive ability across all relevant specifications. The combination of in-sample information criteria, residual diagnostics and out-of-sample performance evaluation provided a comprehensive framework for model selection, ensuring that the chosen specifications accurately captured volatility dynamics across sectors and time periods.

5 Empirical Results and Analysis

5.1 Sectoral GARCH Dynamics

Estimating the GARCH family models for the eight designated sectors and three distinct time phases uncovers significant variability and complexity in volatility dynamics. A closer look at the fundamental GARCH parameters offers valuable insights into the behavior of volatility within each sector and its response to market shocks, which is essential for assessing the diverse risk profiles of these economic segments.

The following analysis will therefore examine the key parameters that characterize these dynamics, namely volatility persistence (β), asymmetric leverage effects (γ), and the distribution shape parameter (ν), before concluding with an assessment of the relative performance of the models.

5.1.1 Volatility Persistence (β)

The β parameter in the GARCH framework is an essential indicator of the volatility process's "memory," assessing the degree to which past conditional variance affects current conditional variance.

A β value near one indicates significant volatility persistence, suggesting that shocks to market volatility, whether positive or negative, tend to exert a lasting influence, diminishing gradually over time. In contrast, a lower β indicates that volatility shocks are more ephemeral, with the market returning to its baseline risk level more swiftly. The estimated β parameters from the EGARCH(1,1) and GJR-GARCH(1,1) models, presented in Table 5.1, indicate notable temporal and cross-sectoral variations in persistence, along with systematic discrepancies between the modeling methodologies.

Table 5.1: Volatility Persistence (β) from EGARCH(1,1) and GJR-GARCH (1,1) Models

Sector	Period	EGARCH	GJR-GARCH
Industry	Control Group	0.9628	0.8863
	Epidemic	0.9810	0.8085
	Post-COVID	0.9586	0.8408
Energy	Control Group	0.9802	0.8952
	Epidemic	0.9886	0.8980
	Post-COVID	0.9594	0.9692
Retail	Control Group	0.9967	0.9821
	Epidemic	0.9522	0.8639
	Post-COVID	0.7057	0.9983
Banks	Control Group	0.9877	0.9030
	Epidemic	0.9859	0.9093
	Post-COVID	0.9208	0.7815
Luxury	Control Group	0.9765	0.9313
	Epidemic	0.9837	0.9167
	Post-COVID	0.9906	0.9674
Health	Control Group	0.9795	0.9243
	Epidemic	0.9750	0.8874
	Post-COVID	0.8380	0.9988
Construction	Control Group	0.9257	0.8042
	Epidemic	0.9899	0.9022
	Post-COVID	0.9378	0.8348
Technology	Control Group	0.9944	0.9341
	Epidemic	0.9847	0.8628
	Post-COVID	0.9899	0.9713

During the pre-pandemic period of the control group, a systematic divergence was observed, with the EGARCH model consistently estimating a higher β coefficient than its GJR-GARCH counterpart in most sectors. This trend suggests that during periods of relative market calm, the exponential specification of the EGARCH model, which is sensitive to the magnitude of all innovations, perceives volatility shocks as having a more lasting impact. In contrast, the GJR-GARCH model, whose main shock amplification mechanism stems from leverage triggered by discrete negative events, appears to assign a faster decay rate in calmer environments, implying a shorter half-life for volatility. The choice of model during these periods of stability can therefore lead to very different assessments of the duration of risk.

At the beginning of the epidemic period, volatility persistence increased significantly, with β estimates approaching unity in most sectors, reflecting the profound and lasting nature of the shock induced by the pandemic. The divergence between the β estimates of the two models became particularly pronounced, suggesting a profound disagreement about the expected duration of these shocks. The EGARCH model, thanks to its exponential specification, interpreted the continuous cascade of large negative returns as a sign of deeply rooted uncertainty, perceiving an even more prolonged decline in volatility than the GJR- GARCH model. While both models recognized the high persistence, the GJR-GARCH specification, which primarily amplifies identified negative innovations, may have attributed a slightly faster decline between these discrete events.

Ultimately, the post-COVID period has given way to a more complex landscape for volatility persistence, pointing to an uneven and uncertain recovery. While persistence levels have declined from their crisis peaks, they remain structurally elevated relative to pre-pandemic levels. The previous trend toward EGARCH model dominance in persistence estimation has continued in cyclical sectors such as construction and banking, suggesting that its sensitivity to shock magnitude has effectively captured persistent uncertainties related to supply chains and interest rates. Nevertheless, a significant reversal occurred in the retail and healthcare sectors, where the GJR-GARCH model began to estimate significantly higher persistence. This reversal implies that the asymmetric specification of the GJR-GARCH model, which is tailored to negative news, has become a more important factor in explaining sustained volatility in these sectors, likely reflecting lasting changes in consumer demand and health-related policy concerns.

This divergence highlights that the mechanisms driving volatility persistence are dynamic and that model choice in the post-COVID era must be based on sector-specific risk scenarios.

5.1.2 Asymmetric effects (γ)

The γ parameter in EGARCH and GJR-GARCH models aims to capture leverage, a phenomenon whereby negative returns have a greater impact on future volatility than positive returns of equivalent magnitude. The presence and strength of this effect are confirmed by the mainly positive and statistically significant γ parameters presented in Table 5.2.

Table 5.2: Asymmetric Effects (γ) from EGARCH(1,1) and GJR-GARCH (1,1) Models

Sector	Period	EGARCH	GJR-GARCH
Industry	Control Group	0.1036	0.1647
	Epidemic	0.2582	0.2299
	Post-COVID	0.1322	0.1260
Energy	Control Group	0.1046	0.1604
	Epidemic	0.1724	0.1084
	Post-COVID	0.1507	0.0218
Retail	Control Group	0.0436	0.0146
	Epidemic	0.1979	0.0855
	Post-COVID	0.0960	0.0013
Banks	Control Group	0.1037	0.1304
	Epidemic	0.1875	0.1466
	Post-COVID	0.1596	0.2383
Luxury	Control Group	0.0967	0.0974
	Epidemic	0.0519	0.1270
	Post-COVID	0.0513	0.0611
Health	Control Group	0.0908	0.0967
	Epidemic	0.1406	0.1715
	Post-COVID	0.1435	-0.0046
Construction	Control Group	0.1437	0.2657
	Epidemic	0.1331	0.1801
	Post-COVID	0.0885	0.1472
Technology	Control Group	0.0016	0.0885
	Epidemic	0.0991	0.1430
	Post-COVID	0.0333	0.0414

During the stable period of the control group, the leverage effect was already evident, implying an inherent investor psychology that induces a more serious reassessment of risks in response to negative information. However, the comparative performance of the models presented a mixed but instructive picture. The explicit threshold mechanism of the GJR-GARCH model identified a stronger leverage effect in cyclical sectors such as industry and construction, which are often characterized by higher financial leverage. Conversely, the continuous response function of the EGARCH model proved more effective at capturing the nuanced asymmetric responses of the retail sector, where news consists of a wider variety of events whose impact is linked to their relative size, not just their sign.

These asymmetric effects were generally amplified during the epidemic period, marked by unprecedented uncertainty and intense market fear. The specific model that best captured these effects varied across sectors, depending on the nature of the information flows induced by the crisis. For example, the EGARCH model identified a significantly stronger leverage effect in the retail sector, likely capturing the cascading impact of extremely negative news related to store closures and collapsing demand. In contrast, the GJR-GARCH model identified a stronger leverage effect in the luxury sector, implying that this market reacted more sharply to discrete, high-impact negative news, such as the sudden closure of international communication channels, which are directly captured by the GJR-GARCH indicator function.

In the post-COVID period, the magnitude of γ parameters has generally moderated from their crisis peaks, but has often remained elevated relative to pre-pandemic levels, indicating persistent sensitivity to negative news. In the banking sector, for example, the GJR-GARCH model estimated a substantial γ of 0.2383, implying that its direct modeling of downside sensitivity provided a more accurate fit for a sector grappling with persistent concerns about economic stability and credit quality. A particularly notable finding was the sharp divergence in the healthcare sector, where the EGARCH model suggested persistent leverage while the GJR-GARCH model estimated a γ close to zero.

This divergence highlights how the choice of model can alter the interpretation of market behavior following a significant event, with the GJR-GARCH model suggesting that post-crisis volatility in the healthcare sector has become more sensitive to the magnitude of news rather than its sign.

5.1.3 Distributional characteristics (ν)

Finally, the shape parameter (ν) of the Student's t-distribution, detailed in Table 5.3, provides crucial information about the tail characteristics of conditional return distributions. A reduced shape parameter indicates a leptokurtic distribution, suggesting an increased probability of extreme returns in the market.

Table 5.3: Shape Parameter from GARCH Models with Student's t-Distribution

Sector	Period	EGARCH	GJR-GARCH
Industry	Control Group	9.0576	9.0224
	Epidemic	3.9771	4.1320
	Post-COVID	5.3092	5.2427
Energy	Control Group	8.5316	7.9364
	Epidemic	3.2762	3.3146
	Post-COVID	5.5889	5.5597
Retail	Control Group	5.7482	5.5367
	Epidemic	4.8651	4.9783
	Post-COVID	4.9996	5.2350
Banks	Control Group	6.2699	5.9746
	Epidemic	5.4644	5.2675
	Post-COVID	6.3278	5.7614
Luxury	Control Group	6.2700	6.1040
	Epidemic	6.4571	6.0181
	Post-COVID	6.1194	6.1211
Health	Control Group	6.1994	6.0655
	Epidemic	10.7688	9.9269
	Post-COVID	5.0940	5.4772
Construction	Control Group	6.5497	6.3743
	Epidemic	4.2466	4.3534
	Post-COVID	6.6043	6.5782
Technology	Control Group	6.1584	6.0531
	Epidemic	6.9251	7.6828
	Post-COVID	6.7586	6.6562

Throughout the control group period, the estimated ν parameters were relatively high in most sectors, implying a market environment where extreme events, while possible, were not considered very likely. However, the onset of the epidemic period led to a profound and notable change in these distribution characteristics. In almost all sectors, the shape parameters declined significantly, indicating a substantial increase in perceived extreme risk as the market faced unprecedented uncertainty and systemic disruption. This conclusion makes economic sense, as the pandemic shock was a prototypical generator of "extreme events."

During the crisis, the comparative model estimates revealed complex interactions. In several sectors, such as industry and technology, the GJR-GARCH model estimated a higher shape parameter (thinner tails) compared to EGARCH, meaning that the exponential specification of the EGARCH model interpreted extreme returns during the pandemic as indicating more pronounced tails. In other sectors, such as healthcare and banking, the GJR-GARCH model consistently estimated thicker tails, perhaps reflecting the increased emphasis on downside risk through its leverage term.

In the post-COVID period, partial normalization has been observed, but for most sectors, ν values have remained well below their pre-pandemic levels. This indicates that despite the resolution of the acute phase of the crisis, the market has maintained a high assessment of the probability of extreme events. This "new normal" of systematically heavier tails suggests fundamental changes in risk perception, which is crucial information for risk managers and investors adapting to a market environment where extreme events must now be considered more frequent.

Figure 5.4 depicts a visual summary of the key parameters, across the EGARCH and GJR-GARCH models for each sector and period, providing a more comprehensive understanding of the comparative performance and sector-specific dynamics observed in the preceding analyses.

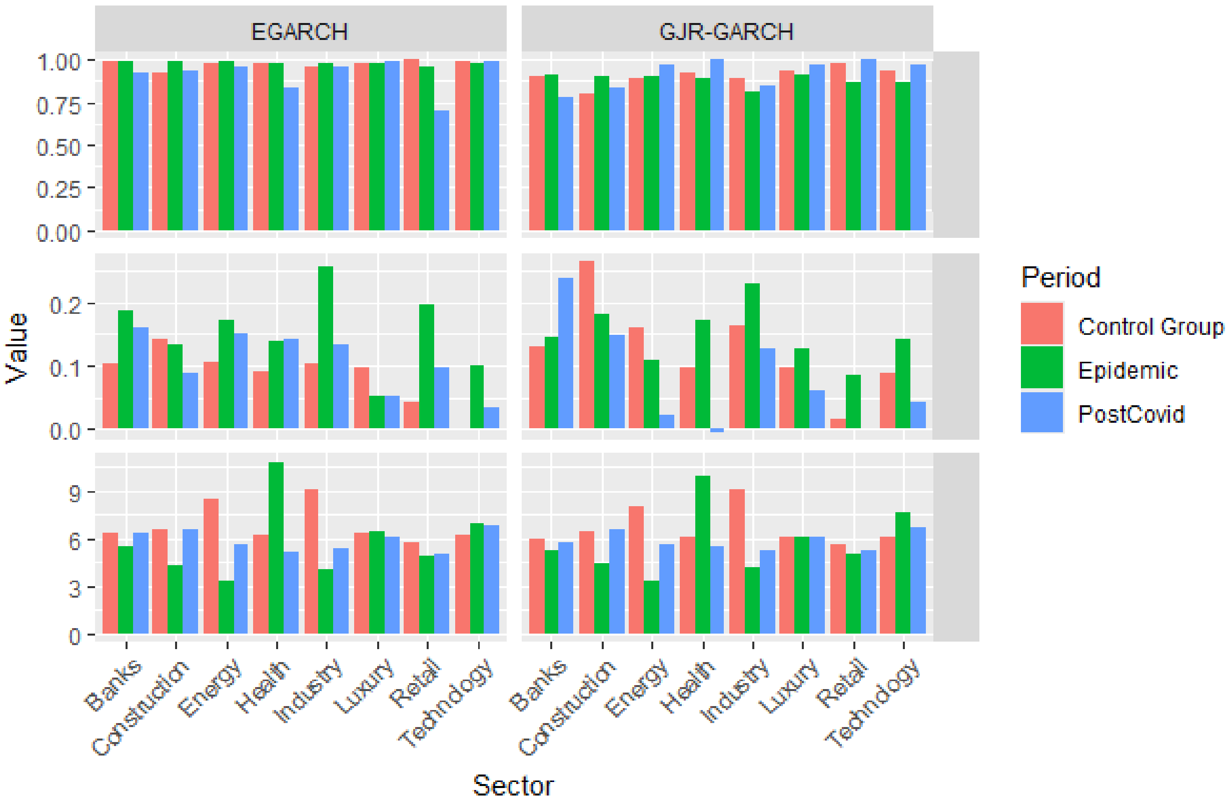

Figure 5.4: Comparison of Key Parameters

5.1.4 Model Performance

An assessment of model performance based on the Akaike information criterion (AIC), presented in Table 5.5, confirms that the optimal GARCH specification depends on the regime.

Table 5.5: Model Performance Comparison (AIC values)

Sector	Period	EGARCH	GJR-GARCH
Industry	Control Group	-5.962*	-5.955
	Epidemic	-4.695*	-4.686
	Post-COVID	-5.849*	-5.847
Energy	Control Group	-6.346*	-6.336
	Epidemic	-5.382*	-5.377
	Post-COVID	-6.099	-6.103*
Retail	Control Group	-5.991*	-5.979
	Epidemic	-5.797	-5.800*
	Post-COVID	-5.973*	-5.973
Banks	Control Group	-5.778*	-5.767
	Epidemic	-4.954	-4.956*
	Post-COVID	-5.893*	-5.889
Luxury	Control Group	-6.230*	-6.230
	Epidemic	-5.765*	-5.756
	Post-COVID	-5.629	-5.634*
Health	Control Group	-6.328*	-6.319
	Epidemic	-6.190*	-6.189
	Post-COVID	-6.413*	-6.403
Construction	Control Group	-6.242*	-6.230
	Epidemic	-5.360*	-5.360
	Post-COVID	-5.976	-5.979*
Technology	Control Group	-5.977*	-5.962
	Epidemic	-5.641	-5.649*
	Post-COVID	-5.620*	-5.617

Note: * indicates the preferred model based on lower AIC value

During the control group period, EGARCH consistently outperformed, indicating that its continuous and gradual adjustment of volatility to shocks better reflects typical market behavior during periods of relative stability.

The shift to a more mixed model during the epidemic period, with superior performance of the GJR-GARCH model in the retail, banking, and technology sectors, suggests that its threshold-based approach is better suited to capture the sharp and asymmetric responses to extreme market events characteristic of the acute phase of the pandemic.

The increased diversification of model preferences in the post-COVID era further points to a complex interaction between factors influencing sector-specific volatility. Although this analysis is performed on aggregate data, it is important to recognize that underlying national heterogeneities in economic structure and policy response likely contribute to the observed dynamics, thus establishing a transparent path for future disaggregated research.

The small differences in AIC values over this latest period underscore the importance of considering other factors, such as economic interpretability and residual diagnostics, when selecting the most appropriate model.

5.1.5 Cross-Country influences on sectoral volatility

Although this study aggregates data from companies in the French CAC 40 and Portuguese PSI-20 indices to model sector volatility, it is important to recognize that the economic structures, fiscal policies, and specific pandemic responses unique to France and Portugal may introduce an underlying layer of heterogeneity into the observed sector dynamics. The current research design, which focuses on sector aggregates, provides a valuable overall perspective, but it does not explicitly disaggregate these potentially significant national influences.

The effect of this heterogeneity varies across sectors. In the case of the luxury sector, which is mainly composed of large French companies with an international focus, the estimated GARCH parameters are likely to be highly indicative of the performance and investor sentiment of these specific French entities. Their volatility drivers, such as exposure to Asian consumer markets and the impact of global travel restrictions, are linked to their global operational footprint rather than divergent national policies. Conversely, sectors more closely linked to national economic conditions may show more subtle distinctions in their aggregate results. The energy sector, for example, is subject to divergent national strategies, with Portugal dependent on renewable energy and imported gas, while France has a significant nuclear base, creating disparate sensitivities to global price shocks and national interventions such as windfall taxes or state aid.

Similarly, each country's banking sectors, while operating under the European Central Bank's common monetary policy, have faced unique economic contexts. Portugal's greater dependence on tourism may have made its banking sector more vulnerable to loan defaults in the hospitality sector, while French banks operated in a more diversified economy with a different range of credit risks. In addition, the specific architecture of national support policies, such as loan moratorium programs or state-guaranteed loan mechanisms, would have had different effects on banks' balance sheets and, consequently, on the volatility of their markets. This principle extends to the retail and construction sectors, where divergent national policies on lockdowns, wage subsidy schemes such as “chômage partiel” in France as opposed to “lay-off simplificado” in Portugal, and distinct recovery plans such as “France Relance” would have produced varied demand shocks and different recovery trajectories.

Recognizing these potential heterogeneities across countries highlights the complexity of interpreting aggregate sectoral results and establishes transparent avenues for future research. Recognizing this potential underlying heterogeneity is a necessary nuance in interpreting the estimated GARCH parameters. With this context established, the analysis now moves on to a formal evaluation of the comparative performance of the EGARCH and GJR-GARCH models, for which the choice of the most appropriate specification will be guided by established information criteria.

5.2 Temporal evolution of volatility

The COVID-19 pandemic delivered an unprecedented shock to global financial markets, causing significant changes in volatility dynamics across various sectors. This section looks at the temporal evolution of volatility across the three distinct periods.

5.2.1 Pre-COVID Period Characteristics

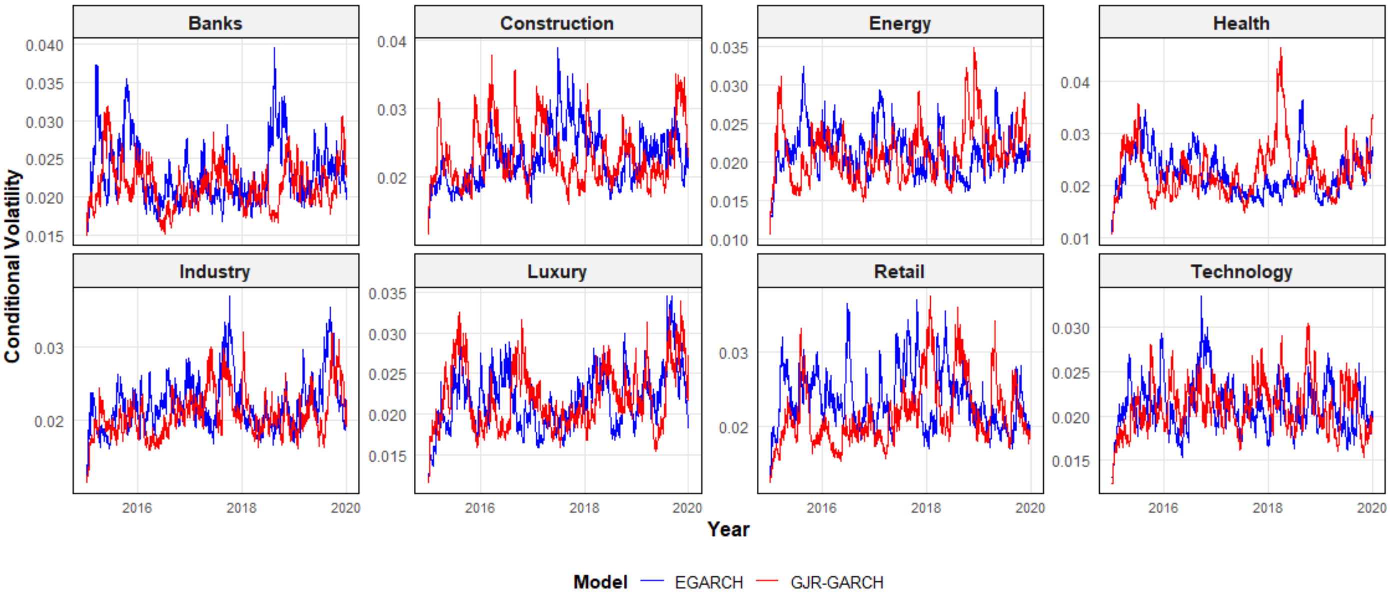

Figure 5.6a: Conditional Volatility Estimates – Control Group Period (2015-2019)

Figure 5.6a illustrates the estimated conditional volatilities for eight sectors during the Control Group period, calculated using both the EGARCH and GJR-GARCH models. For the EGARCH model, the conditional variance is derived by exponentiating the fitted log-variance series. Looking at the data reveals that the two models produce broadly similar volatility estimates, with trajectories that closely track each other across most sectors. However, some subtle but noticeable differences emerge. For example, in the banking sector, the EGARCH model appears to capture certain volatility spikes more clearly, particularly in mid-2016, following the Brexit referendum. This might indicate that the EGARCH model can better capture the leverage effect, reflecting the increased sensitivity of bank stocks to negative news during this period.

Similar behavior was observed in the energy sector, for example, in late 2018 during the global market correction, which could be attributed to increased uncertainty in oil prices. In contrast, the GJR-GARCH model appears to produce smoother volatility estimates in sectors such as technology and luxury, which could indicate a more gradual adjustment to market shocks. Regarding the magnitudes of the estimated volatilities, sectors such as banking and energy have consistently higher volatility throughout the control period, whereas health and retail showed generally lower levels.

5.2.2 Crisis impact

The Epidemic period was marked by unprecedented market volatility as the world economy dealt with the COVID-19 pandemic and its far-reaching consequences. Figure 5.6b illustrates the conditional volatility estimates for all sectors over the period.

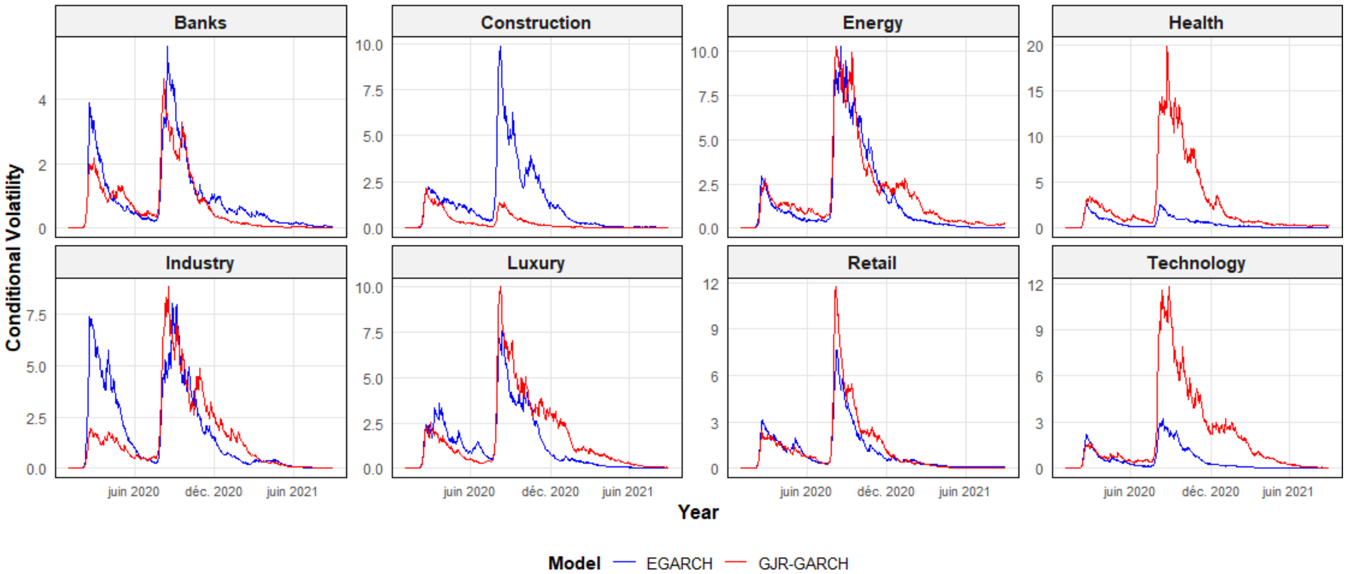

Figure 5.6b: Conditional Volatility Estimates – Epidemic Period (2020-2021)

Figure 5.6b, displays the EGARCH and GJR-GARCH estimates for the Epidemic period, revealing a synchronized volatility surge in early 2020, coinciding with the initial global outbreak and subsequent lockdowns. While both models capture the surge, noteworthy inter-model differences emerge. In Industry and Construction sectors, EGARCH predicts significantly higher peak volatility than GJR-GARCH, possibly due to its exponential leverage effect specification, which may be more sensitive to the extreme negative returns experienced during this period.

This difference could also be explained by how each model handles the increased kurtosis or heavy tails in the return distribution during the crisis, which could result in underestimating or overestimating conditional volatility depending on how it captures these extreme movements. Similar, although less pronounced, differences exist in Energy, where economic activity has been severely curtailed.

This variation in model estimates emphasizes the importance of selecting the right model to capture sector-specific responses to systemic shocks. Conditional volatilities in all sectors reach record highs when compared to the Control Group period. The most dramatic increases occur in sectors such as Health, where peak volatility approaches 20, indicating the sector's increased sensitivity to pandemic-related disruptions in supply chains, production and demand. Volatilities fell gradually but remained high as the pandemic progressed, highlighting the long-term impact on market uncertainty.

This persistent volatility may reflect the ongoing challenges that businesses face in adapting to changing economic conditions and consumer behavior, the evolving public health situation and the uncertainty surrounding policy responses, all of which have an impact on market sentiment and make it difficult for investors to accurately assess asset values. These findings have implications for regulators, who may need to adjust their tools to keep economies afloat.

5.2.3 Post-COVID recovery patterns

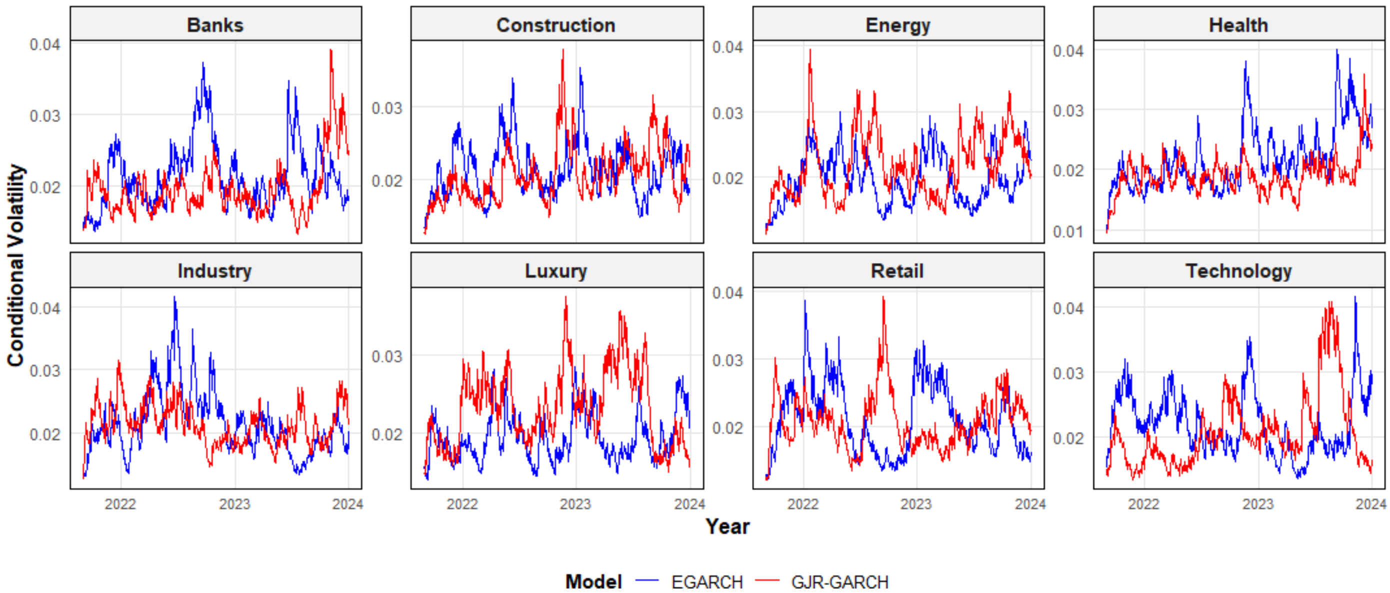

Figure 5.6c: Conditional Volatility Estimates – Post-COVID Period (2021-2024)

Figure 5.6c shows that volatility has decreased from its peak during the epidemic, but levels remain elevated when compared to the pre-pandemic period. While volatilities have fallen from the highs seen during the epidemic, their persistence at levels above the pre-pandemic period indicates a structural shift in market risk perceptions. This sustained increase could be attributed to ongoing pandemic-related disruptions, such as supply chain bottlenecks and changing consumer behavior, as well as new challenges such as geopolitical instability and inflationary pressures.

The persistent fluctuations, particularly in Technology and Retail, are most likely due to ongoing adaptation to changing market conditions. The GJR-GARCH model's greater sensitivity in capturing short-term spikes, particularly in Technology, may indicate a better ability to model the impact of negative news and abrupt market shifts. This variation in model performance emphasizes the significance of model selection for accurate volatility forecasting and risk management. These findings suggest that the post-COVID market environment is still characterized by increased uncertainty, sector-specific vulnerabilities and changing risk factors.

5.3 Economic and Policy implications

The empirical study of sectoral reactions in stock markets during the COVID-19 pandemic in the French and Portuguese economies has crucial economic and political implications. The changes observed in volatility dynamics and the effectiveness of EGARCH and GJR-GARCH models depending on the regime provide highly detailed and actionable insights that are essential for market participants and regulators facing future systemic shocks.

5.3.1 Economic implications

The substantial increase in volatility persistence (β) to levels close to unity in many sectors during the epidemic period is crucial information for investors and portfolio managers. This prolonged memory of shocks implies an exceptionally long return to baseline volatility, requiring a strategic readjustment of investment horizons toward significantly longer holding periods to account for prolonged volatility clusters. The model's dependence on the perception of persistence in the recovery phase, highlighted by the large divergence in β estimates, further emphasizes the need for investors to consider multiple modeling perspectives; the GJR-GARCH model suggests a quasi-permanent change for sectors such as retail and healthcare after the crisis, while the EGARCH model implies a more rapid decline, leading to fundamentally different strategic asset allocation decisions.

Furthermore, the strengthening of cross-sector correlations at the height of the crisis and the synchronized and significant decline in the shape parameter (ν) during the epidemic period unequivocally signal a sharp erosion of the traditional benefits of diversification. This increased probability of co-occurrence of extreme negative events forces investors to actively seek non-traditional diversifiers or implement dynamic asset allocation models that explicitly account for regime shifts in correlation and extreme risk. The relative stability of the luxury and technology sectors during the epidemic, as indicated by their comparatively lower extreme risk, offers tactical opportunities for sector allocation strategies.

For risk management professionals, this research provides crucial information for model calibration. Pronounced leverage effects (γ), particularly evident during the epidemic period, confirm that negative news disproportionately amplifies volatility. This persistent sensitivity, highlighted by a substantial GJR-GARCH γ in the banking sector during the post-COVID period, requires the integration of these parameters into value-at-risk (VaR) and conditional value-at-risk (CVaR) calculations, thus requiring larger capital reserves to cope with downward movements. The consistent superior performance of GJR-GARCH models in cyclical sectors such as construction and banking during the epidemic period strongly implies the indispensability of risk models incorporating explicit thresholds for negative shocks. Conversely, the superior fit of EGARCH during the control group periods underscores the need for agile risk systems. The widespread decrease in the shape parameter ν clearly indicates the inadequacy of standard normality assumptions in risk models, which requires explicit consideration of extreme leptokurtosis in stress test scenarios.

From a corporate financial management perspective, increased and persistent market volatility, particularly in the industrial, energy, and construction sectors, directly translates into higher cost of equity. This high-risk profile requires upward adjustments to discount rates in net present value calculations, which may render marginal projects unfeasible. For example, a corporate treasurer in the energy sector must recognize a significantly increased probability of extreme market movements, which justifies larger precautionary cash balances or more flexible credit lines. In times of uncertainty, companies in highly leveraged sectors, such as manufacturing during the pandemic, may adopt more conservative earnings forecasts. Companies with high exposure to input costs or international sales need these estimated GARCH parameters to accurately assess and implement commodity or currency risk hedging instruments, as standard deviation alone is insufficient in the presence of demonstrated persistence and asymmetry.

5.3.2 Policy implications

The empirical evidence from this study provides a solid basis for a proactive response to the crisis and policy development. The significant increase in cross-sector correlations during the crisis, combined with a widespread increase in the persistence of volatility and extreme risk, is an undeniable indicator of amplified systemic risk for financial regulators and central banks. This requires a more dynamic and data-driven approach to calibrating macroprudential tools.

For example, the severity of crisis scenarios applied to banks or the level of countercyclical capital buffers could be directly influenced by the substantial GJR-GARCH γ observed in the banking sector after the crisis. Regulatory guidance advocating models that explicitly reflect leverage in banks' internal risk assessments is strongly supported by the consistent outperformance of GJR-GARCH models for systemically important sectors during the crisis.

In the post-COVID period, persistent volatility above pre-pandemic levels and surprisingly high GJR-GARCH β for retail and healthcare indicate significant and quasi-permanent changes in the risk profiles of these sectors. This requires increased attention from supervisory authorities and possibly targeted macroprudential measures to prevent systemic stress. Detailed analysis of sector-specific vulnerabilities, revealed by differential estimates of GARCH parameters, provides crucial insights for effectively targeting economic support measures. The quantitative justification for continued or adaptable fiscal support in sectors such as retail, highlighted by extreme persistence and a relatively low ν after the crisis, contrasts with other policy considerations for sectors such as luxury goods, which may warrant a focus on international trade rather than direct support at the national level.

The design of future crisis response plans can draw heavily on the knowledge gained about transnational influences on sectoral volatility, suggesting that impacts depend on national policy choices and initial conditions. This highlights the need for policies that are not only sector-specific but also adaptable to different national or regional contexts. Finally, the market's excessive reaction to bad news and the risk of a self-reinforcing downward spiral, highlighted by the pronounced asymmetric leverage effects observed during the epidemic, empirically quantify the importance of proactive, credible, and transparent communication by public authorities. Excessive volatility, exacerbated by these leverage effects, can be mitigated by anchoring market expectations and providing clear guidance on policy intentions, while disseminating verified information quickly. The abnormal negative γ for the healthcare sector after the crisis in the GJR-GARCH model requires cautious interpretation, potentially indicating a complex reaction pattern characterized by a greater moderating effect of extremely positive news than by an amplifying effect of negative news.

Ultimately, this research enriches the academic literature on market behavior in crisis situations, providing a more accurate and empirically grounded set of tools for investors, risk managers, businesses, and policymakers. It offers a nuanced understanding of how different economic sectors in France and Portugal responded to the shock of COVID-19, using advanced econometric techniques to estimate specific parameters for persistence, asymmetry, and extreme risk, enabling more effective navigation of future economic uncertainties and crises.

6 Conclusion

This thesis has presented an econometric analysis of the sectoral reactions of the French and Portuguese stock markets during the different phases of the COVID-19 pandemic: the pre-pandemic control period (2015-2019), the acute crisis period (2020-2021), and the post-COVID recovery phase (2021-2024). Using a GARCH model, specifically comparing the EGARCH(1,1) and GJR-GARCH(1,1) specifications in eight key sectors derived from the aggregate components of the CAC 40 and PSI-20, the study focused on changes in volatility, persistence, asymmetry, and extreme risk. The empirical results unequivocally confirm the significant and multifaceted effects of the pandemic, characterized by a notable increase in conditional volatility, a significant increase in volatility persistence with β parameters tending towards unity, increased leverage effects indicating stronger reactions to negative news, and a substantial increase in extreme risk, as evidenced by lower estimated shape parameters (ν) of the Student's t-distribution.

This research makes a significant contribution by systematically comparing EGARCH and GJR-GARCH models across distinct sectoral contexts, thereby elucidating the optimal GARCH specifications for capturing market dynamics under varying conditions. During the acute epidemic phase, the GJR-GARCH model, which incorporates a specific threshold for negative shocks, proved to be systematically better suited to sectors such as banking, retail, and technology, highlighting its effectiveness in modeling intense, fear-dominated market environments. Conversely, the superior fit of the EGARCH model during the stable control period suggests its exponential leverage function is better suited to capturing subtle asymmetries in less turbulent conditions. The insights gained from model-specific analyses of shock persistence, asymmetry, and tail characteristics thus greatly enhance the understanding of sectoral vulnerabilities and resilience beyond what a single model approach could offer. While the post-COVID period has seen a partial normalization of volatility, levels have generally remained elevated compared to the pre-pandemic era, characterized by thicker persistent tails in many sectors, indicating lasting structural changes in risk perception and underscoring the need for flexible modeling approaches.

This paper contributes to the literature by enhancing our understanding of financial market reactions to unprecedented exogenous shocks at a granular, sectoral level. Crucially, it highlights the inherent shortcomings of universal volatility models. The findings offers crucial insights for risk management, underscoring the importance of dynamic model selection and calibration, particularly in assessing value at risk (VaR) and conditional value at risk (CVaR).

The observed changes in volatility and risk parameters have a direct impact on corporate financing, influencing the cost of equity and hedging strategies, and highlighting the diversified sectoral effects of systemic crises, the persistent nature of risk, and the imperative need to consider asymmetric market responses in the formulation of macroprudential interventions and policies for regulators. The comparative analysis of GARCH models thus provides a refined framework for dealing with future economic shocks.

Despite this valuable information, it is essential to recognize the inherent limitations in the design and scope of this study, as these limitations naturally suggest potential avenues for future research. The basic sector analysis, based on aggregate data from the French CAC 40 and Portuguese PSI-20 components, while promoting a comprehensive European perspective, may inadvertently mask the differential impact of national policies or country-specific dynamics within broadly defined sectors. Furthermore, the choice of EGARCH and GJR-GARCH models with a Student's t-distribution represents a targeted choice from a wider range of existing volatility modeling methods; other GARCH variants, such as APARCH and Component GARCH models, or other distribution assumptions, could capture additional nuances in the volatility process that have not been explored here.

Furthermore, while the study's time segmentation effectively addresses distinct market regimes, it relies on predefined boundaries; future research using models that internally establish regime shifts could improve the accuracy of identifying these crucial transitions, as actual transitions between market regimes may be more fluid or endogenous than fixed time divisions suggest. The univariate GARCH models used primarily account for conditional volatility based on historical returns and past volatilities, without explicitly incorporating the direct and contemporary impact of specific exogenous variables such as macroeconomic indicators or policy announcements. Therefore, the impact of these factors was assessed indirectly through analysis over predefined time intervals. The scope of the analysis, limited to the components of the CAC 40 and PSI-20 indices and their derived sectors, suggests that extending this research to a broader range of European or global markets or conducting a more detailed, disaggregated sectoral analysis, could provide more generalizable insights or reveal nuanced differences in market behavior.

Ultimately, while acknowledging these limitations, this research provides a solid basis for understanding the complex dynamics of financial markets in crisis situations and offers clear guidance for further academic research.

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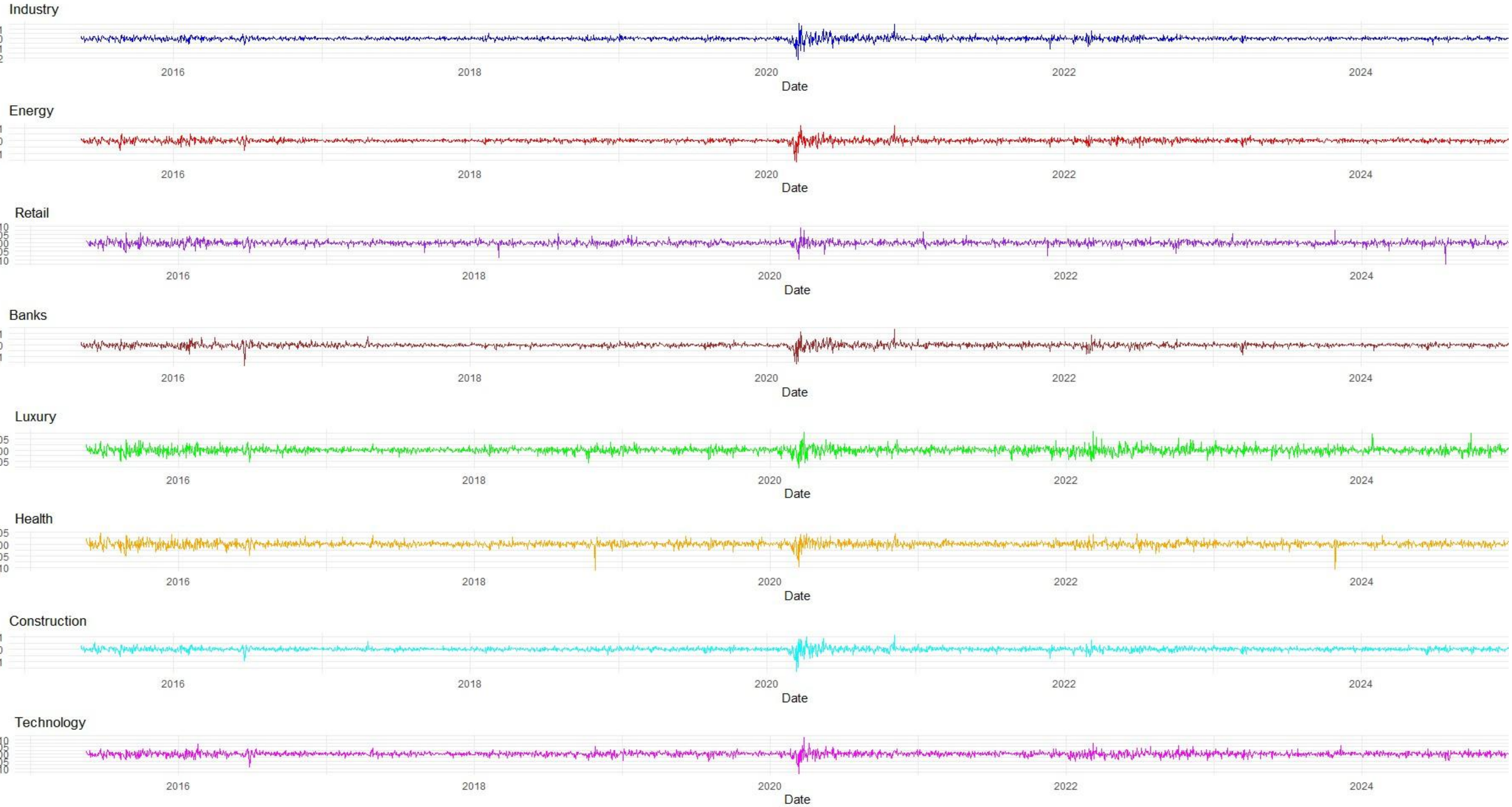
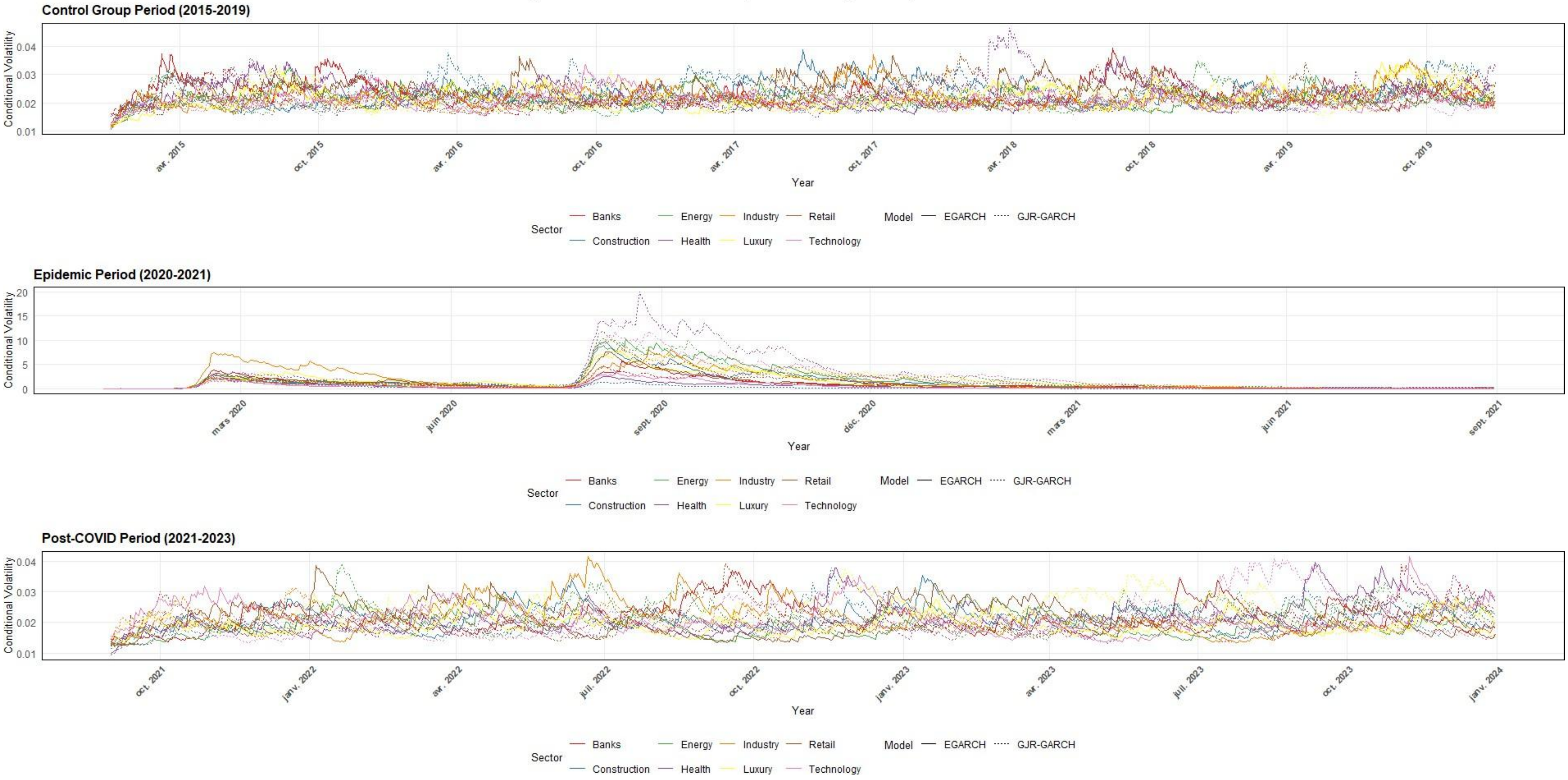
Appendices

Appendix A: Visualization of Weighted Log-Returns per Sector



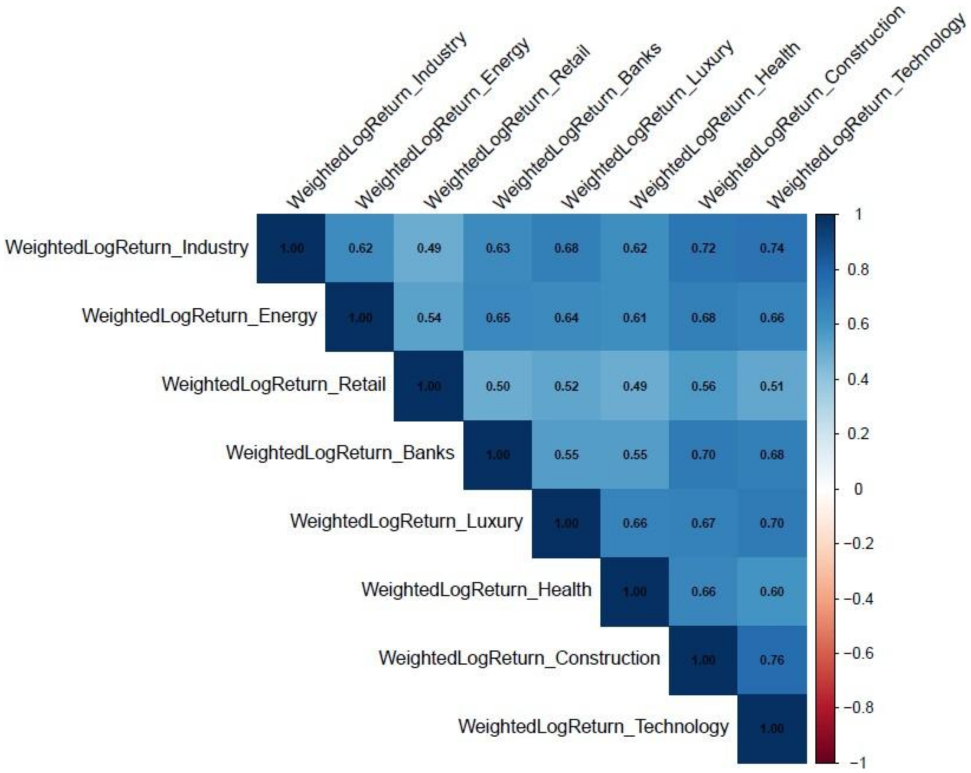
Appendix B: Conditional Volatility Estimates by Period, Sector and Model

Figure 5.6: Conditional Volatility Estimates by Period, Sector and Model

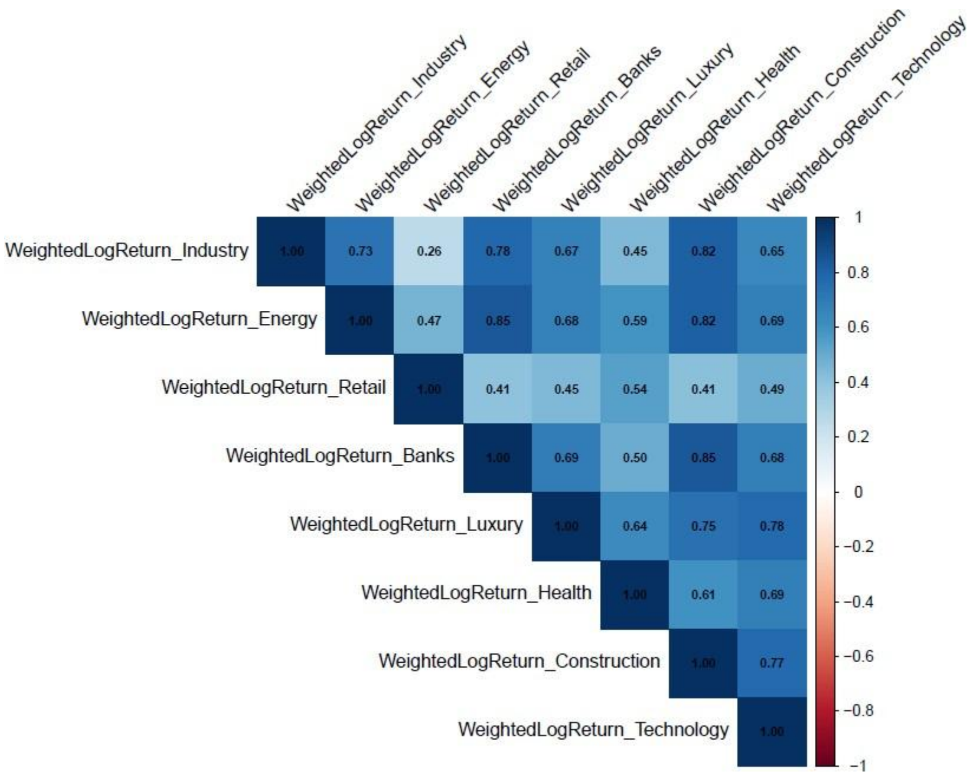


Appendix C: Correlation matrix by period and sector

Panel A: Control Group (2015-2019)



Panel B: Epidemic Period (2020-2021)



Panel C: Post-COVID Period (2021-2024)