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Mutual Fund Volatility in Election Years: Low Risk or High Risk?

Riedwan Adhie Saputra[1], Leonny Noviyana Sakti Pamungkas[2], Setyaningtyas Honggowati[3]

[1,2,3] Accountancy, Universitas Sebelas Maret, Surakarta, Indonesia

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Corresponding Author:
Riedwan Adhie Saputra
Accountancy,
Universitas Sebelas Maret,
Surakarta, Indonesia.
Email:
riedwanadhie.ra@gmail.com

ABSTRACT

This research aims to analyze the patterns of price fluctuations in mutual funds over a specific time frame, particularly in relation to political events such as national elections. The primary objective is to evaluate the risk levels of mutual funds in countries undergoing election cycles, which are often associated with heightened economic and political uncertainty. To achieve this, the study employs Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models—two widely recognized econometric tools for analyzing time series data exhibiting volatility clustering. These models enable the classification and comparison of both low and high volatility conditions in mutual fund performance. The dataset comprises mutual fund data from 10 different countries, covering the period between 2019 and 2024. Each selected country has a mature mutual fund market with a focus on equity (stocks) and fixed-income (bonds) instruments. The findings reveal distinct variations in volatility levels among the countries studied, influenced by their respective political climates during election periods. The application of ARCH and GARCH modeling proves effective in capturing these fluctuations. The results offer valuable insights for investors seeking to minimize risk by diversifying their portfolios across more stable mutual funds, especially during times of political transition. This research contributes to better-informed investment decision-making in politically dynamic environments.

Keywords: Volatility, ARCH, GARCH, election years

1. INTRODUCTION

Volatility is an important factor to consider in investments, especially when discussing mutual funds. Mutual funds are investment instruments that facilitate the pooling of funds from various investors to be managed and invested in diverse assets such as stocks, bonds, or both, with predetermined investment objectives. Within the scope of mutual funds, volatility refers to the fluctuations in the total value of the investment portfolio over time (Chen, 2023). The level of volatility can vary depending on the type of mutual fund and its asset composition.

As we enter political years, political policies and changes in government often take center stage, which can significantly impact economic conditions and financial markets. Evolving political trends can create uncertainty in the markets, influencing investor behavior and causing significant price fluctuations. Changes in fiscal policies, regulations, and geopolitical factors are major determinants in shaping market movements during political years. Investors tend to be more cautious and closely monitor political dynamics, as significant changes in the political environment can have broad implications for their investment portfolios. Therefore, understanding the relationship between politics and financial markets is key to planning appropriate investment strategies during political periods.

In this context, it is important to understand how mutual fund volatility can influence investment decisions and investor risk management strategies. Mutual fund managers may adopt different approaches in portfolio management (Hasnaoui et al., 2021) and (Entezari & Fuinhas, 2024). Investors seek ways to diversify risk during political periods such as greater diversification, the use of derivative instruments to protect portfolios from risk, or other tactics aimed at reducing the impact of market volatility on investment performance.

This research employs an approach using the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models in analyzing and understanding the level of mutual fund volatility. By utilizing both models, this study aims to investigate the patterns of price fluctuations occurring within mutual funds over a specified period of time. The ARCH and GARCH approaches are known for their ability to capture and model heteroskedastic volatility, which is volatility that can vary over time and is not constant (Vukovic et al., 2024). Thus, both models are highly relevant in the context of mutual fund analysis, where the level of volatility can be influenced by various factors such as market conditions, political issues, or economic events.

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2. LITERATURE REVIEW

A literature review on mutual fund volatility becomes an important area for research. Research conducted by Chhapra et al., (2018) identified several factors of mutual fund success through volatility testing. The study applied unit root tests to identify the data's properties and examined variations in performance feedback. The results can depict the dynamics of mutual fund returns.

Sampling in the study by Li & You (2020) utilized daily frequency samples. These samples were used to measure volatility and liquidity capability. The research found that the samples could demonstrate fluidity and volatility in investments. Stable fluidity has a better ability to determine volatility timing.

Petrova & Todorov (2023) utilized a complex analytical methodology in their research to estimate the daily volatility of investment funds. Employing a risk attribution quantification model using GARCH (1,1), EGARCH (1,1), GARCHM (1,1), and TGARCH (1,1) to predict investment volatility. The focus was on forecasting investment fund risk concentration through comprehensive testing. Research findings indicated that, according to the three GARCH models, EGARCH and GARCH-M showed the highest values of investment fund risk concentration.

GARCH modeling was also employed by Malhotra & Sinha (2024) to analyze the volatility of financial time series data during the COVID-19 pandemic. The study was divided into two periods: pre- and post-COVID-19. The DCC GARCH model supported hypotheses regarding significant spillover effects on the index balancing and also depicted long-term volatility by indicating the presence of contagion effects.

Another study by Nguyen & Nguyen (2019) utilized GARCH, EGARCH, and TGARCH models to analyze the volatility of the Ho Chi Minh Stock Exchange (HSX) stock prices. The results showed that the GARCH (1,1) and EGARCH (1,1) models were most suitable for measuring symmetric and asymmetric volatility levels of the VN-Index. These models could also be used for future forecasting in case of market downturns.

This research aims to focus on mutual fund volatility during periods of political upheaval with the goal of revealing fluctuating risk levels. Considering the political dynamics that can influence financial markets, this study will investigate how mutual funds react to political changes and associated uncertainties.

3. RESEARCH METHOD

a. Data and Sample

This research utilizes time series data of closing prices obtained from Yahoo Finance. The time series data is divided into pre- and post periods (Zebrowska-Suchodolska et al., 2022). The data is further divided into 3 long-term periods of 28 days, medium-term periods of 21 days, and short-term periods of 14 days. The sample is limited to the years 2019-2024 with the condition of having undergone elections and having their own mutual funds investing in stocks and bonds. A total of 10 countries that meet the criteria and pass the test are included in the sample, namely the UK, India (IND), South Africa (ZAF), the United States (USA), Canada (CAN), Austria (AUT), Denmark (DNK), Indonesia (INA), France (FRA), and Portugal (PRT).

b. Research Model

Return Daily Average, Daily average return is used to evaluate the performance of an investment or investment portfolio over time. By comparing the daily average returns from specific periods, namely pre- and post-election periods. The formula is as follows:

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

ARCH Model (Autoregressive Conditionally Heteroscedastic)

The ARCH model is used to describe variance. It is particularly useful in situations where there is a possibility of sudden increases in variability over time. The ARCH model is often applied in cases where there is potential for significant fluctuations in short periods. Estimation of the ARCH model is conducted using the Least Squares method. Here is the formula:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots\ldots + \alpha_q y_{t-q} + \varepsilon_t$$

GARCH Model (Generalized Autoregressive Conditional Heteroskedasticity)

The GARCH model is used to measure high volatility or low volatility (Franke & Krahnen, 2008). If $\alpha_1 + \beta_1 < 1$ indicates low volatility, $\alpha_1 + \beta_1 = 1$ indicates high volatility, and $\alpha_1 + \beta_1 > 1$ indicates very high volatility (Brooks, 2008). In this study, the simplest GARCH model is used with the mean and variance equations as follows:

$$\square^2/t = \omega + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \square^2_{t-1}$$

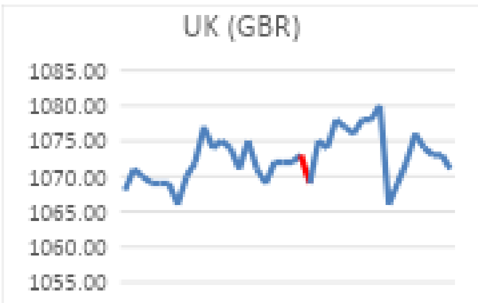
This variance stems from past or historical data, hence termed as conditional variance. The conditional variance equation involves stock returns (□), a constant term (ω), ARCH (Autoregressive Conditional Heteroskedasticity) coefficients, return errors (ε), and GARCH (β) coefficients. The GARCH (p,q) model refers to the impact of GARCH on the first order (p) and the influence of ARCH at level one (q)..

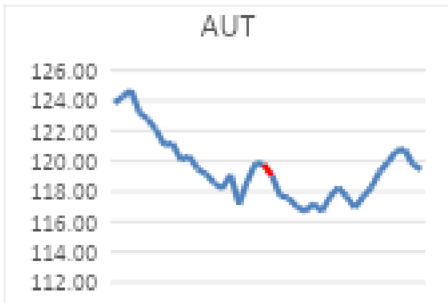
4. RESULTS AND ANALYSIS

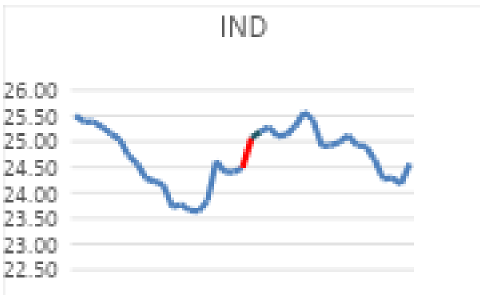
Table 1: Daily Average Return in Mutual Funds

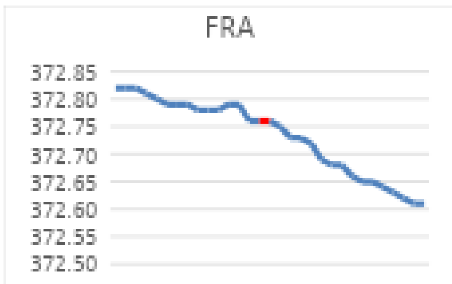
NO	CTRY	PRA			PASCA		
		Last 28 Days	**Last 21 Days**	**Last 14 Days**	**Next 14 Days**	**Next 21 Days**	**Next 28 Days**
1	UK(GBR)	0,010%	0,011%	-0,004%	0,056%	0,011%	0,005%
2	IND	-0,107%	-0,103%	0,021%	0,082%	0,053%	0,007%
3	USA	-0,059%	-0,185%	-0,155%	0,333%	0,249%	0,214%
4	ZAF	-0,008%	0,004%	-0,002%	-0,035%	-0,038%	-0,024%
5	CAN	0,017%	0,013%	-0,001%	-0,099%	-0,059%	-0,015%
6	AUT	-0,091%	-0,078%	-0,019%	-0,078%	0,024%	0,009%
7	FRA	-0,001%	0,000%	0,000%	-0,001%	-0,001%	-0,001%
8	DNK	0,083%	0,109%	0,166%	0,067%	0,046%	0,028%
9	INA	-0,018%	0,043%	0,131%	0,016%	0,034%	0,028%
10	PRT	0,016%	-0,016%	-0,073%	0,044%	0,077%	0,044%

Based on Table 1, the impact of general elections on mutual fund performance varies in each country and demonstrates different patterns in the short-term, medium-term, and long-term periods. Some show positive effects while others show negative effects. Generally, the influence of general elections on mutual funds tends to be more significant in the short term, where stock price changes generally occur more frequently, and mutual funds may experience considerable volatility in response to political uncertainty. Over time, the impact of general elections tends to decrease. The positive and negative effects of general elections diminish further in the medium term and decline even further in the long term. The following describes the volatility in each country:









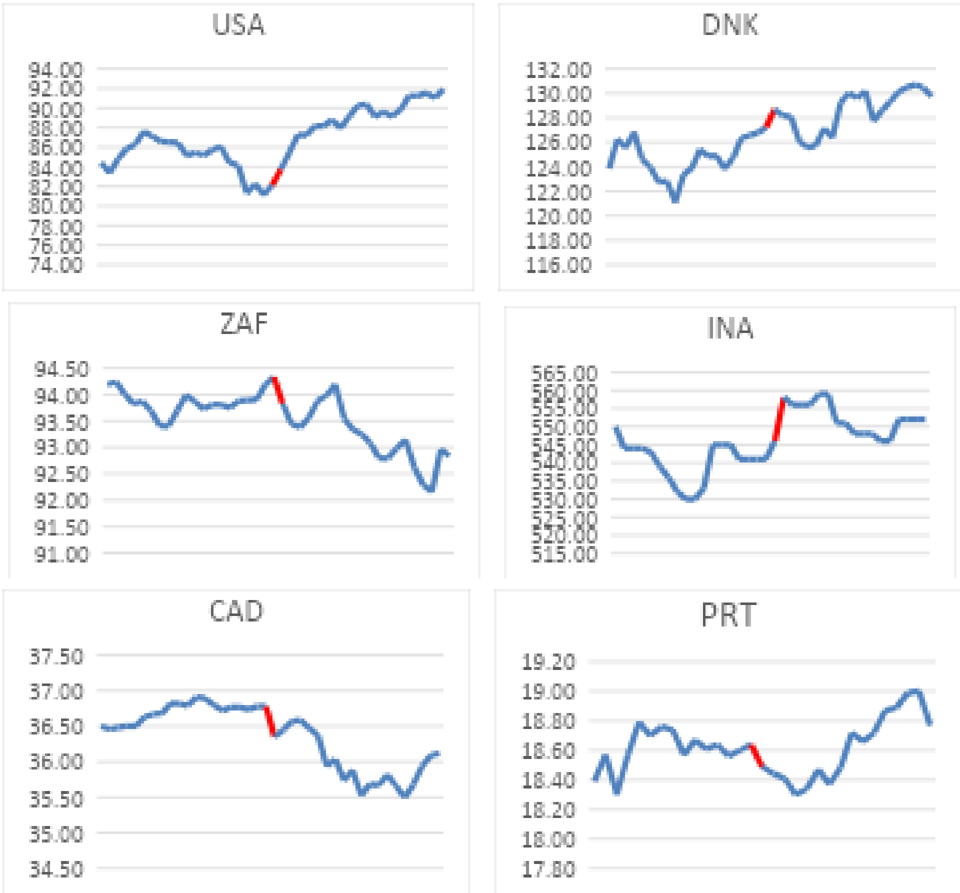


Figure 1. Mutual fund volatility in each country

Figure 1 illustrates a subjective comparison of volatility between the periods before and after general elections in various countries. This graph provides a visual representation of how general elections can affect mutual funds. By observing the graph, it can be seen that each country exhibits different patterns in terms of changes in volatility before and after general elections. Some countries may experience a drastic increase in volatility after general elections, while others may experience a decrease or even remain stable.

Tabel 2. Statistik Descriptif

	Mean	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	Prob. KS
UK(GBR)	1.072,581	1.080,000	1.066,000	3,70382	0.138072	2,151156	0.59774
IND	24,74516	25,57000	23,64000	0,599071	-0,517124	2,024788	0,27116
USA	85,74645	90,25000	81,13000	2,25782	-0,272743	2,613415	0.74924
ZAF	93,77323	94,33000	93,08000	0,308376	-0,287308	2,505687	0,69001
CAN	36,51419	36,91000	35,53000	0,34955	-1,315373	3,965302	0,00627
AUT	119,4681	124,6600	116,6800	2,366911	0,811219	2,557623	0,16098
FRA	372,7319	372,8200	372,6100	0.070115	-0.439272	1,748651	0.22096
DNK	125,8194	130,0000	121,1100	2,130607	0,054762	2,585741	0,88818
INA	545,3548	559,0000	530,0000	8,159037	-0,105826	2,433768	0,78978

PRT	18,61387	19,00000	18,30000	0,189555	0,18332	2,39267	0,72251

Mutual funds in political years have different average impacts in each country. The standard deviation indicates the presence of high risk. This means that the higher the standard deviation, the higher the potential risk. A positive skewness value indicates that there is a slight tendency for more high returns than low returns.

Tabel 3. Stationarity test for rate of return of VN-Index

NO	NEGARA	ADF	P-value	Test Critical Values		
				1% level	5% level	10% level
1	UK(GBR)	-7,95317	0.0000	-4,234972	-3,540328	-3,202445
2	IND	-4,77213	0.0025	-4,226815	-3,536601	-3,200320
3	USA	-12,67459	0.0000	-4,219126	-3,533083	-3,198312
4	ZAF	-5,35331	0.0005	-4,234972	-3,540328	-3,202445
5	CAN	-6,85324	0.0000	-4,219126	-3,533083	-3,198312
6	AUT	-6,20176	0.0001	-4,234972	-3,540328	-3,202445
7	FRA	-5,81064	0.0003	-4,323979	-3,580623	-3,225334
8	DNK	-7,18049	0.0000	-4,219126	-3,533083	-3,198312
9	INA	-4,71477	0.0032	-4,252879	-3,548490	-3,207094
10	PRT	-6,37311	0.0001	-4,309824	-3,574244	-3,221728

Table 3 represents the second test to determine data stationarity. P-values less than 5% indicate strong evidence to reject the null hypothesis (the hypothesis that the variable is not stationary). Therefore, it can be concluded that the time series used in this study exhibits stationary properties, indicating that the data tends to remain around a mean value and has constant variability over time.

Table 4. Model ARCH

No	Hetero: ARCH	F-statistic	Obs*Rsquare	Pob. F (1,35)	Prob. Chi Square	AIC	SC
1	UK(GBR)	10,0024	82,2372	0.0032	0.0041	7,91601	8,003089
2	IND	42,6147	20,5987	0.0000	0.0000	-0.135873	-0.049684
3	USA	48,2677	22,3804	0.0000	0.0000	6,55744	6,6419
4	ZAF	23,1862	15,0244	0.0000	0.0001	0,60041	0,68572
5	CAN	33,7405	18,6015	0.0000	0.0000	-1,14452	-1,05921
6	AUT	100,8320	27,4662	0.0000	0.0000	5,13254	5,21961
7	FRA	322,8077	27,6055	0.0000	0.0000	-10,52740	-10,43399
8	DNK	24,1793	15,4136	0.0000	0.0001	6,19954	6,28485
9	INA	39,8538	19,1463	0.0000	0.0000	10,80616	10,89504
10	PRT	7,3932	6,2666	0.0111	0.0123	-3,62164	-3,52823

Table 4 represents the ARCH modeling using Least Squares. The Chi-Square probability values are less than the 5% significance level, indicating that the ARCH model can be used to predict future volatility. The F probability values are less than the 5% significance level, showing strong evidence that the error variance depends on the previous error.

Table 5. Model GARCH (p,q)

No	VARIANCE EQUATION	COST.	RESID	GARCH	Result	Keterangan
1	UK(GBR)	-0,069881	-0,421626	1,435901	1,01	Ex. High Volatility
2	IND	-0,001136	-0,424499	1,500422	1,08	Ex. High Volatility
3	USA	1,232393	-0,116763	-0,869224	-0,99	Low Volatility
4	ZAF	0,003887	1,206707	0,856025	2,06	Ex. High Volatility
5	CAN	-0,000159	-0,561796	1,256978	0,70	Low Volatility
6	AUT	0,884751	0,185288	-0,887384	-0,70	Low Volatility
7	FRA	0,000000	-0,431770	1,422092	1,00	High Volatility
8	DNK	0,370428	-0,156635	0,704887	0,55	Low Volatility
9	INA	1,259939	-0,142901	1,069125	0,93	Low Volatility
10	PRT	0,001180	-0,497333	1,478105	0,98	Low Volatility

Table 5 presents the GARCH modeling to measure the levels of high volatility and low volatility. The research findings using the GARCH model indicate significant differences in the volatility levels of financial markets across various countries. Based on the analysis, countries such as the UK, India (IND), and South Africa (ZAF) were found to experience extremely high volatility levels. This suggests that financial markets in these countries tend to be highly fluctuating, with substantial and rapid changes in prices or asset values over a relatively short period. On the other hand, countries like the United States (USA), Canada (CAN), Austria (AUT), Denmark (DNK), Indonesia (INA), and Portugal (PRT) experienced low volatility levels. This indicates that financial markets in these countries tend to be more stable, with smaller and slower changes in prices or asset values.

5. CONCLUSION

This research aims to determine the level of mutual fund volatility in each country holding elections and to identify the highs and lows of volatility using ARCH-GARCHM modeling by finding the best modeling. Based on the analysis results conducted in this study, it can be concluded that:

1. The ARCH model can be used to model volatility in mutual fund performance over time. This helps analysts and investment managers understand the level of fluctuation or risk associated with the fund. By understanding these volatility patterns, investors can make better decisions about asset allocation and risk management.
2. GARCH modeling helps in analyzing volatility by distinguishing between low volatility and high volatility, which can help investors understand price fluctuation patterns more deeply. This means providing an overview of bad news and good news about current and future volatility.
3. Each country has different volatility before and after elections. Three countries, the UK, India (IND), and South Africa (ZAF), experience extremely high volatility levels. Meanwhile, the United States (USA), Canada (CAN), Austria (AUT), Denmark (DNK), Indonesia (INA), and Portugal (PRT) experience low volatility levels, while France (FRA) experiences high volatility.

It can be suggested that researchers advise the public and investors to be more cautious when diversifying their assets in mutual funds during political years. Choose mutual funds that have stability against political, economic, or other factors. The implications of this research help investors make good decisions about asset allocation and risk management. Additionally, ARCH and GARCH models help investors assess the suitability of established risk tolerances so that they can manage risks wisely and effectively.

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