International Journal of Accounting and Economics Studies, 12 (5) (2025) 1038-1049

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/286jqz20
Research paper

Using Financial Risk Analysis to Examine Investing Behavior During and After A Crisis, Based on VaR and GARCH Models

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Received: July 31, 2025, Accepted: September 21, 2025, Published: September 27, 2025

Abstract

The assessment of financial risk provides important information for forecasting and investment decision-making. The purpose of this study is to examine investors' behavior during and after a financial crisis and how the stock market indexes are affected. Two forecasting techniques, namely Value at Risk (VaR) and Generalized Autoregressive Conditional Heteroskedastic (GARCH) models, are used in a comparison of three European stock market indexes in Germany, Spain, and Ireland. It was especially of interest to examine if investors had incomplete information about the development of the economy and how their actions would affect future returns. The results provide a means for delving deeper into the variables that affect the performance of the stock market and the factors that investors consider when making financial decisions. The findings thus give valuable lessons to be used in relation to behaviors under the regime of uncertainty.

Keywords: *Financial risk; Value at Risk (VaR); Generalized Autoregressive Conditional Heteroskedasticity (GARCH); Returns; Investing; Financial Crisis*

1. Introduction

In recent years, due to the increased volatility in global markets along with the rapid development of technology, there have been significant changes in the international financial environment. Organizations or investors involved in domestic and international economic activities are confronted daily with the need for strategic planning and decision-making in order to handle financial risks that arise from unexpected fluctuations in the financial markets. The main categories of risks that may arise include market risk, credit risk, liquidity risk, operational risk, and interest rate risk (Jorion, 2007; Caouette et al., 2008; Angelopoulos & Mourdoukoutas, 2001). The financial risks arising from financial markets are based on the size of the investors' exposure and could result in loss of funds due to the unexpected fall in the prices of shares or bonds and the default of financial obligations. Efficient processes of assessing and managing risk, in combination with organizational job redesign strategies for increasing productivity and business performance, are thus of particular interest (Serhan & Tsangari, 2019, 2022, 2023; Amankwah-Amoah et al., 2021, Black et al., 2016).

In fact, through the globalization of markets, technological development, and market deregulation, new risks have emerged, which have made financial markets even more vulnerable and susceptible to crises. One such example was the American subprime mortgage crisis that started in 2007, where a large proportion of loans became unsecured, resulting in high price volatility, limiting liquid assets from large financial institutions. The globalization of the market led to the crisis of 2008 in the rest of the world and especially in the European market, followed by the Eurozone crisis around 2012 and Brexit in 2016 (Saleh, 2023; Tsangari & Mantara, 2021). The Eurozone crisis resulted in fiscal adjustment programs and tough monitoring and austerity policies to ensure fiscal sustainability, with a severe effect on the public finances of several European and OECD countries, including Ireland, Portugal, as well as countries without external institutions monitoring, like Italy and Spain (Grigorakis et al., 2017, 2018). The crisis posed large economic shocks to national economies (GDP declines, rising debts, high deficits, high unemployment rates, low tax revenues) as well as to households (falling incomes, greater indebtedness, job losses, financial insecurity) (Grigorakis et al., 2018; Cylus & Pearson, 2015; Lane, 2012).

With economic globalization and the constant innovation of financial products, the financial industry is facing high risks while simultaneously booming. The continuous volatility of financial markets over the past decades has led to large capital losses mainly due to poor oversight and management of upcoming risks, with the only common factor being the constant high volatility. Therefore, investors and financial institutions are focusing on financial risk management, especially after the outbreak of the global financial crisis. Financial risk management has become an indispensable part of investment, decision-making, and supervision, including risk identification, risk measurement, risk decision, and risk control (Huang et al., 2020). There is a demand for more effort to this end, to develop strategies that will maximize the value of portfolios or protect investments from periods of recession or unforeseen events.

The purpose of the current study is to examine empirically the investment behavior from the outbreak of the global financial crisis and for a long period afterwards, using financial risk analysis with models such as VaR and GARCH, and by comparing stock market indexes of different economies. More specifically, the indices of Germany, Spain, and Ireland have been selected. The findings can provide useful insight and can be utilized as lessons taken for future strategies.

2. Literature Review and Theoretical Background

2.1 The global financial crisis of 2008: investor behavior and economic impact

The financial crisis of 2008 affected economies worldwide. It has been empirically evidenced that investor behavior, heterogeneity, and sentiment during and after a financial crisis play an important role in financial market dynamics, driving investor decisions, strategies, and, consequently, stability of financial markets. Such turmoil periods are generally accompanied by market overreaction, contrary to the hypotheses of market efficiency and investor rationality, where irrational beliefs are driven by emotions rather than fundamentals (Ameur et al., 2024). The global crisis was accompanied by international portfolio adjustment and changes in bond holdings of different types of investors (Galstyan & Lane, 2013; Timmer, 2018). In addition, during a financial crisis, there is unavoidably market risk caused by the extreme stock price jumps due to unexpected positive information shocks. The impact of such information shocks on investors' trading behavior and the related stock price crash risk has also been assessed in related studies, together with the possibility of using such information to diagnose potential market instability (Cui et al., 2022).

Given that the vulnerability to sovereign stress varies between countries, some countries were more fiscally vulnerable and subject to market scrutiny during and after the global financial crisis of 2008. Among European Union (EU) countries, such severely affected cases included, for example, Ireland, Greece, Spain, Italy, Cyprus, Portugal, and Slovenia (Stoian et al. 2018).

Ireland was one of the first Eurozone countries to fall into recession. Its severe banking crisis was caused by the housing bubble, as well as the crisis behavior attributes of the key players in the financial market, in other words, the "herd behavior" of banks, consumers, investors, media, and policymakers. The Irish economy has bounced back strongly since 2012, primarily due to its globalization and foreign direct investment, and accompanied by a rapid growth in employment (Whelan, 2014). The relative scale of the Irish banking crisis, the effective policy responses, and the developments in the external macroeconomic environment played a role in the eventual resolution of the crisis.

Spain experienced a profound crisis, starting in 2008. The banking sector, together with the construction and property development sectors, had an essential role in the detonation and extension of the crisis: the banking system was weakened by the real estate bubble and by the poorly governed savings banks. Excessive private debt peaked in 2010, when corporate debt was at 120% of its GDP in consolidated terms, 42 percentage points higher than companies in the wider eurozone, followed by severe unemployment and stagnation (Carballo-Cruz, 2011). In mid-2012, the government formally requested financial assistance from the European authorities. Deeper reform measures managed to contain the crisis, although its economic recovery is still slow.

Germany was also affected by the crisis, with a decline in its GDP, unusually high levels of debt, and the loss of its leading position in export markets to China in 2008-2009. However, its economy recovered rapidly in 2010, when exports soared and unemployment returned to nearly pre-crisis levels (Barsauskas et al., 2011). The successful economic recovery was attributed to fiscal supporting programmes, new increasing investment, but especially the so-called "labor market miracle", in other words, the low unemployment due to flexible hours, active labor market reforms, and short-time work schemes (Hutter & Weber, 2021).

The three countries have been selected for the analysis in the present study due to their structural differences and interesting economic characteristics during and after the crisis.

2.2 Value at Risk (VaR) methodology

Value at Risk (VaR) is a measure of risk, created by J. P. Morgan, motivated by the large capital losses of the 1990s, aiming at managing market risks more effectively and establishing a general standard for financial risk management and quantification of risks (Morgan, 1996). It is based on Markowitz portfolio theory, financial risk management theory, and the valuation of derivative financial products (Markowitz, 1991).

VaR has become a widely used risk measurement and management method for the calculation of market risk and is implemented by financial institutions, regulatory authorities, banks, and insurance companies that trade and hold investment portfolios of currencies, shares, and bonds (Salo et al., 2024; Wang et al., 2022a; Al Janabi, 2007; Linsmeier & Pearson, 1996). This is mainly due to the method's simplicity in calculation and intuitive interpretation.

VaR provides sufficient and reliable information regarding the maximum expected loss of a portfolio at a given time horizon or a given period for a given confidence interval. Using this method, investors can measure the capital that can be lost due to the fluctuations of a portfolio with the goal of maximizing the portfolio return through controlling its variance. Overall, VaR can be used for informing management about the level of risk exposure of traded securities, for applying limits to securities trading based on risk, for allocating investment funds more efficiently, for evaluating performance through monitoring the "return-to-risk" ratio of each trader and for regulating the financial system through limits and rules on the capital adequacy of financial institutions (Franzen, 2010; Al Janabi, 2007). VaR models have also been used for estimations in volatile emerging markets (Dimitrakopoulos et al., 2010; Wang et al., 2022a).

2.3 The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model

Many economic and financial time series exhibit heteroskedasticity, where the variability changes are often based on recent past shocks, which cause large or small fluctuations to cluster together. Economic and policy uncertainty exaggerates market volatility and causes time-varying risk characteristics (Baker et al., 2016; Tsangari, 2007). A classical method of modelling the changing variance includes Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (Engle, 1982; 2001; Bollerslev, 1986).

Heteroskedasticity indicates the violation of the assumption of constant variance and results in greater difficulty in terms of investment management. GARCH models consider the variance as a variable to be modelled and, as a result, predictions are calculated for each error term. The variance of today's returns is estimated using estimates of the previous day's variance and the squared values of the previous day's returns (Hansen & Lunde, 2005). The accuracy of the predictions generated is particularly important and becomes more difficult when the risk varies. In addition, this risk might exhibit a degree of autocorrelation in the returns of financial prices. It is noted that an Autoregressive (AR) random process is used to describe time-varying series, by specifying how the variable depends linearly on its own prior values as well as a stochastic term; the Moving Average (MA) component specifies that the output variable depends linearly on the current and past values of the stochastic term. The MA model is always stationary, unlike the AR, which may contain a unit root (Box et

al., 2015; Walter, 2004). GARCH-type models have been created to handle such issues and have, therefore, become a very popular tool in time series analysis, in terms of quantifying risk.
GARCH models are widely used in risk management, portfolio management, option pricing, and interest rate structure. They can also be used in measuring and forecasting volatility in financial time series, in predicting trends of stocks, indexes, and portfolios, for research on cryptocurrencies, for making effective investment decisions and strategies, or for the comparison between short-term and long-term interest rate relationships (Marisetty, 2024; Yan et al., 2022). GARCH modifications have also been developed for modeling specific types of data (e.g., to address asymmetric effects, to allow for dynamic correlations and volatility transmission between multiple financial time series or to capture time-varying correlations between multiple financial assets), such as EGARCH, fGARCH, NGARCH, APARCH, GJR-GARCH, TGARCH, DCC-GARCH, MGARCH, and GARCH-BEKK models (Aue et al., 2017; Sahiner, 2024; Insaidoo et al., 2021). GARCH-type models have also been implemented in literature on investor behavior and emerging markets risks (Wang et al., 2022b; Mishra & Ghate, 2022; Said et al., 2024).
GARCH models are frequently used in VaR estimation (Angelidis et al., 2004; So & Yu, 2005; Syuhada et al., 2024). Applications of GARCH in VaR estimation include, for example, studies for stock exchange or cryptocurrency data, in developed or emerging markets (Smolović et al., 2017; Owusu et al., 2022; Chen et al., 2023).
Alternative risk models have also been developed, including Expected Shortfall (ES) models or copula-based GARCH models (El Khoury et al., 2023; Nazeri-Tahroudi et al., 2022), aiming to provide accurate forecasts. Many studies have compared forecasts of ES and VaR models when using copula-based models as opposed to more traditional models (Kar & Meka, 2025; Righi & Ceretta, 2015; Castillo-Brais et al., 2024). In general, related studies have provided mixed results regarding the accuracy of forecasts, depending on the nature of the data, dependence information, or the aim of the research.
Despite other recently developed models, the simplest form of models in the GARCH family, GARCH(1,1), is still considered a "standard procedure" and is still widely used for measuring volatility in financial time series (e.g., He et al., 2020; Li et al., 2022; Yan et al., 2022; Aharon et al., 2025): it is simple, efficient, accurate, and appropriate for related analyses.

3. Methods

3.1 Data collection

For the study, the indices from three different models of economies will be examined. More specifically, the closing prices of the general stock market indexes of Germany (DAX), Spain (IBEX), and Ireland (ISEQ) will be analyzed. The selection of the stock indexes is made considering that the general indexes of the stock exchange refer to the share prices of listed companies and reflect the average trend of these prices. The general function of the indexes is also a benchmark for evaluating collective investment schemes. They are also frequently used to forecast the average price trend and as an investment strategy tool.
Our sample period will be from 2008 to 2019, in other words, more than 10 years after the beginning of the global financial crisis. The 11-year period under study is sufficient to provide a model from which reliable information on the market trend can be derived.
Through the analysis, it will be investigated whether the information of the previous years had been integrated into the stock market value and consequently how investors moved in the following days. Thus, there will be a direct comparison of the results of the model forecasts and the actual market performance (real data). This will make it possible to see whether the model produces reliable results on which an investment strategy can be based in order to improve the quality of a portfolio.
The specific research objectives are:

1. The extraction of short-term forecasts using the GARCH and VaR methods.
2. The comparison of the evolution of the three indicators over time.
3. The best investment choice to maximize profit and minimize the risk of capital loss.

3.2 Data analysis

The data will be analyzed using the R software. The two models, VaR and GARCH, will be used for the analysis.
First, the closing prices will be processed, and missing data will be handled. For the analysis of the three indices based on these models, the conditions of stationarity, normality, and non-autocorrelation will be examined. To this end, and for more accuracy in the forecasts, the prices will be converted to returns, as in equation (1):

$$R_t = (P_t - P_{t-1})/ P_{t-1} \quad (1)$$

where Rt is the return of the index at time t and Pt is the index price at time t.
The GARCH model is of the form given in equation (2):

$$\sigma^2_\tau = \delta_0 + D(L)\, \sigma^2_{\tau-1} + B(L)\varepsilon^2_{\tau-1} \quad (2)$$

where D(L) is the polynomial of lags of the conditional variance σ^2_τ and B(L) is the polynomial of the lags of the squared residuals. The GARCH model assumes that the conditional variance depends on the previous values of the squared errors as well as on the previous values of the variance.
Therefore, based on equation (2), the GARCH(1,1) formula is given by equation (3):

$$\sigma^2_\tau = \delta_0 + d\, \sigma^2_{\tau-1} + b\, \varepsilon^2_{\tau-1} \quad (3)$$

which shows that the conditional variance at time τ is a linear combination of a constant term, the conditional variance of the previous time, and the squared residual term of the previous time.
GARCH(1,1) models are favored over other stochastic volatility models, due to their simple implementation: since they are given by stochastic difference equations in discrete time, the likelihood function is easier to handle than continuous-time models, and since financial data are generally collected at discrete intervals. This type of model is appropriate for the analysis of financial volatility data, similar to the data in the present study (Hansen & Lunde, 2005).

GARCH models may have the limitations of exhibiting sensitivity to parameter specification or potential overfitting. The GARCH models in the current study will be estimated to provide the optimal fit. The Akaike Information Criterion will be considered to provide the GARCH models with the best fit, by balancing model fit and complexity in terms of estimated parameters.
The analysis of the data using the VaR method will be performed using equation (4), which estimates the maximum possible loss:

$$P\ (L > VaR) \leq 1\text{-}c \tag{4}$$

where P is the probability that the actual loss of the asset value is greater than the maximum possible loss, L is the loss value of the financial asset in a specific holding period, and c is the confidence interval. In other words, the accuracy of VaR depends on three key parameters: a) the time horizon, which reflects portfolio liquidity and investment objectives; b) the confidence level, which indicates the probability that losses will not exceed the VaR estimate and the investor's attitude towards risk (the higher the confidence level the lower the probability that VaR will not predict extreme events); and c) the data window, which determines the time period used for calculations and balances between the sample size and the accuracy of the risk estimate. This is because the larger the observed number, the more accurate the estimate
Although VaR is useful for comparing risks, estimating worst-case losses, and determining capital adequacy, it has limitations in capturing extreme market events. Therefore, it is complemented by validation and stress analysis techniques: Backtesting is a key process that compares historical losses to previous VaR estimates, to assess whether the model's predictions are accurate. It examines how often losses exceed the VaR threshold, whether exceedances cluster, and the magnitude of these losses. A model that is too conservative underestimates potential gains, while one that is too lenient underestimates risk, both of which lead to poor risk perception. It is complemented by Stress testing, which evaluates portfolio performance under extreme but plausible market conditions by applying shocks to key risk factors. These scenarios can be historical, hypothetical, correlated factor shocks, or tailored to portfolio-specific vulnerabilities, and they help identify weaknesses that VaR may overlook. Scenario analysis further explores potential changes in market conditions through a structured process of selecting scenarios, identifying risks, making forecasts, and ensuring internal consistency. Together, these techniques ensure that VaR estimates are not only statistically accurate but also robust to rare, high-impact events, enabling investors to better manage financial risk (Morgan, 1996; Mulvey et al., 1997; Jorion, 2007; Culp et al., 1998).

4. Results

4.1 Graphical representation of the three indices

Figure 1 shows the trends of the DAX (Germany), IBEX (Spain), and ISEQ (Ireland) indexes (in orange, black, and blue colors, respectively). The indices of all three countries at the beginning of the global financial crisis have a downward trend. The largest declines, both in duration and in price level, occur in the indexes of Spain and Ireland, which start to recover after 2013, in contrast to the index of Germany, where there is a milder decline, and within a year in 2009, the recovery starts. From 2013 onwards, the three indices started to follow a similar, slightly upward trend.

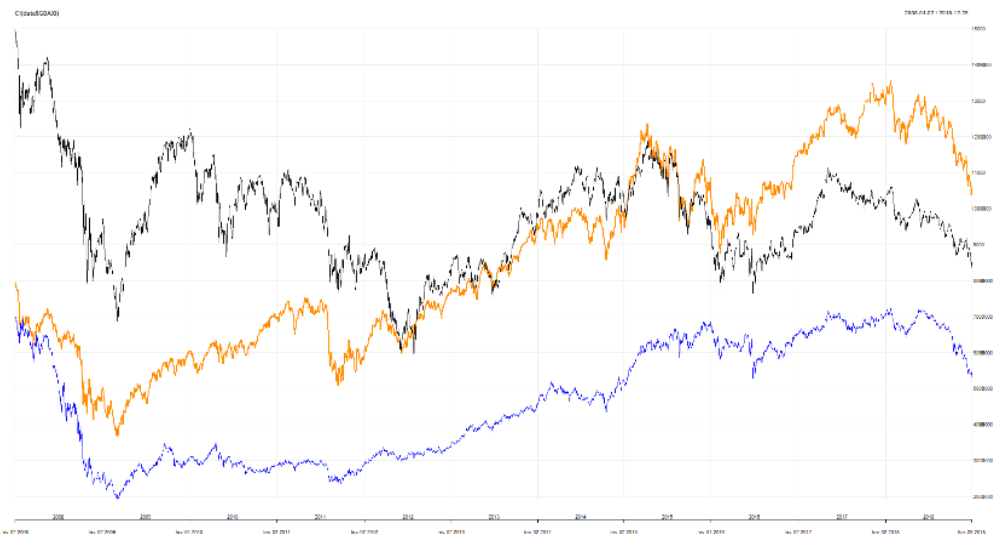

Fig. 1 The trends of the three indexes, DAX (Germany; orange color), IBEX (Spain; black color), and ISEQ (Ireland; blue color), during 2008-2019.

Figures 2-4 show the returns of the three indexes. As in the early years of the crisis, returns increase, with Germany's index returns normalizing more quickly as opposed to the other two countries' high volatility, which lasts for a longer period.

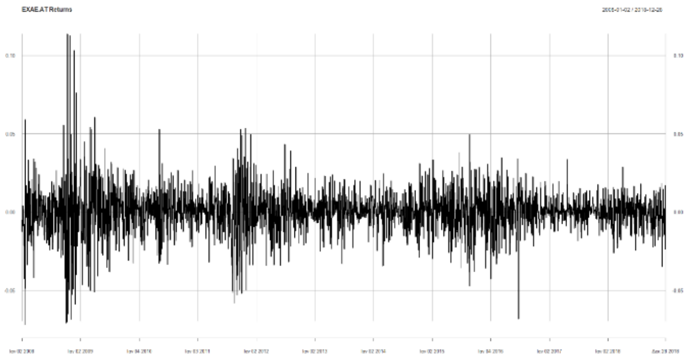

Fig. 2: Returns of the DAX (Germany) Index, 2008-2019.

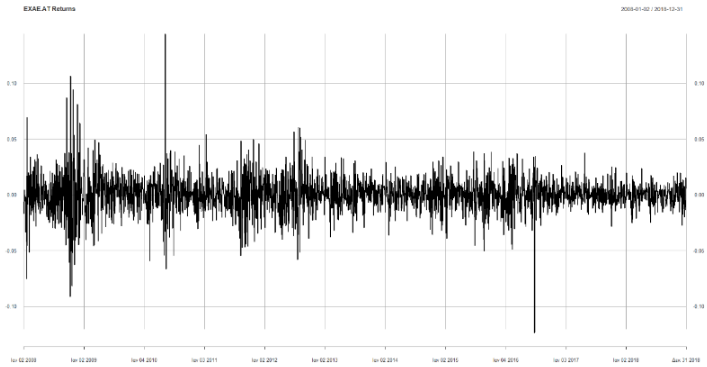

Fig. 3: Returns of the IBEX (Spain) Index, 2008-2019.

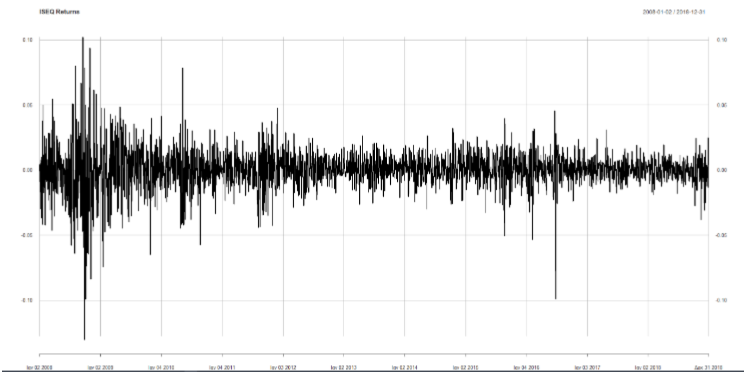

Fig. 4: Returns of the ISEQ (Ireland) Index, 2008-2019.

4.2 Analysis of the German DAX index

The GARCH model obtained from the analysis of DAX was found to be GARCH (1,1), with a normal distribution, while the mean model was ARFIMA(1,0,1), with the Akaike Information Criterion of -5.99. Figure 5 shows the 5-day forecasts for DAX, using GARCH. As we can see, the GARCH predictions for the next five days have a slightly downward trend.

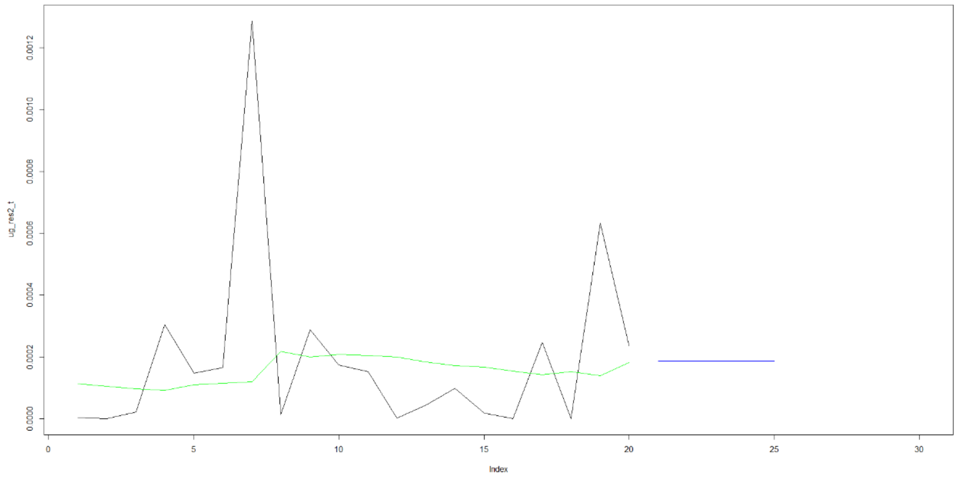

Fig. 5: Five-day out-of-sample forecasts (purple color) for the DAX index, using the GARCH model.

Figure 6 shows the VaR estimation of the DAX Index, with 1% VaR limits, and depicts graphically the Backtest results. More specifically, the Backtest showed that in a test of 2668 observations, the VaR was exceeded 144 times.

Fig. 6: VaR estimation of the DAX index (1% VaR limits) (Backtest results)

In the following Figure (Figure 7), we can see the five-day forecasts for the DAX index, using the VaR method, which are again slightly downward.

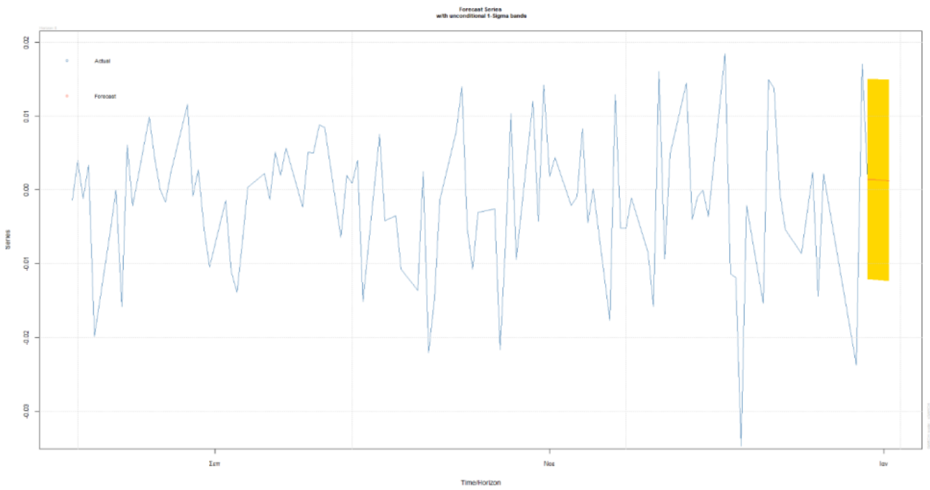

Fig. 7: Five-day forecasts for the DAX Index, using the VaR method

4.3 Analysis of the Spanish IBEX index

The GARCH model obtained from the analysis of IBEX was similarly found to be GARCH (1,1), with a normal distribution, while the mean model was ARFIMA(1,0,1), with the Akaike Information Criterion=-5.74. Figure 8 shows the 5-day forecasts for IBEX, using GARCH, which appear to have a slightly upward trend.

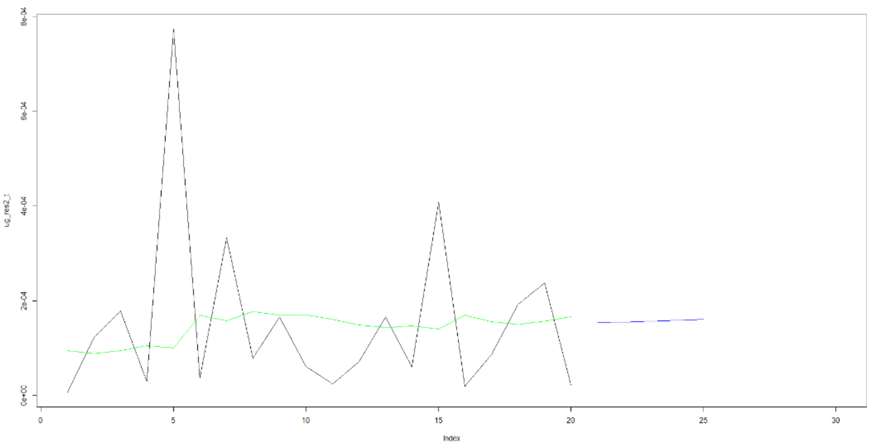

Fig. 8: Five-day out-of-sample forecasts for the IBEX index (purple color), using the GARCH model.

Figure 9 shows the VaR estimation of the IBEX Index, with 1% VaR limits, and depicts graphically the Backtest results. More specifically, the Backtest showed that in a test of 2688 observations, the VaR was exceeded 149 times

Fig. 9: VaR estimation of the IBEX index (1% VaR limits) (Backtest results)

In Figure 10, we can see the five-day forecasts for the IBEX index, using the VaR method, which are again slightly upward.

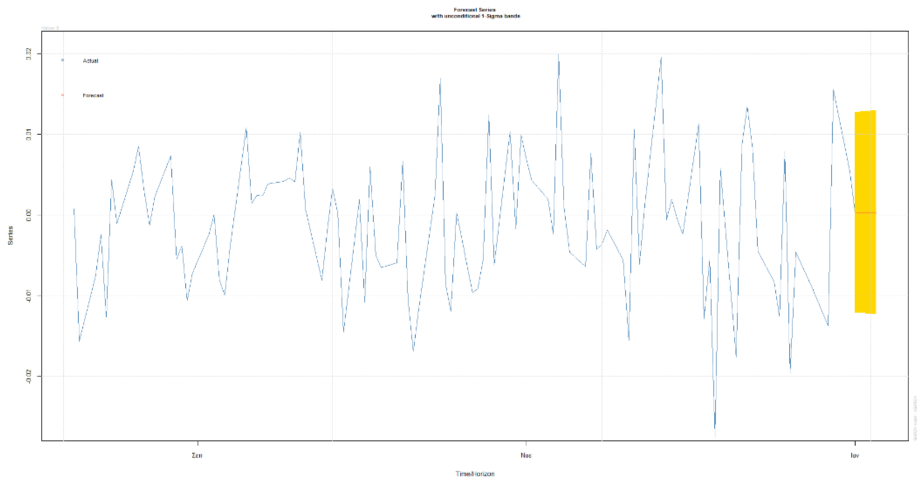

Fig. 10: Five-day forecasts for the IBEX Index, using the VaR method

4.4 Analysis of the Ireland ISEQ index

The GARCH model obtained from the analysis of ISEQ was again found to be GARCH (1,1), with a normal distribution, while the mean model was ARFIMA(1,0,1), with the Akaike Information Criterion of -5.99. Figure 11 shows the 5-day forecasts for ISEQ, using GARCH. As we can see, the GARCH predictions for the next five days have a slightly upward trend.

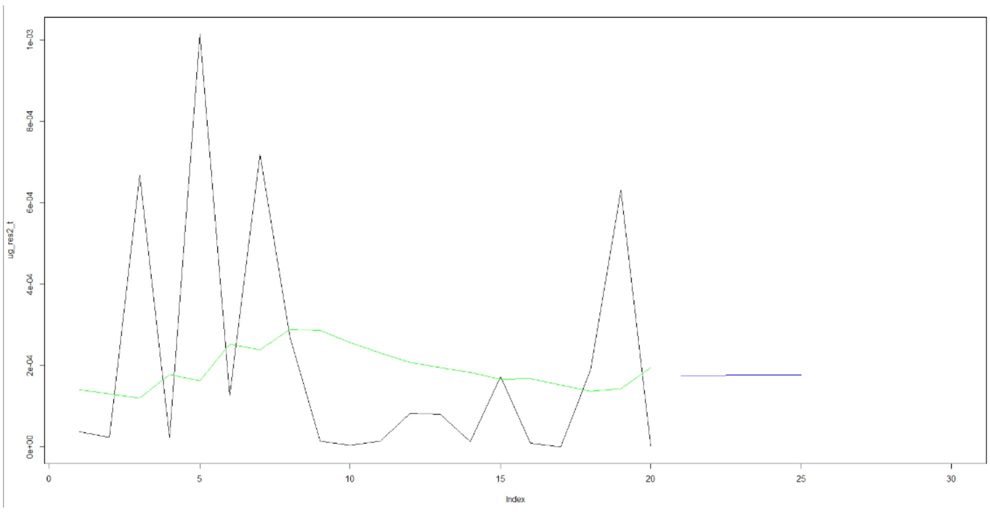

Fig. 11: Five-day out-of-sample forecasts for the ISEQ index (purple color), using the GARCH model.

Figure 12 shows the VaR estimation of the ISEQ Index, with 1% VaR limits, and depicts graphically the Backtest results. More specifically, the Backtest showed that in a test of 2688 observations, the VaR was exceeded 140 times.

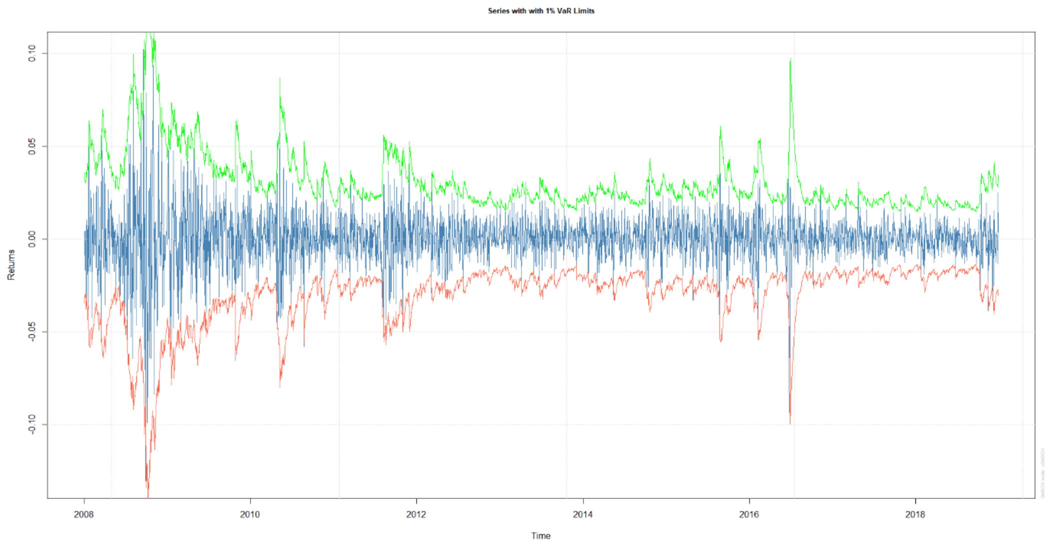

Fig. 12: VaR estimation of the ISEQ index (1% VaR limits) (Backtest results)

In Figure 13, we can see the five-day forecasts for the ISEQ index, using the VaR method, which are again slightly upward.

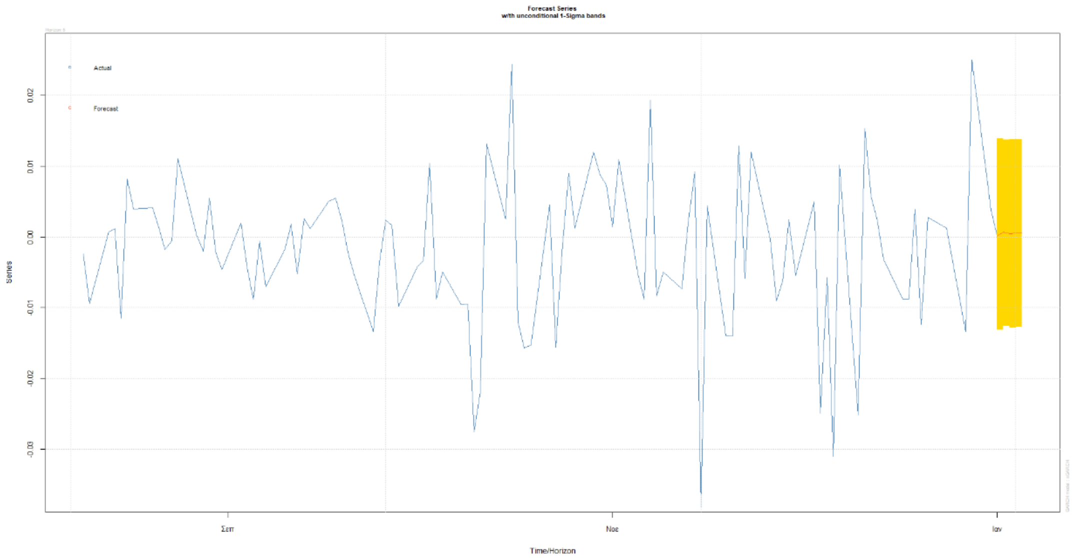

Fig. 13: Five-day forecasts for the ISEQ Index, using the VaR method

4.5 A comparative analysis of the results from the three indexes

Table 1 presents the coefficients of the three indexes from the GARCH models. More specifically, it shows the parameters of interest that are statistically significant ($p<0.05$), such as AR1, which is the AR coefficient of the mean model, MA1 which is the MA coefficient of the mean model, alpha1, which is the coefficient of the squared residuals in the GARCH equation and beta1, which is the coefficient of variance with lagging.

Table 1: Estimated Coefficients of the models from the three indexes DAX, IBEX, and ISEQ.

Parameter/Indicator	DAX	IBEX	ISEQ
AR_1	0.93147	0.37262	0.35167
MA_1	0.94532	0.39216	0.39965
Alpha 1 ($\alpha 1$)	0.08265	0.10009	0.10398
Beta 1 (β_1)	0.90624	0.88803	0.88499

Note. AR = autoregressive term; MA = moving average term; α and β are GARCH model parameters.

Table 2 shows the exact values of the predictions for five days, for the three indexes (DAX, IBEX, ISEQ):

Table 2: Five-day forecasts for the DAX, IBEX, and ISEQ indexes

Forecast/Indicator	DAX	IBEX	ISEQ
T+1	0.00144	0.00024	0.00011
T+2	0.00139	0.00030	0.00067
T+3	0.00134	0.00028	0.00047
T+4	0.00129	0.00029	0.00054
T+5	0.00125	0.00028	0.00052

Note. T+i shows the out-of-sample forecast for the ith day ahead.

Based on the forecasts produced for the three indexes (Table 2), in the short term, the best choice as an investment option appears to be that of the IBEX index, since it has a higher increase than that of the ISEQ index, while the DAX index shows a downward trend. These trends are also shown graphically in Figure 14.

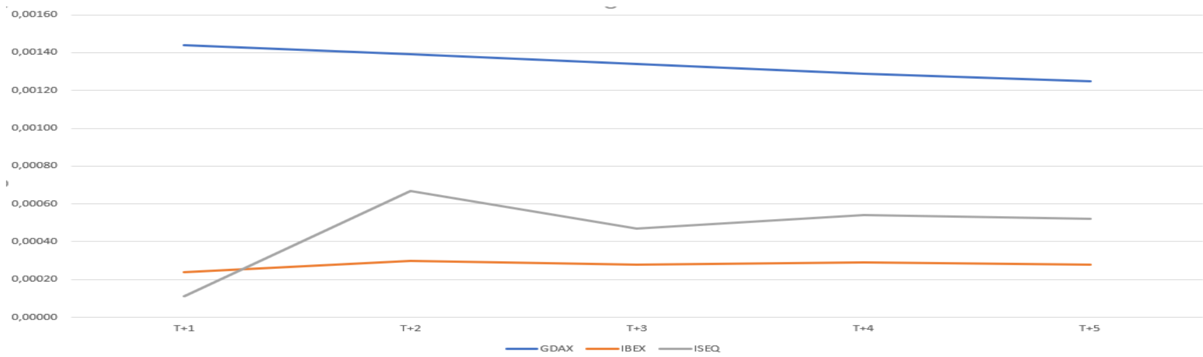

Fig. 14: A comparison of the five-day forecasts for the three indexes

5. Discussion

Financial risk management is constantly evolving, as forecasting models must constantly adapt to new conditions created in the economic environment. The importance, therefore, of identifying financial risks and making investment decisions is a very important process for investors who aim to maximize the value of their portfolios. However, models are constructed based on variables defined by each researcher, resulting in future predictions not always being accurate or leading to misleading results. In addition, conducting forecasts with large sample sizes and many variables for the results to be sufficiently accurate requires a lot of computing power and specialized software to carry out the process.

In the present study, financial risk analysis was conducted using two widely used models, namely GARCH and VaR. Three indices of different economies were examined: those of Germany, Spain, and Ireland. The three countries had different characteristics during and after the global financial crisis (Grigorakis et al., 2018) and, thus, were of interest to analyze. The two models enable investors to assess the impact of the change in variability in financial series and, consequently, to be able to estimate the risk of their portfolio to make sound investment decisions. The two models are used extensively by risk managers to measure, quantify, and leverage financial risk. The VaR presents the degree of risk in a single value, which also helps in more effective communication between managers and investors so that investment decisions can be made more quickly. This simplicity is one of the reasons why its use has been established. Thus, the use of these methods adds value to investors and the institutions that use them to measure their risk exposure and forecast returns as risk management becomes a central topic of discussion in financial institutions and businesses.

The cases presented for the general stock market indexes of Germany, Spain, and Ireland illustrated the attitudes of investors towards the risks they faced, as risks come from different sources. However, the strategy for dealing with them was common.

The risk in Ireland occurred largely after the financial crisis in the U.S., where there was a large exposure of Irish banks to financial products that collapsed, and consequently, the banks faced liquidity problems, which greatly affected the economy of the country (O'Sullivan, 2010). Inward foreign direct investment (FDI), globalization, and the favorable tax environment led to employment growth and contributed to the recovery of the economy (Whelan, 2014). In contrast, the crisis in Spain was created due to institutional problems in its own structure. The country had accumulated a particularly high level of debt, and combined with a decline in the growth rate of the construction sector, which was a driving force for it, it inevitably led to a long-term recession (Quaglia & Royo, 2015). The main reasons for the delay in the economic recovery of Spain are unemployment, low productivity, and high debt (Carballo-Cruz, 2011). Germany had a more stable and stronger economy during the same time. Although there was a small increase in unemployment in 2009, by the end of 2010 it had already been reversed. The German government introduced an austerity budget, cutting nearly 100 billion USD in spending by 2014. It appears that immediate banking stabilization, stimulus packages, and active labor market measures supported companies, safeguarded employment, and bolstered private consumption. Its strong industrial base (machinery, medical, environmental technology) and its exports were additional growth drivers. Germany also took a new role in foreign affairs, assisting severely affected countries in the EU, including Spain (Barsauskas et al., 2011; Hutter & Weber, 2021).

The above facts became evident from the results of the present study, as depicted in the decline in index prices as well as returns over time. This decline appears to have resulted in risk aversion among investors. Thus, their reaction was immediate to the risks they faced, such as market risk, credit risk, liquidity risk, and country risk. Therefore, the investors' strategy to minimize losses led them to invest in safer markets despite low returns, such as Germany.

Finally, comparing the three countries as short-term investment strategies for the time examined, the findings indicate some important conclusions from the models used. The forecast results from the estimations showed that to minimize the risk of capital loss and maximize returns, investors should have focused on the Spanish and Irish indexes and avoided Germany, as it was the only declining index. This can be combined with the Backtest results, where the one for the ISEQ index is the smallest (with 140), compared to the other two indexes, with 144 for DAX and 149 for IBEX.

The consideration of past historical data from the three countries has provided a useful guide for scenario analysis and has practical implications in understanding paths to recovery and for short-term forecasting. The three countries had some similarities in terms of how they were impacted by the global financial crisis of 2008, but they also had some basic structural differences in their recovery. Regarding their similarities, they were all exposed through their banking systems and real estate bubbles, although Ireland and Spain more severely, and Germany, rather indirectly. Also, debt increased dramatically in all cases (government debt in Ireland and Germany, corporate/household debt in Spain). Finally, the recovery paths of all three countries were shaped by European Central Bank (ECB) policies and fiscal constraints (Whelan, 2014; Carballo-Cruz, 2011; Barsauskas et al., 2011; Hutter & Weber, 2021).

Regarding the structural differences of the three countries under examination, Germany had the fastest speed of recovery, due to its structural strengths and labor reforms, followed by Ireland and then Spain. The early recognition of bank losses and the swift policy responses, the bailouts and fiscal adjustments in Ireland were shown to be instrumental: its post-crisis growth was strongly tied to multinational corporations and global integration, while investor confidence was preserved due to credible fiscal disciplines and adherence to a needed fiscal adjustment (Hutter & Weber, 2021; Whelan, 2014; Carballo-Cruz, 2011). Spain had slow and hesitant reforms until the EU bailout forced deeper action. Although the Spanish economy continues to grow and the outlook is favorable, Spain still lags the EU average in terms of GDP per capita and faces long-term structural challenges in productivity and employment. Reversing these trends requires ambition and major political agreements to ensure that the reforms needed can be sustained. In addition, the fight against climate change and the green transition are two of the biggest challenges currently facing our society, and Spain is one of the most exposed developed countries.

The sample period of the present study included the years 2008-2019, focusing on the years after the global financial crisis of 2008 and excluding the period that followed the Coronavirus (COVID-19) pandemic. The COVID-19 pandemic, although it cannot be considered a pure "financial crisis", had a global effect, pushing economies into recession, reproducing volatility. However, including data from the years during and after the pandemic was beyond the scope of the present study, as they could give misleading information and affect the results in the context of the current analysis: First, the shocks on the global economy, during and after the pandemic, appear to have been faster and more severe compared to other crises and with a possible asymmetric reaction of volatility; the negative influence of volatility on financial returns and the multiple crashes on international investment have caused extreme market stress (Khan et al., 2023; Corbet et al., 2021; Chaudhary et al., 2020). Therefore, the uncertain nature of the pandemic and its unclear economic impact have made it difficult for both investors to assess the dynamics of volatility in the markets, as well as for policymakers to develop appropriate economic policies (Ullah et al., 2023; Zhang et al., 2020; Ibrahim et al., 2020). Second, the pandemic and the lockdowns affected the quality of life and mental health of people worldwide and thus the results could be misleading also in terms of investor behavior, which might not be representative of investor behaviors after a financial crisis (Kramer & Kramer, 2020; Tsangari et al., 2022, 2023; Rajkumar, 2020; Ramakau et al., 2025).

In future research, it would be of interest to include post-2019 data to see how they might affect the results, providing a comparative analysis. Different GARCH-type models could be implemented to accommodate any existing asymmetries in volatility and to juxtapose results using short vs. long data windows, which are issues with contradictory evidence in related literature (Ullah et al., 2023). Given the COVID-19 pandemic, the ongoing global economic uncertainties, and the political turbulence, the long-term impact in terms of business failure and unemployment could also be assessed (Amankwah-Amoah et al., 2021; Montenovo et al., 2022). The disruptive events of the last two decades have reshaped the foundational dynamics of global financial markets and have altered individual investors' decision-making frameworks, reflecting a new era of interconnectedness and complexity in global finance (Ameur et al., 2024). The world today faces greater global economic and geopolitical competition, and it is more integrated compared to the past. Future studies should thus investigate the degree of change and the optimal strategies ahead.

Other future research directions may include an extension of the analysis to other markets, beyond European or developed countries, especially focusing on emerging markets, to compare investing behaviors and modeling results. In addition, potential challenges in applying these models in real-world settings include computational demands and data quality issues. Therefore, recently developed models, such as machine learning-based forecasting models, could additionally be incorporated to this end. These might contribute towards efficient and fast analysis of large datasets and identification of new, complex underlying patterns, and thus complement or enhance the traditional forecasting methods.

6. Conclusion

The present study has provided more insight into the use of financial risk analysis for the examination of investment decision-making and behavior in periods during and after a crisis in three European countries with different characteristics. The results delve deeper into the factors that affect the performance of the stock market and the methods that investors can consider when making financial decisions, and they have practical and policy implications. For example, they can be used for informing key regulatory policy measures, such as stress testing and risk disclosure standards, aimed at improving financial stability after a global financial crisis like the crisis of 2008. On one hand, the empirical evidence from the models of the three indexes and their post-crisis behavior can be implemented in stress testing, as a direction for improving financial stability, by ensuring resilience to economic downturns and by increasing transparency for investors. Through stress testing, an assessment of the ability to absorb losses under such severe economic conditions can be made, influencing capital requirements. On the other hand, the findings can be used for informing risk disclosure standards, being an important requirement for the public reporting of potential risks, allowing investors to better understand firms' financial health and to promote market discipline. Overall, the current analysis gives valuable lessons to be used in relation to investing behaviors under the regime of uncertainty, which follows times of financial crisis.

Acknowledgement

The author would like to thank Mr. Nikolaos Papanikolaou for his contribution to the study.

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