Eurozone Crisis, Policy Actions and Financial Market Volatility

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***Abstract*—After the outbreak of the Eurozone crisis, the overall stability of the euro area was undermined. European countries have adopted different policy actions. We analyzed the reaction of German, Spanish and Irish stock market indices to announcements of policy action between January 1, 2000 and December 31, 2016. Past papers have analyzed the impact of policy actions on financial markets and the economy of Europe as a whole. Our paper focuses on stock indices and establishes the relationship between stock indices and policy actions through the generalized autoregressive conditional heteroskedasticity (GARCH) model. Through the analysis of the model test results, we find that the policies issued after the eurozone crisis have no significant impact on the volatility of financial markets.**

***Index Terms*—Eurozone crisis, Policy action, Volatility, GARCH model**

I. Introduction

The eurozone crisis is one of the most important economic events of recent years. At its peak, the impact of the crisis put the outcome of the euro project at serious risk, exposing the weaknesses and vulnerabilities inherent in the monetary union. As a result, many EU economies have been in stagnation or marked recession since the end of 2011.

If we want to track the causes of the eurozone crisis, we find that it is the spread of global imbalances and related capital flows, which is also known as the global savings surplus hypothesis [1]. The European banking crisis is a basic condition for the European sovereign debt crisis [2]. The reasons for the crisis can be divided into three categories: Firstly, in the early 2000s, the economies of Germany and other countries in the eurozone were completely integrated, so their governments' bond prices were always set at the same level [3]. Secondly, the abolition of national currencies has increased the importance of national currencies – Fiscal Policy as a Countercyclical Macroeconomic Policy Tool [4]. Thirdly, the two pillars of the EU member states' over-indebtedness treaty, the Stability and Growth Pact (SGP) and the auxiliary clauses, were insufficient to prevent the crisis. The eurozone countries have exceeded the national deficit ceiling of 3% at least once [5].

To solve the economic losses caused by the eurozone crisis, the European Central Bank(ECB) issued a series of general and unusual monetary policies during that period [6]. Interest rates were lowered to unprecedented levels[6]. In addition, the composition of the balance sheet changed, mainly during the first phase of the crisis (qualitative easing) and expanded significantly in the second phase (quantitative easing) [7]. This was in the early stage of the eurozone crisis, from August to September 2007. Lehman Brothers went bankrupt in 2008 and for this reason, the European Central Bank issued a notice that there would be three countermeasures. These were almost unlimited overnight liquidity, temporary swap lines, and additional longer-term refinancing operations (LTRO). In September 2008, there was a panic in the European financial markets, and interest rates suddenly rose sharply. The main reason for this was that the solvency of many financial institutions had been questioned by the public, so the stability of the entire financial industry was threatened [7]. Spreads can reduce the leverage of credit institutions and therefore have a negative impact on the real economy. In October 2008, the ECB launched an expanded credit support program to help banks manage their banking assets [7]. The ECB decided to carry out two LTROs in October 2011, one with a term of approx. 12 months and the other with a term of approx. 13 months, in December 2011.

In addition, in June 2014, the European Central Bank announced that they would start a series of operations, targeted longer-term financing transactions (TLTRO). The reason for doing so was because they hoped to bring loan opportunities to some private companies in Europe that were not in the financial industry. This series of operations replaced several different plans, namely The Third Covered Bond Purchase Programme(CBPP3), Asset Backed Securities Purchase Plan (ABSPP) and Public Sector Procurement Plan (PSPP) [8]. Since the European Central Bank issued this series of measures starting in 2008, these policies have had an obvious impact on short-term interest rates, and this is believed to have led to the regaining of confidence in the normal workings of financial markets. Then, the unconventional plan of the European Central Bank only had a positive effect on Greece and had other effects on other European countries. The cumulative and average impact of the Securities Markets Program(SMP) and Outright Monetary Transactions(OMT) events on sovereign debt crisis

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mitigation is much stronger than that of the LTRO announcements. Reference [9] pays attention to LTRO and defends the important role of the three years in reducing liquidity and capital. Banking risks in turn drive the economy. In addition, LTRO appears to support economic financing through quantitative easing loans rather than lowering financing costs. Reference [10] confirms that unconventional monetary policy can have positive effects on the economy by lowering government bond yields; however, economic recovery in the Organization for Economic Co-operation and Development(OECD) countries remains slow. Reference [11] agrees with the general literature; the unconventional monetary policy of the ECB has had a significant negative impact on the yield spread between Germany and Italy and has also increased the return of the Eurozone Stock 50 Index. If the euro stock 50 index is replaced by the FTSE100 index, these results do not change. The effectiveness of the unconventional policies of the ECB can also be evaluated in the context of weak monetary policy that increases uncertainty and reduces willingness to take risks [12]. Reference [13] constructs a conservative monetary policy innovation measure based on the heteroscedasticity method of Reference [14] and examined the response of stock market indices, derivatives volatility indices and public debt yields within the country and the eurozone. Moreover, it is found that financial market participants react more strongly to monetary policy after the global financial crisis. Reference [15] takes the view that traditional monetary policy instruments cannot overcome the crisis effectively, neither quantitative easing nor negative interest rate policy have been effective, and their continued application will only exacerbate the crisis. It is worth mentioning that the large-scale introduction of new technologies into scientific research should be encouraged because the result will be an increase in labor productivity, which raises the level of the average interest rate and thus creates opportunities for effective monetary policy. Reference [16] shows model specification does not accurately explain the persistence of volatility, nor does it ignore the potential downward bias caused by using the noise volatility proxy in this study and empirical understanding of the time-varying volatility measurement model. A recent study by reference [17] calls for more research on the relationship between monetary policy and stock market volatility. Reference [17] suggests that the implementation of flexible monetary policy may indicate a recovery in the stock market and that imperfect rationality of investors will lead to more frequent fluctuations in the stock market. The idea that the ECB acts as the government's "lender of last resort" (LOLR) is seriously flawed and based on dubious theoretical foundations. Central banks can play such a role in providing temporary liquidity to commercial banks to avoid depositors' panic. However, in practice, it's far more frequently difficult to differentiate between inadequate liquidity and the financial disaster of banks [18]. This is especially true in the case of sovereign debt. In this case, the market's belief in the government's solvency relies upon diverse ex-ante assumptions which might be tough to confirm and are suffering from more than one equilibrium. Reference [19] uses the structural vector autoregressive (SVAR) model to review policy and therefore the volatility of the Spanish stock market and financial policy shocks, which have had a substantial impact on the long returns of the Spanish stock market. It also shows that within the pre-crisis and post-crisis samples, the monetary policy shock of the ECB's monetary policy has crystal rectifier to totally different long-term effects. However, in many relevant articles and studies on the eurozone market's policies, it is difficult to find literature on the correlation between policies and the stock market, let alone the results of research on whether policies have an impact on stock prices. Only the work of Reference [20] addresses the moment of the financial crisis. However, in their research, they do not concentrate on the euro area market, but instead focus more on the issue of how the market is oriented.

At the same time, it is not difficult to find that the research on the relationship between policy and volatility in the euro zone crisis is relatively limited and is rather research on policy and volatility during the global financial crisis. Regarding the choice of model, differing from the SVAR model used in the existing literature, we use the GARCH(1,1) model in the GARCH family of models. Reference [21] is the earliest to compare the accuracy of the GARCH model with other models, and carried out in-depth research on the data fit. Their research analyzed the daily returns of the US stock market, and Akgiray concluded that the GARCH model can predict volatility very accurately. Additionally, it is relatively easy to build the model and get good results.

This paper establishes a GARCH model to find the relationship between post-crisis policy actions in the Eurozone and financial market volatility.

II. Data

This section focuses on the description of the data set used to analyze and predict the volatility of the financial markets. It also examines some key features of the entire set of income equations that provide a solid foundation for choosing future models.

A. *Data Description*

To examine and predict the volatility in the financial markets, we employ three major stock market indices, from Germany, Greece and Ireland respectively. To be more specific, they are the German stock market index (DAX30), the Greek stock market index (ASE20), and the Irish Stock market index (ISEQ). The size of each index selected for the entire sample is based on the monthly closing price between January 1, 2000 and December 31, 2016, and is based on traceable data collected by Bloomberg. During the above period, DAX30 has 205 observations; ASE20 has 205 observations, and 205 observations were collected for ISEQ. Using these observations, we performed a complete analysis of the closing prices of these three indices. However, as the closing line chart depicted in Fig. 1, Fig. 2 and Fig. 3 show there are intensive and large fluctuations. Therefore, we have taken the logarithm of the closing prices separately.

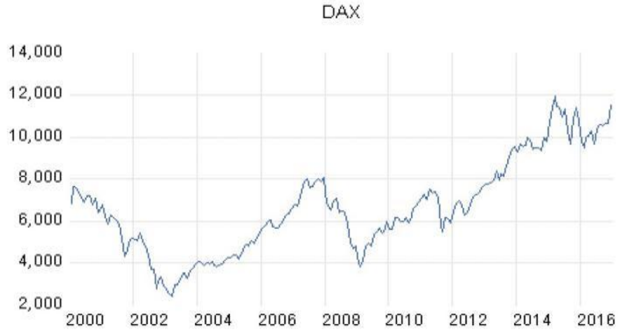

Figure 1. Monthly price of the German Stock Market Index from 2000 to the end of 2016

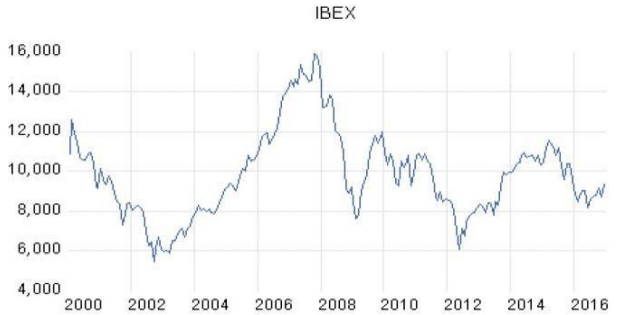

Figure 2. Monthly price of the Spanish Stock Market Index from 2000 to the end of 2016

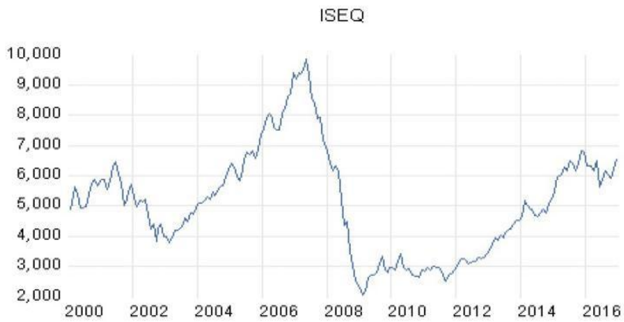

Figure 3. Monthly price of the Irish Stock Market Index from 2000 to the end of 2016

The monthly return of markets can be calculated as:

$$r_t = \ln(\frac{P_t}{P_{t-1}}) \tag{1}$$

where P_t denotes the adjusting closing price of the market at time $'t'$ and P_{t-1} represents the adjusting closing price of the market at time $'t-1'$. R_t indicates the continuous rate of return, also called logarithmic return of markets.

The DAX, also known as the German Stock Exchange Index, is a share index that comprises 30 of the largest and most liquid German companies listed on the Frankfurt Stock Exchange. At the same time, IBEX 35 is the benchmark index of the Madrid Stock Exchange. It was established in 1992. The Madrid Stock Exchange is known as the most important stock exchange in Spain. There is also an index of our choice, ISEQ 20, a benchmark stock index. It is composed of companies listed on Euronext Dublin. The index was launched on December 31, 2004. Because it has been established for a long time, it is often used as representative of Irish stocks.

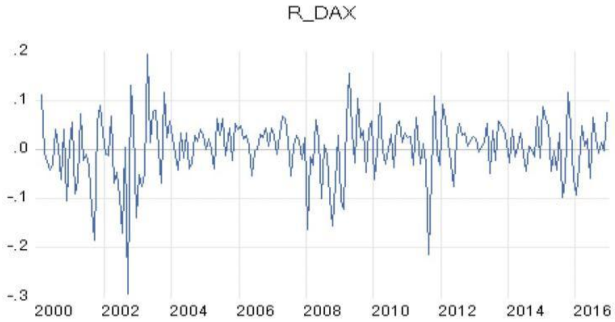

Figure 4. Monthly returns of the German Stock Market Index from 2000 to the end of 2016.

From the Fig. 4, the linear graph of the logarithmic return sequence r of the German stock market index, we can observe the "clustering" phenomenon of the volatility of the logarithmic return; it illustrates the volatility clustering property of the German stock market. From Fig. 4, significant changes in stock prices tend to cluster together, as in 2001 to 2002 and 2008 to 2011, which leads to persisting price changes in the long run. In the process of establishing a model of stock returns, volatility clusters are often generated, which means that a larger fluctuation is often accompanied by a larger fluctuation, and a small fluctuation will also appear in the same way as a small fluctuation in a similar period. A quantitative manifestation of this fact is that while the returns themselves are uncorrelated, the absolute returns |rt| or their squares show a positive, significant, and slowly decaying auto correlation function: corr (|rt|, |rt|+ τ)> 0 for τ in the range from about minutes to several weeks.

The emergence of this phenomenon is due to the sustained impact of external shocks on stock price fluctuations, and the distribution of returns is characterized by sharp peaks and fat tails.

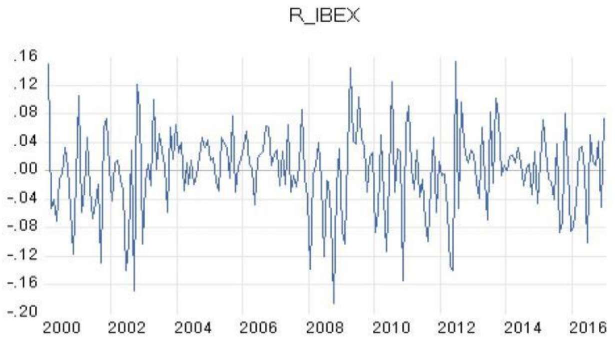

Figure 5. Monthly returns of the Spanish Stock Market Index from 2000 to the end of 2016

Fig. 5 reveals that the Spanish stock market experienced significant fluctuations in 2002, 2008, 2010, and 2012.

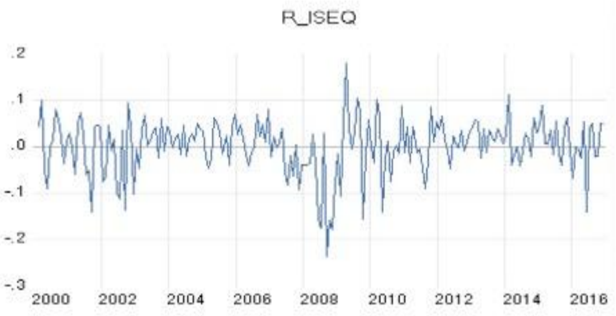

Figure 6. Monthly returns of the Irish Stock Market Index from 2000 to the end of 2016

From the linear graph of the logarithmic return sequence r of the Irish stock market index, Fig. 6, the phenomenon of volatility clustering can be observed, especially from 2008 to 2010.

By observing the volatility of the three graphs, Fig. 4, Fig. 5 and Fig. 6, a phenomenon is revealed that after the Eurozone crisis broke out it brought uncertainty to the financial market. The stock markets in Germany, Spain, and Ireland all experienced unusual turbulence.

TABLE I. DESCRIPTIVE STATISTICS

	DAX	R_DAX	IBEX	R_IBEX	ISEQ	R_ISEQ
Mean	6610.916	0.002554	9801.186	-0.000725	5097.565	0.001402
Median	6372.330	0.009571	9544.200	0.006080	5103.480	0.010101
Maximum	11966.17	0.193738	15890.50	0.153789	9854.860	0.178253
Minimum	2423.870	-0.293327	5431.700	-0.186727	2074.320	-0.235823
Std. Dev.	2234.784	0.063225	2169.294	0.059229	1770.223	0.059390
Skewness	0.420018	-0.926033	0.599219	-0.366500	0.432523	-0.943425
Kurtosis	2.470969	5.886433	3.175073	3.667326	2.685045	4.780837
Jarque-Bera	8.335971	99.48390	12.40755	8.311263	7.168452	56.93796
Probability	0.015483	0.000000	3.175073	0.015676	0.027758	0.000000
Observations	203	203	203	203	203	203

From Table I, the asymmetry of the logarithmic yield series of the DAX index is less than 0. This phenomenon can be seen in the distribution of the long-tail sequence on the left, and it also shows that the kurtosis is greater than the kurtosis value 3 of the normal distribution. This shows that the performance series have the characteristics of sharp points and sharp tails. In addition, the P value of the Jarque-Bera statistic is 0.00000, and the null hypothesis is rejected and obeyed.

Similarly, the skewness of the logarithmic return series of the IBEX index and the ISEQ index is also less than 0, which represents the long-tailed sequence distribution on the left, indicating that the return series have the characteristics of sharp peaks and thickness. The result of rejecting the assumption of normal distribution can also be obtained by observing the P value of the Jarque-Bera statistic.

B. Detecting Stationarity

In the first step, we need to pass many unit root tests to confirm whether our series is stationary. Only when the sequence has a stable nature for a long period of time, can we revert to its mean. Moreover, in this process, what cannot be ignored is that some sequences only have stationarity in a short period of time. So, we need to prove the stationarity of the series by analyzing the related graphical results. The autocorrelation decreases to zero as the delay duration increases. However, unfortunately, during the operation of this technology, it is easy to cause the final period due to some static and no fluctuations. The result is the same pattern.

1) Unit root test

Additional native unit tests are then required to provide the final confirmation of the integration sequence. The latter refers to the number of stages that an unstable sequence needs to convert to a static one. Therefore, when the number of steps is zero, fixation occurs. This article uses the Augmented Dickey Fuller (ADF) method to test batch stability. The main idea of the test is to provide a high-order autoregressive model (selection of an appropriate delay order) to eliminate autocorrelation of the residual terms. In a first order autoregression model, the Phillips Perron (PP) test was performed to improve the reliability of the results using the Akaike Information Criterion (AIC) and t-statistic of recovery. In contrast to the ADF test, the PP allows slight changes in the variance, which is also applied in the case of Kwiatkowski Phillips Schmidt Shin (KPSS). In contrast to most unit root tests, the existence of a unit root is not the null hypothesis, but the alternative. The KPSS test is also not a stationarity test, but due to the trend stationarity design, this is an important difference as it is possible that a time series is not stationary, has no unit root, but is stationary when trending. For both unit root and stationary trend processes, the mean can rise or fall over time; in the event of a shock, however, the stationary trend processes have a mean value reversal, while the unit root processes influence the mean value permanently [22].

Augmented Dickey Fuller (ADF) Test:

ADF method tests the stationarity of the series. The basic idea of the ADF test is to introduce a higher-order autoregressive model rather than the Dickey-Fuller (DF) method (by choosing an appropriate lag order) to eliminate the autocorrelation of the residual terms in the first-order autoregressive model.

After choosing the appropriate lag orders at p, the residual term ϵ_t of the following AR(p) model is made to be independent white noise, which can be expressed as:

$$y_t=\beta_0+\beta_1 y_{t-1}+...+\beta_p y_{t-p}+\epsilon_t \tag{2}$$

To facilitate the test, the equation (2) can be transformed into the following form:

$$y_t=\beta_0+\gamma_t+\rho y_{t-1}+\gamma_1 \Delta y_{t-1}+...+\gamma_{p-1}\Delta y_{t-p-1}+\epsilon_t \tag{3}$$

where β_0 denotes the intercept term; y_t indicates the time trend term, and $\triangle y_{t-p+1}$ represents the lagged difference term. The test for ADF is a left tailed test with the null hypothesis of ρ=1, while the alternative hypothesis is ρ<1. Like the DF test, the ADF test is also a left unilateral test, and its rejection domain falls only on the left of the distribution. The statistical critical value of the ADF test is also obtained from the Monte Carlo simulation.

Phillips Perron (PP) test:

Reference [22] proposed a nonparametric test to test the robustness of a first-order AR (1) regression equation, assuming the null hypothesis that there is a unit root and it does not. three critical values, the null hypothesis is accepted, that is, the sequence has a single beginning.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests:

The KPSS test constructs the statistic Lagrange Multiplier (LM), which removes the intercept term and the trend term from the inspected sequence. The estimation of residual sequence is obtained by the least square regression, and whether the original sequence has a unit root judged by testing that whether the residual has a unit root.

If the value of the LM statistic is less than three critical values, reject the null hypothesis that the sequence has a unit root.

TABLE II. STATIONARITY DETECTION WITH UNIT ROOT TESTS

Indices	DAX	IBEX	ISEQ
Method	statistic	statistic	statistic
ADF	-13.142***	-13.657***	-11.478***
PP	-13.157***	-13.660***	-11.820***
KPSS	0.213	0.075	0.132
Stationarity	detected	detected	detected

Notes:***Indicates statistical significance at 1% level

According to the different properties of the data, different types are used to test them, as shown in Table II. It can be clearly stated that stationarity is found in the three series, although the null hypothesis of the ADF test and the PP test (non-trend) assume that the sequence is not stationary. The test results show that the null hypothesis is rejected, both tests assume that the sequence is stationary. In addition, the KPSS test shows that the sequence of the null hypothesis is stationary while that the test results cannot reject the null hypothesis, so all three tests conclude that the sequence is stationary.

2) Examining ARCH effects

To repair conditional heteroscedasticity, the GARCH family model is needed. Before using the GARCH model, the Autoregressive Conditional Variance Model (ARCH) effect (heteroscedasticity) test should be conducted on the residual terms. Heteroscedasticity test results of the residual terms of the three regression equations are as follows:

TABLE III. HETEROSKEDASTICITY TEST: ARCH_DAX

F-statistic	Obs*R-squared	Prob. F(2,198)	Prob. Chi-Square(2)
4.064568	7.926857	0.0186	0.0190

TABLE IV. HETEROSKEDASTICITY TEST: ARCH_IBEX

F-statistic	Obs*R-squared	Prob. F(2,198)	Prob. Chi-Square(2)
2.662461	5.264034	0.0723	0.0719

TABLE V. HETEROSKEDASTICITY TEST: ARCH_ISEQ

F-statistic	Obs*R-squared	Prob. F(2,198)	Prob. Chi-Square(2)
20.72629	34.79591	0.0000	0.0000

The three sub-tables in Table III, Table IV, Table V, each test the heteroskedasticity of the performance of the German share index, the Spanish share index and the Irish share index with the remaining term in the regression equation for the investor sentiment index.

The test results show that the results of the F test and the X^2 test are both less than 10%, which proves the rejection of the null hypothesis that the residual square of the model is the same variance, that is, all models have ARCH effects (heteroscedasticity), that is, there is a serial correlation between the volatility of the stock market. Large fluctuations are followed by large fluctuations, and small fluctuations are mostly followed by small fluctuations. Hence, it is necessary to construct a GARCH model to eliminate the ARCH effect.

III. METHODOLOGY

A. ARCH Model

The ARCH model is often used by researchers to observe financial time series.

For the usual regression model:

$$y_t = x_t'\beta + \epsilon_t \tag{4}$$

Which assumes that the mean value of the return data is zero, the residual sequence has heteroscedasticity, denoted as:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-a}^2 + \mu_t \text{ , t=1,2,...,n} \tag{5}$$

The advantages of the ARCH model are:

The model describes the grouping of financial time series that can accurately map the volatility properties of financial time series. Building on the original model, a number of new models have been developed to take volatility into account.

B. GARCH Model

Any model has its limitations, and the ARCH model is no exception, it is applicable for short-term autocorrelation of the function of variation of a variable, while most of the rest of the financial data series have high-order autocorrelation. Reference [23] proposes the general form of the ARCH model, which is called a generalized autoregressive model of conditional variables. The application of the ARCH model usually results in a long lag in the conditional variance equation. As an extension of the ARCH model, the GARCH model attempts to model with more memory and a flexible delay structure [24].

The GARCH model assumes that the conditional variance of the current period is a linear combination of the conditional variance of the previous period and the square of the series, while the series is the product of the conditional variance of the previous period. Current phase and white noise, denoted as:

$$\sigma_t^2 = \alpha_0 + \sum_{a=1}^{p} \alpha_a \sigma_{t-a}^2 + \sum_{b=1}^{q} \alpha_b \varepsilon_{t-b}^2 \quad (6)$$

where p is the autoregressive lags of the GARCH term σ_t^2, q is the lag order of the ARCH term ϵ_t^2.

The GARCH model is an extension of the ARCH model, it is clear from the model expression that it is as effective as the ARCH model in capturing the group characteristics of financial market variables. Since the conditional variance h of the GARCH model is a function of the squared residuals and the conditional variance, the GARCH model can easily reduce the computational burden of the ARCH model, thus it can have wider applications.

C. GARCH (1,1) Model

Similarly, we must consider the corresponding delay orders for the ARCH member and GARCH clause in the GARCH model. In theory, there is no time limit in the GARCH model; however, the lagging order of the GARCH clauses can be repeated in an infinite number of ARCH members, so the GARCH model (1,1) is chosen in this study and the results are shown in Table IV, Table V and Table VI, which also show three different error distributions (normal distribution, student's T distribution and general error distribution (GED)).

Reference [24] proposes that the simplest but very practical model of the GARCH model is undoubtedly GARCH (1,1), which can be expressed as:

$$V = \frac{\alpha_0}{1-(\alpha_1+\gamma_1)} \quad (7)$$

Among them, as defined in GARCH (p, q), t is a real-valued time discrete random process, t is the information set on the o-domain that contains all the information at time t, $\alpha_1 + \gamma_1 < 1$ is the necessary and sufficient condition for GARCH (1,1) to be wide and stable. For this kind of simple GARCH model, Reference [24] pointed out that the necessary and sufficient condition for the existence of 2m moments in GARCH (1,1).

The model's variance equation has the following form:

$$\mathrm{r_t} = \mathrm{c} + \epsilon_\mathrm{t} \quad (8)$$

where c denotes the is constant term and ϵ_t represents the residual.

Akaike information criteria (AIC):

$$AIC = 2k - 2\ln(L) \quad (9)$$

where k denotes the number of parameters and L is the likelihood function.

The errors in the model are assumed to obey an independent normal distribution. The AIC encourages data fit optimization but tries to avoid overfitting. Therefore, the model with the lowest AIC value should be preferred. Akaike's approach to content criteria is to find a model that can best interpret the data but contains the least number of free parameters.

In addition, you can also see three different distributions of the error term (normal distribution, Student's T distribution, and total error distribution). For the GARCH model constructed using the DAX rate of return regression equation, the model regression results are shown in Table IV.

TABLE IV: GARCH(1, 1) MODELS FOR RDAX

	Normal	Student's T	GED
Mean Equation			
C1	0.009420** (Standard Error)	0.011635* (Standard Error)	0.012249* (Standard Error)
Conditional Variance Equation			
C2	0.000483* (Standard Error)	0.000302 (Standard Error)	0.000368 (Standard Error)
GARCH(1)	0.599818*** (Standard Error)	0.726214*** (Standard Error)	0.702521*** (Standard Error)
ARCH(1)	0.219708** (Standard Error)	0.214505* (Standard Error)	0.217059* (Standard Error)
AIC	-2.786896	-2.868033	-2.839835
Log likelihood	286.8699	296.1053	293.2433
LM statistic	0.161448	0.161394	0.150793
P.(LM statistic)	0.9224	0.9225	0.9274

Note: GARCH(1) and ARCH(1) represent σ_{t-1}^2 and ϵ_{t-1}^2 in the GARCH(1, 1) model, respectively. LM F-statistic is the statistic for testing the ARCH effect of the models, which lags at 1 order, Prob.(F) is the corresponding P value. *,** and *** indicate significance at the 10%,5% and 1% levels, respectively.

To be able to achieve that there is no longer a variable good variance in the residual of our regression equation, we need to test the residual again, and at the same time, we must also test whether there is an ARCH effect. This result test is necessary when dealing with the model; it is an indispensable link, as shown in Table IV. From the test results the value is greater than 5%, so the residual square of the null hypothesis model is the same variance, that is, the numerical residual term of the regression equation returned by DAX is constructing a GARCH model with the same variance.

At the same time, it also indicates three different distributions (normal distribution, student's T distribution and GED) for the error term. For the GARCH model constructed by the IBEX rate of return regression equation, the model regression results are shown in Table V.

TABLE V. GARCH(1, 1) MODELS FOR RIBEX

	Normal	Student's T	GED
	Mean Equation		
C1	0.004485	0.005744	0.006510*
	(Standard Error)	(Standard Error)	(Standard Error)
	Conditional Variance Equation		
C2	0.000237	0.000261	0.000224
	(Standard Error)	(Standard Error)	(Standard Error)
GARCH(1)	0.806108***	0.796321***	0.799442***
	(Standard Error)	(Standard Error)	(Standard Error)
ARCH(1)	0.127128**	0.133781*	0.131479*
	(Standard Error)	(Standard Error)	(Standard Error)
AIC	-2.836447	-2.849535	-2.857956
Log likelihood	391.8994	294.2278	295.0826
LM statistic	0.247213	0.315594	0.363174
P.(LM statistic)	0.8837	0.8540	0.8339

Note: the same as in Table IV.

For the GARCH model constructed by the ISEQ rate of return regression equation, the model regression results are shown in Table VI.

TABLE VI. GARCH(1, 1) MODELS FOR RISEQ

	Normal	Student's T	GED
	Mean Equation		
C1	0.009867**	0.0108005***	0.010887***
	(Standard Error)	(Standard Error)	(Standard Error)
	Conditional Variance Equation		
C2	0.000231*	0.000213	0.000224
	(Standard Error)	(Standard Error)	(Standard Error)
GARCH(1)	0.753173***	0.763777***	0.757231***
	(Standard Error)	(Standard Error)	(Standard Error)
ARCH(1)	0.180540**	0.175406**	0.177623**
	(Standard Error)	(Standard Error)	(Standard Error)
AIC	-2.979099	-2.984134	-2.978237
Log likelihood	-385.8542	-386.9536	-387.2023
LM statistic	0.055962	0.077260	0.069651
P.(LM statistic)	0.9724	0.9621	0.9658

Note: the same as in Table IV.

The residuals of GARCH(1,1) model of IBEX and ISEQ were tested, and the same results were obtained as those of IDAX

According to these three models, the sum of the coefficients of GARCH term and ARCH term of each model is less than 1, which proves that all GARCH(1,1) models are stable. However, the model with error term follows the Student's T model that leads to the lowest AIC, so we choose GARCH(1, 1)-Student's T model as the most appropriate model for r_DAX and r_ISEQ. GARCH(1, 1)-GED model is the most suitable one for r_IBEX.

After establishing the GARCH(1,1) model, we can see that the fluctuation rule in Fig. 7, Fig. 8, Fig. 9 is similar to that in the regression curve in Fig. 4, Fig. 5, Fig. 6.

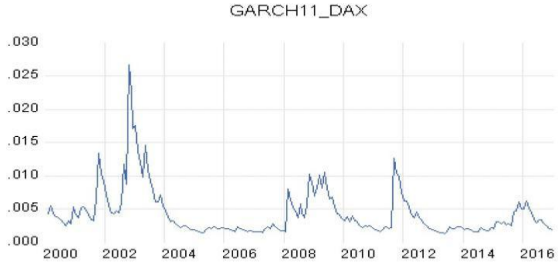

Figure 7. The German Stock Market Index with Garch(1,1)

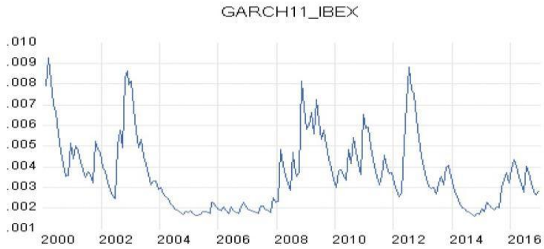

Figure 8. The Spanish Stock Market Index with Garch(1,1)

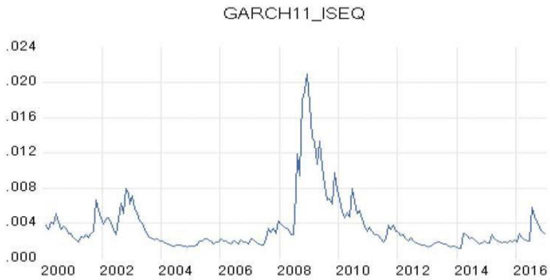

Figure 9. The Irish Stock Market Index with Garch(1,1)

IV. RESULTS

In this section, we set the policy release time when the eurozone crisis occurs as a dummy variable and substitute it into the definite GARCH(1,1) model. In this way, it can be observed whether the financial market fluctuations in Germany, Spain and Ireland are affected by the policy release time.

Because of the need to seek financial support from the European Union, the Greek government issued a commitment to the European Union after the eurozone crisis and was willing to greatly reduce its fiscal budget in the next few years. At the same time, the Spanish government also stated that it would adopt many austerity policies to face the eurozone crisis, even including reducing government expenditures. In addition, other European countries, such as Italy and Portugal, announced that they would reduce their budgets. Even an economic power such as Germany agreed to reduce its budget to deal with the crisis. The reason these countries adopted fiscal austerity policies was to ease the economic crisis by easing the fiscal situation. Meanwhile, the Executive

Council of the European Central Bank (ECB) in 2011 decided to conduct two LTROs, one with a maturity of about 12 months, due in October 2011, and the other with a maturity of about 13 months to take place in December 2011. Therefore, in this article, we chose to set the LTRO policy starting in October 2011 as a dummy variable, and then embed the dummy variable into the GARCH(1,1) model. The value of this variable is 1 and 0. Particularly, when a policy announcement occurs, it is 1; otherwise, it is 0.

$$Vol_t = c + \rho Vol_{t-1} + \beta * PolicyDummy \quad (10)$$

TABLE VII. THE RESULTS OF DUMMY VARIABLES IN THE GARCH MODEL

Indices	DAX	IBEX	ISEQ
P(LTRO)	0.5386	0.6434	0.6798
P(AR(1))	0	0	0

According to the results of Table VII, it can be concluded that the p value of LTRO after model processing is greater than 10%, which is not significant and does not obey the original hypothesis. From this, it can be concluded that policy changes will not have a significant impact on the volatility of the stock market index. The fluctuations in the previous period have a positive impact on the fluctuations in the current period.

From the above GARCH model parameter estimation results, we can get the following conclusions: The γ_1 coefficients of the GARCH model family are relatively large and pass the significance test, indicating that stock price fluctuations have "long-term memory", that is, past price fluctuations and their infinite long-term. The size of price fluctuations is related. In the conditional variance equation, the coefficients α_1 and γ_1 are both significantly positive, indicating that past volatility has a positive and slowing effect on the future volatility of the market, which makes the stock market volatility clustered. α_1+ γ_1 are all close to 1, which indicates that the response function of stock market volatility to external shocks is decreasing at a relatively slow speed. Once a large stock market volatility occurs, it is difficult to eliminate it in the short term.

The results of the GARCH (1,1) model research are basically consistent with the volatility results in Fig. 4, Fig. 5, and Fig. 6. During the time period when the quantitative easing policy was introduced, the stock market prices of the three countries did not experience significant fluctuations compared to before the policy was introduced.

V. CONCLUSION

A suitable regression sequence model to observe the impact of policy actions on stock market volatility is established. By observing the volatility of the stock market indices of the three countries, we chose to perform regression processing on the stock market indices first to obtain relatively stable data. Then we perform unit root tests on the processed data, get the result of rejecting the null hypothesis through ADF and PP tests, and passed the KPSS test again to verify that the data ran smoothly. Subsequently, the ARCH effect is tested in the three stock return series, and the analysis found that there is an ARCH effect. Therefore, this study chose to establish a more appropriate GARCH model to observe the impact of policy actions on financial market volatility. A further ARCH-LM test proved that the GARCH(1,1) model successfully eliminates the heteroscedasticity of the return series. Finally, the policy introduced after the eurozone crisis is substituted as a dummy variable into the model for testing, and the experimental results are obtained, which demonstrated that policy actions have no significant impact on stock market volatility. At the same time, it is also observed that the volatility of the previous period has a positive impact on the current volatility.

Such experimental results also confirm the conclusions of other related studies to a certain extent. Reference [15] believes that traditional monetary policy tools cannot effectively overcome the crisis, and neither will quantitatively be easing, nor negative interest rate policies succeed.

Through the experimental results, knowledge of the impact of policy actions on financial market volatility after the eurozone crisis is expanded. Although a relatively accurate model is used for testing, the policy choices are too singular, requiring multiple experiments and analyses through different policies and data from different countries to improve the accuracy of the results.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

There is only one author for this work.

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