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Investors' Herding Behavior, Economic Policy Uncertainty, and Volatility of Amman Exchange Market

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Abstract
This paper demonstrates the dynamic connection between the volatility of Amman's stock market, herding behavior, and Economic policy uncertainty. The financial system and national economy's health as well as the rate of urbanization's growth are both impacted by Amman's stock market development quality. Based on the time series VAR model and EViews, this paper uses herding behavior and Economic policy uncertainty to conduct an empirical analysis of the fluctuations in Amman's stock market. The experimental results demonstrate, through computer simulation and computation, that changes in economic policy uncertainty have a bigger influence on Amman's stock market volatility than do changes in herding behavior, while both effects are quite small.

Keywords: Economic Policy Uncertainty, Realized Volatility, Herding Behavior, Cross-Sectional Absolute Deviation (CSAD), VAR Model, Granger Causality Test.

1. Introduction

At present, Amman's stock market has experienced many years of development. The Jordanian economy has grown quickly since reform and liberalization. The stock market in Amman has also gradually grown. However, Amman's stock market experiences significant market fluctuations. The greater the market fluctuation, the more likely it is to have a negative impact on the financial system and national economy. To effectively lower market volatility and support the healthy growth of the stock market, many academics have conducted extensive theoretical and applied research on the elements influencing market volatility and examined the mechanism and degree of influence. Among them, By summarizing these research results, it can be concluded that the influencing factors of Amman's stock market volatility are very complex. At the same time, When investor sentiment changes and the "herd effect" is formed in the established market, the consensus expectation formed by market participants is bound to have an impact on the market. Uncertainty in the economy is, of course, greatly influenced by stock market volatility. Therefore, it may be claimed that the endogenous nature of the policy uncertainty variable and the volatility of the Amman stock market accounts for the substantial marginal effect of EPU. In reality, a bigger portion of policy uncertainty stems from uncertainty around macroeconomic factors connected to policy, such as the consumer price index, the government budget, and federal spending. These variables are exogenous to stock market volatility at least in the short-term. Events that are exogenous to stock market volatility, like the Gulf Wars and the Clinton and Obama Election, also contribute significantly to policy uncertainty. Our policy uncertainty variable is mostly exogenous to Amman's stock market volatility, according to the study above. Additionally, according to Baker et al. (2013), their policy uncertainty measure exhibits significant independent fluctuation from VIX.

Friedman, who discovered that irrational investors destabilized prices by buying when prices were high and selling when prices were low, while rational investors tended to move prices in the direction of their fundamentals by buying low and selling high, was the first to make the connection between investor behavior and market volatility [1]. Given that price changes resulting from misinformed trading tend to return, Hellwig and Wang asserted that volatility is driven by uninformed or liquidity trading, following Friedman and the theory of Noisy Rational Expectations. The latter author notes that information asymmetry may be a factor in volatility and that ignorant investors typically have a propensity to follow market trends, purchasing when prices are rising and selling when they are falling—behavior that may be compared to herding. According to Wang, even if this conduct is uninformed trading, it may be logical among less experienced investors if it occurs in an environment with unequal information [2,3]. Additionally, Froot et al. came to the conclusion that investor imitation is what causes volatility. Avramov et al., who assert that both herding and contrarian trading have a significant influence on daily volatility, have more recently shown evidence of this association [4,5].

This paper makes numerous significant literary contributions. First, it is the unique study of the relationship between Amman's Exchange Market volatility and macroeconomic policy uncertainty. The markets differ in a number of other ways as well. They vary, for instance, in terms of company disclosures and investor protection [6]. Additionally, Market volatility shows notable differences. Second, a thorough understanding of how herding behavior affects the Amman's Exchange Market volatility is provided by this study. This demonstrates how, along with the advantages of globalization, there will also be greater risks and uncertainties for nations to deal with. Furthermore, even in areas that are not directly related to international trade, similar uncertainties may be present (for example, in financial analysts). Thus, starting with two aspects of Investors' Herding Behavior and Economic Policy Uncertainty, this paper will choose the appropriate indexes, build a VAR model using EViews to conduct empirical analysis of Amman's Exchange Market volatility, and further investigate the dynamic relationship between Amman's Exchange Market volatility, Herding Behavior, and Economic Policy Uncertainty.

2. Literature Review

2.1 Research on Economic Policy Uncertainty and Herding Behavior

According to the research, investors' decisions to herd may be motivated by irrational or reasonable factors. For instance, the informational cascades model put forward by Bikhchanding et al. demonstrates how rational people may disregard their own knowledge and base their judgments on those of other investors. Scharfstein and Stein contend that managers who care about their reputation will decide to disregard their private knowledge and follow others, whereas Banerjee makes a similar case using the sequential decision model. The other cause of herding behavior has also been compensation [7,8,9]. The distinction between deliberate and spurious herding behavior is made later by Bikhchandani and Sharma (2001). The former is seen to represent the logical response of investors to the same fundamental information, while the latter is thought to be irrationally motivated by human emotions. Herding conduct has been linked to price bubbles in a variety of studies, regardless of whether it stems from reasonable or irrational motivations. Shiller makes the case that even if a person may be rationally following the consensus of the market, excessive herding in the financial market can nonetheless result in market inefficiencies [1,11].

With reference to the South African housing market, Cakan et al. investigate the relationship between financial market herding and the unpredictability of economic policy [12]. Our dynamic model, which is based on a two-regime Markov switching specification, only detects herding during the high volatility regime, which is in line with the idea that increased market uncertainty is the main cause of herd behavior. They further demonstrate their research using quantile regressions, demonstrating a relationship between policy uncertainty and herding behavior by demonstrating that higher quantiles of policy uncertainty are related with increased chance of being in the herding regime. Overall, their research indicates that market inefficiencies, which in our instance are caused by the existence of herding, may be caused by policy uncertainty. Chen et al. For investors, analysts, business managers, and policymakers, this study offers novel and comprehensive evidence of the effects of policy uncertainty on a crucial information intermediary that has a considerable impact on capital market efficiency [13]. By demonstrating that economic policy uncertainty on a national and international level has a substantial influence on the actions of domestic analysts in the United Kingdom.

In particular, domestic economic policy uncertainty has little effect on analyst coverage in the UK but has a strong negative influence on analyst earnings estimate accuracy, dispersion, and both upgrades and downgrades. The impact of policy uncertainty on analyst behavior varies across sectors, according to an industry analysis. Furthermore, while U.S. policy uncertainty displays unique implications, European and global economic policy uncertainty have similar cross-country effects on analyst behaviors as U.K. policy uncertainty does in the United Kingdom. Economic policy uncertainty's (EPU) impact on the herding behaviors of US REITs is examined by Lina and Lib (2019). According to the empirical results, EPU may account for several types of herding effects in the REITs market. The U.S. REITs herding takes the detrimental impact of EPU into account. Uncertainties in economic policy can be avoided by the REITs market. In addition, the quantile regression empirical results demonstrate positive association between EPU and CSAD during market volatility among real estate investors. More crucially, even during times of more market volatility, herding pattern can still be seen.

2.2 Herding and Market Volatility

Regarding the second question, which is whether herding (de)stabilizes stock markets, there is conflicting data in the literature. On the one hand, institutional investors herd to protect their reputations, according to Scharfstein and Stein's (1990) theoretical argument. It causes bubbles to form and then price corrections, which destabilizes the stock market. On the other hand, Hirshleifer et al. demonstrate that herding stabilizes stock markets and motivate it as a result of the sequential flow of information arriving [14]. At the overall stock market level, Lakonishok et al. and Wermers find little empirical support for institutional herding. More recently, Jiao and Ye provide evidence that mutual funds herd hedge funds into or out of the same stocks, resulting in sharp price reversal in the following quarter, while Choi and Skiba examine institutional herding in 41 countries and conclude that herding stabilizes stock prices [15-18]. These studies focus on the (de)stabilizing impact in terms of stock return dynamics, but the same effect may also be examined through the analysis of the volatility, or second moment, of the return distribution.

Herding has varying effects on market volatility depending on whether it is (un)intentional, according to Bikhchandani and Sharma (2001). Intentional herding is typically caused by management reputation or includes the unconscious imitating of others (Bikhchandani et al., 1992). It causes excessive volatility and undermines market stability. This frequently runs counter to unintended herding, which occurs when rational investors make the same investment choice based on the same considerations (Hirshleifer et al., or are drawn to companies with comparable characteristics [14,19]. In addition, the theoretical framework in Wang and Wang (2018) suggests that, depending on the quality of the private information from opinion leaders, i.e., gurus, herding will either result in market efficiency and lower market volatility or deviation from fundamentals and higher market volatility [8,9]. Finally, Hwang et al. claim that excessive trading by overconfident investors also leads to positive beta herding in a recent research that builds on investor behavioral biases [20]. Herding, which might be seen as one of the elements of irrational trading, was examined by BLASCO et al. in relation to the volatility of the Spanish stock market [21]. Herding is evaluated using the Patterson and Sharma (Working Paper, University of Michigan-Dearborn, 2006) herding intensity measure at the intraday level, which is thought to be the most accurate sample frequency for identifying this kind of investor behavior. There are three types of volatility metrics used: historical, realized, and implied. Although the associated intensity is not always the same, the results show that herding has a direct linear influence on volatility for each volatility measure taken into consideration. In fact, when volatility is viewed as a major component, herding characteristics appear to be helpful in anticipating volatility and, consequently, in decision-making. Huang et al. look at the effect of idiosyncratic volatility on market participants' investing behavior in Taiwan's equities market [22]. According to empirical findings, this equity market exhibits herd behavior, which exhibits varied patterns under different portfolios based on idiosyncratic volatility. The financial crisis of 2007–2008, especially in portfolios with more idiosyncratic volatility, strengthens herding, which is consistent with intuition. In periods of market stress, across stock portfolios with various levels of idiosyncratic volatility, an unbalanced response to news is not typical. Results for the banking and financial sectors offer an intriguing comparison to other businesses. The findings also demonstrate that different herd behaviors are reflective of the nature of that particular enterprise. The effect of investor herding behavior on stock market volatility is examined by Fei and Liu in 2021. On the basis of the fluctuation in cross-sectional stock betas, they use a direct herding measure. Investors may easily distinguish between the measure's positive and negative components, moving toward or away from the market portfolio, accordingly. They demonstrate that market volatility is Granger induced by the measure and that there is an unbalanced influence between positive and unfavorable herding on volatility using A-shares listed on the Chinese equities market from August 2005 to March 2021.

2.3. Economic Policy Uncertainty and Market Volatility

Recent research has shown that EPU is effective in forecasting stock market volatility and has a large impact on predicted returns (Karnizova, Li, 2014, Arouri, Estay, Rault, 2016, Christou, Cunado, Gupta, Hassapis, 2017). This research was conducted by Karnizova, Li, Liu, Zhang, Bekiros, Gupta, and Kyei. According to Kang and Ratti (2014), EPU in China had a detrimental impact on stock market returns that was delayed. Chulia et al. (2017) discovered that policy uncertainty has a detrimental impact on stock markets' dynamics, particularly in developing nations, during periods of financial crisis. EPUs have an impact on the banking sector through the loan channel as well. According to Bordo et al., excessive EPU may impede the development of all bank loans. According to Lee et al. , EPU may have an impact on leveraging decisions by altering lending practices and risk-taking ability. This study by Liua, B. and Zhang examines the relationship between stock market volatility and the predictability of economic policy uncertainty (EPU). According to our in-sample data, increasing EPU causes a noticeable rise in market volatility [23-26]. Out-of-sample results demonstrate that adding EPU as an extra predictive variable to the current volatility prediction models greatly enhances these models' forecasting performance. The enhancement stands up to model requirements. According to Antonakakis et al. (2013), increased policy uncertainty raises the unpredictability of stock market returns. Out-of-sample outcomes further imply that EPU contributes significantly to the forecasting of realized market volatility. Overall, we discover that EPU helps in both in-sample and out-of-sample market volatility prediction. Our findings are inherently compatible with those of Karnizova and Li, who evaluated the accuracy of economic policy uncertainty indices created by Baker et al. (2013) for forecasting future US recessions using probit recession forecasting models [23]. Policy indices are included in the model parameters both separately and in conjunction with financial factors including interest rate spreads, stock returns, and stock market volatility. The policy uncertainty indices appear to be statistically and economically significant in predicting recessions at time horizons longer than five quarters, according to both in-sample and out-of-sample analyses.

At the longer prediction horizons, the index based on newspaper stories performs better than the term spread, making it the best predictor. A general equilibrium model created by Pastor and Veronesi, who wrote this work on how changes in governmental policy impact stock prices, may be used to explain the predictability of EPU to stock volatility [27]. The general equilibrium model includes a government with both economic and non-economic goals, as well as uncertainty over its policies. Following declines in performance in the private sector, the government frequently modifies its policies. On average, stock values drop when policy changes are announced. If there is a significant amount of ambiguity around government policy, as well as if the policy shift is preceded by a brief or shallow drop, a significant price decline is anticipated. Changes in policy raise stock market volatility, risk premiums, and correlations.

2.4. Characteristics of Amman Stock Exchange

similar to any emerging market, the Amman Stock Exchange is characterized by a low turnover ratio, low liquidity, limited transparency, and a lack of market makers. These ratios are reported to be quite low, and the Amman Stock Exchange market is thought to have relatively little trading activity. Furthermore, the Amman Stock Exchange sets daily cost controls on stock prices. These restrictions are specified as being plus or minus a particular percentage of the closing price from the previous day. This action is taken to protect small investors from big investors who can influence stock prices by selling and buying large quantities in the trading session. These limits were changed through the years, it was 10% before the Gulf War, and was reduced to 2% during the Gulf War on 1991. After 1991 until now the price limit are set at 5%. The two main restrictions of 5% daily price limits along with the restriction on short selling have major implication on stock prices, such as producing high correlation between stock prices, making future prices predictable and reducing the efficiency of the market. The results from the previous literature about price limit is, however, controversial, while some argue that price limits reduce the market volatility and investor's overreaction, others found that price limits neither reduce market volatility nor the investor's overreaction.

3. Research Design

3.1. Data Source and Variable Selection

This paper conducts empirical analysis based on quarterly data from the first quarter 1992 to the second quarter 2023 from the FRED Economic DATA of St. Louis world to measure economic policy uncertainty by uncertainty index for Jordan and Amman Stock Exchange dataset the data comprise both firm-specific data and market data including quarterly stock prices and trading volume of all firms traded on the Amman Stock Exchange (ASE). The weighted index is used as the proxy for market indicator to estimate market returns with a quarterly frequency. Each variable contains 126 sample data. EViews, short for Econometrics Views, is a time series software package developed specifically for large organizations to process time series data. Therefore, the empirical analysis part of this paper uses EViews to conduct a series of data processing and model construction.

4. Measurement of Variables

4.1. Herding Behavior

Investor herding behavior variable measurement. Identification of market-wide herding is the aim of the study strategy. The latter happens when market participants ignore the special characteristics of assets and instead focus only on the market's performance. This basic process's simplicity is an advantage. The strategy's disadvantage is that, after considering the performance of the market as a whole, individual investors' decisions are still based on individual views or expertise. According to Chang, Cheng, and Khorana (2000), the researcher employs the CSADt as a measure of investor herding behavior to account for all market conditions and prevent restricting the model to stressful circumstances. Since the CSSDt is sensitive to, they calculated the dispersion of the results using:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \qquad (1)$$

The quarterly stock returns $R_{i,t}$ are determined by applying the formula:

$$R_{i,t} = \frac{P_{i,t} * P_{0,t}}{P_{0,t}} \qquad (2)$$

Pi,t represents the quarterly closing prices of stock i at time t while P0,t represents the quarterly opening prices of stock 0 at time t. The quarterly average returns of the sample $R_{i,m}$ are determined by applying the formula:

$$R_{m,t} = \frac{P_{i,t} * P_{0,t}}{P_{0,t}} \qquad (3)$$

Pi,t represents the current quarterly average returns of the sample at time t while P0,t represents the previous quarterly average returns of the sample at time t.

Where:

➢ $CSADt$ is the Cross-Section Absolute Deviation of individual stocks' returns around the market.
➢ Ri,t is stock's i return at time t
➢ Rm,t is the average return of the sample at time t
➢ N is the number of companies included in the sample

4.2. Volatility Stock Market

In risk management, asset allocation, and derivatives pricing, volatility is a key factor. It is frequently measured using the standard deviation or variance of returns from a financial instrument or market index. The two historical metrics of volatility are realized volatility and implied volatility, which are both covered in this section. Previous volatility gauges stock movement based on past prices, whereas implied volatility shows market predictions for a company's future price. It examines movements in a certain stock or index over a predetermined time period. Implied Volatility at its most refined. The Black-Scholes' options pricing model from Black and Scholes (model-based estimation) or the formula for the options market price are the two sources of implied volatility, also known as the ex-ante measure of volatility (model-free estimate). The number of days to expiration, the stock price, put options, the risk-free rate of interest, and the actual call/put price are just a few of the variables that these measurements take into account.

Therefore, modifications to these variables will result in a change in the implied volatility. Purified implied volatility (PV), according to Rousan and Al-Khouri (2005), is used to decrease the impact of stock price changes. in this work by using historical volatility (realized volatility). Volatility prediction continues to be a difficult problem since it involves a non-observable variable that cannot be precisely measured but can only be recovered with a reasonable margin of error. By adding the squares of intraday returns calculated using high-frequency data, Andersen et al. (2001) demonstrate how to create an accurate volatility estimator. They also discover that, as data frequency tends towards infinity, it is possible to create a volatility estimator that is error-free and equal to the real volatility. The integrated variance σ_t^2 is a natural indicator of actual volatility and represents the variance of discrete returns assessed at various periods.

The integrated volatility estimator, known as realized volatility, is obtained by summing intraday squared returns (m) according to the following expression:

$$\sigma_R = \bar{\sigma}_t^2(m) = \sum_{k=1}^{m} r_{t+k/m}^2 \qquad (4)$$

where $r_{t+k/m}$ is the return for each of the short intervals into which the trading session is divided.

4.3. Economic Policy Uncertainty

Based on a variety of factors, Baker creates a new measure of economic policy uncertainty (EPU). The measure of policy uncertainty, according to his empirical findings, predicts losses in investment, production, economic growth, and employment in the United States. Economic or political shocks are viewed as a significant source of uncertainty for businesses since they will have a significant impact on their expenses, sales, and earnings. Later, a large number of further research papers centered on the financial and capital market impact of EPU. In order to explain variances and modifications in herding behavior and volatility in the Amman Exchange Market, we designate the EPU as an indicator for policy information risk in this research.

5. Data Analysis

The closing price quarterly of the Weighted Index is set as the dependent variable, and Investors' Herding Behavior, Economic Policy Uncertainty are set as the independent variables. To establish the relationship model between variables, and the model is empirically analyzed through EViews software. The basic form of the function is as follows:

$$V = \alpha \mathrm{H} + \beta \mathrm{EPU} + \mu \qquad (5)$$

Where V is the closing price quarterly of the Weighted Index, H is the Herding Behavior, EPU is the Economic Policy Uncertainty, α and β are the elastic coefficients of factors, and μ is the influence of random interference ($\mu \leq 1$). The summary statistics of realized volatility and CSAD and policy uncertainty index.are given in Table 1.

	Mean	Max.	Min.	Std.dev.	Skewness	Kurtosis
Realized_Volatility	1405.953	155191.1	-0.584188	14071.53	10.83298	118.8735
CSAD	22.93973	940.5860	4.962220	85.25858	10.39418	111.9143
Uncertainty_Index	0.095207	0.476986	0.000000	0.117734	1.436432	4.534024

Table 1: Descriptive statistics of realized volatility and CSAD and policy uncertainty index

The Correlation analysis of variables to get correlations between variables.

Correlation t-Statistic Probability	Realized_Volatility	CSAD	Uncertainty_Index
Realized_Volatility	1.000000	0.001006 0.011016 0.9912	-0.033443 -0.366557 0.7146
CSAD	0.001006 0.011016 0.9912	1.000000	0.118772 1.310356 0.1926
Uncertainty_Index	-0.033443 -0.366557 0.7146	0.118772 1.310356 0.1926	1.000000

Table 2: Correlation analysis

As can be seen from Table 2, the correlation coefficient between realized volatility and CSAD is 0.001006, indicating an insignificant positive correlation. The correlation coefficient between realized volatility and uncertainty index is -0.033443, indicating an insignificant negative correlation. The correlation coefficient between CSAD and uncertainty index is 0.118772, indicating insignificant positive correlation.

After a simple regression analysis of Formula (6), get:

$$V = 0.833302 \text{ H} + -4068.813 \text{ EPU} + 1774.216$$
$$P = \quad (0.9565) \qquad (0.7128) \qquad (0.2899) \qquad (6)$$
$$\bar{\bar{R}}^2 = 0.001144$$

Regression sum of squares (ESS) and total sum of squares (TSS) can be used to calculate the decidable coefficient, which can be used to measure the goodness of fit of the equation in the results of the regression analysis. Where determination coefficient $R2 = SSR/SST$, and modified determination coefficient $\overline{\overline{R2}} = 1 - [RSS/(n - k)]/[TSS/(n - 1)]$. The goodness of fit of this regression equation is 0.11 %, indicating that there is not a certain linear regression relationship between the realized volatility and CSAD, and the uncertainty index. However, this equation's goodness of fit is not outstanding, requiring gradual model modifications.

6. VAR Model Specification

The samples in this research are primarily examined using a VAR model. Typically, stationary data are chosen for the VAR model, which takes each variable as the explained variable and regresses many lag values of both itself and other explained variables. A large degree of multicollinearity between the variables, which results in nonsignificant variables, is likely to exist since the VAR model often consists of numerous variables and multiple periods of delay. As a result, the significance of the variables is typically not confirmed, but the audit analysis uses the impulsive response and variance decomposition of the VAR model. Due to the interdependence of each variable in the VAR model, the independent coefficient estimation can only provide partial insight. Impulse response (IR) is used to assess if the variables have a long-term equilibrium link in order to more thoroughly analyze the dynamic behavior of the model. The standard deviation of the random disturbance brought on by the influence of an endogenous variable is measured using the impulse response function. Once one variable in the VAR model is affected, the function could reflect the dynamic effect of other model variables. The dynamic changes in these variables over time following the application of this shock are used to construct the impulse response graphs.

The impulse response function, when it gets an effect in the VAR model, may be used to indicate the influence of one endogenous variable on other endogenous variables. While variance decomposition can show the percentage of changes in the sequence caused by its influence and other factors, it cannot be used to quantify the degree to which various variables have an impact. As a result, the method of variance decomposition will be employed in the empirical analysis of the article to investigate the extent to which the first variable will be influenced by the other two variables in the future changes in addition to being influenced by its impact.

7. Empirical Results

7.1. Stationarity Test

The stationarity of the data must be taken into account before building the VAR model, so the unit root test uses the ADF test to determine whether the sequence is stationary. If the ADF test is successful, the sequence will be stationary. Unless this is the case, the sequence is non-stationary, and the ADF test must be run after differentially processing the original sequence. The results of the ADF test of the original sequence are shown in Table 2.

	t-statistic	p-value
Realized Volatility	-10.04301	0.0000*
CSAD	-10.94538	0.0000*
Uncertainty Index	-2.085054	0.2511

* represent significance at the 5% level.

Table 3: ADF test

From the ADF test results of the original sequence in Table 3, the P-value corresponding to uncertainty index in the original sequence is greater than 0.05, which accepts the null hypothesis, that is, there is a unit root, and R is a non-stationary sequence. At a 5% significance level, the P-values for realized volatility and CSAD in the original sequence are both less than 0.05, rejecting the null hypothesis. That is, there is no unit root, and realized volatility and CSAD are both stationary sequences. Therefore, the unit root test should be performed after differential processing of the original sequence. The ADF test results of the above four original sequences after first-order difference processing are shown in Table 4.

	t-statistic	p-value
D(realized volatility)	-106.2356	0.0001*
D(CSAD)	-9.233612	0.0000*
D(uncertainty index)	-9.776646	0.0000*

* represent significance at the 5% level.

Table 4: Revised ADF test

According to the revised ADF test results in Table 4, the P values corresponding to ADF tests of uncertainty index, realized volatility and CSAD are all 0.0000, meaning that all sequences reject the null hypothesis at the significance level of 1%, that is, there is no unit root. The results show that sequences after first-order differential processing are stationary sequences, therefore, the differential data is used for the establishment of vector autoregression (VAR) models.

7.2 VAR Order Identification

Before the VAR model, the optimal lag order should be determined. The lag structure test is conducted to determine the optimal lag order. The test results are shown in Table 5.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1959.749	NA	9.98e+10	33.84049	33.91171	33.86940
1	-1921.890	73.10556	6.07e+10	33.34294	33.62779	33.45857
2	-1887.052	65.47273	3.89e+10	32.89744	33.39594*	33.09980*
3	-1876.608	19.08719*	3.80e+10*	32.87255*	33.58468	33.16163
4	-1870.939	10.06630	4.03e+10	32.92999	33.85576	33.30580
5	-1866.504	7.646601	4.37e+10	33.00870	34.14811	33.47123

*indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error.
AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

The VAR(m) model is constructed based on the results shown in Table 4, where M represents. the selected lag orders. According to the asterisk marked automatically by the software, it can be judged that the order that satisfies the greatest number of criteria to be met is 3 order. Therefore, the optimal lag order in the 3 order, that is, the 3 order is selected as the lag order to establish a VAR (3) model.

7.3 Stationarity Test of Var Model

Before moving on to impulsive response and VAR-based variance decomposition, the model must pass the AR root test because if it doesn't work, the pulse response chart will be emanative and it cannot be confirmed. If the model is unsteady, the test cannot be carried out because all the roots of the AR(P) characteristic polynomial must be within the unit circle.

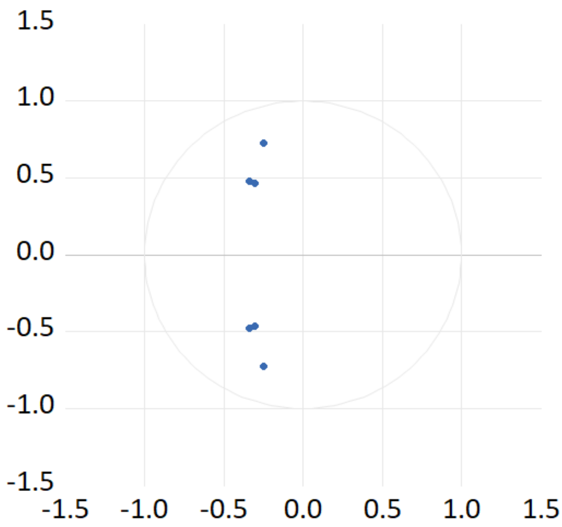

Figure 1: AR root test

The VAR (3) model has passed the test and is stable, so the model is ready for further testing and may be used to generate impulse response graphs and a variance decomposition table. The AR root test results from Figure 1 show that all points are in the unit circle, and all characteristic polynomial coefficients of AR are less than 1.

7.4 Granger Causality Test

The purpose of the Granger causality test is to confirm the causal relationship among variables, that is, to see if one variable's combined lag impacts another variable. Table 6 presents the outcomes of the Granger causality test.

Dependent variable: DRealized Volatility				Dependent variable: DCSAD				Dependent variable: DUncertainty Index			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DCSAD	0.004038	2	0.9980	DRealized Volatility	0.000398	2	0.9998	DRealized Volatility	2.496251	2	0.2870
DUncertainty Index	0.250336	2	0.8823	DUncertainty Index	0.000978	2	0.9995	DCSAD	0.556823	2	0.7570
All	0.252374	4	0.9927	All	0.001380	4	1.0000	All	3.089037	4	0.5430

Table 6: Granger causality test

The probability of P-value corresponding to the chi-square value is 0.9980 when assessing if CSAD seems to be the cause of realized volatility change. Rejecting the null hypothesis at a significance level of 5%, CSAD isn't the Granger cause of the realized volatility change. The probability of P-value corresponding to the chi-square value is 0.8823 when assessing if uncertainty index seems to be the cause of realized volatility change. Rejecting the null hypothesis at a significance level of 5%, CSAD isn't the Granger cause of the realized volatility change. Also realized volatility isn't the Granger cause of the CSAD. uncertainty index isn't the Granger cause of the CSAD. realized volatility isn't the Granger cause of the uncertainty index. CSAD isn't the Granger cause of the uncertainty index. In addition, the VAR model is overall insignificant, that is, from the perspective of long-term development, all factors are endogenous variables, which can be analyzed in the next step.

7.5 Impulse response analysis of VAR model

The impulse response can response to the dynamic interaction among variables. The direction of brief fluctuations induced by fluctuations and fluctuations changes with time once a variable has each unit standard error impact on another variable. The diagram presented in figure 2 are respectively Realized Volatility for Realized Volatility, Realized Volatility for CSAD, and Realized Volatility for Uncertainty Index impulse response figure, take 10 period study period.

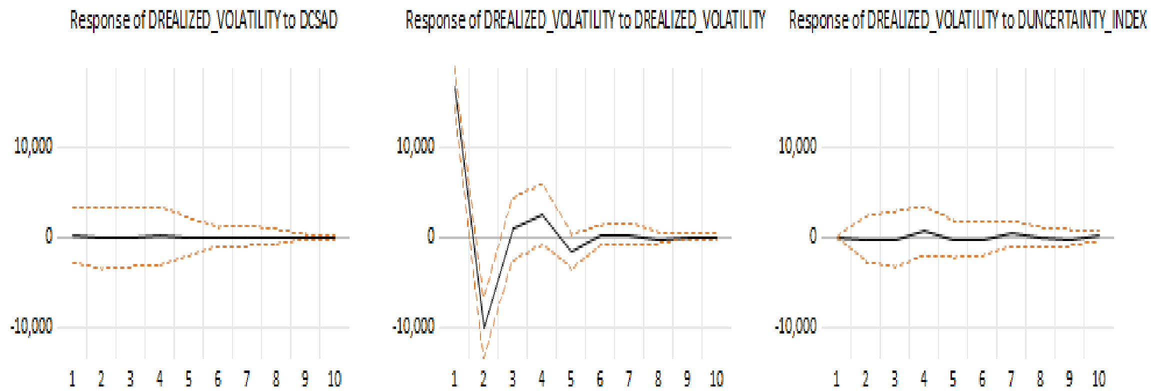

Figure 2: Impulse response

According to Figure 2, when the DRealized Volatility produces a unit of the standard deviation of negative impact on itself, DRealized Volatility at the first stage is the maximum of forwarding impact response, and then increases rapidly. After a period of fluctuation, DRealized Volatility converges to 0 after the seventh stage. The impact intensity and duration of shock reaction indicate that the closing price of the index fluctuates greatly after being impacted, so we should pay close attention to the changes in Amman share market in real-time. When DUncertainty Index produces a unit of the standard deviation of positive impact on DRealized Volatility, DRealized Volatility in the first phase of the response is 0. After then, there is a positive impact response. In the 4th step, the positive impact reaction reached its peak. Then, it progressively declined and began to swing around zero.

The effect of DUncertainty Index is contrary of DCSAD on DRealized Volatility. When the DCSAD produces a unit of the standard deviation of positive impact on DRealized Volatility, DRealized Volatility in the first phase of the response is stable. after the fourth stage DRealized Volatility the response is decreases. it progressively declined and began to swing around zero. The results show that, over time, changes in the Uncertainty Index and CSAD will have a positive influence on Amman's Realized Volatility over time, with Uncertainty Index having a bigger impact than the CSAD, but the impact of both are limited.

7.6 Variance Decomposition

After the positive and negative impacts of independent variables on dependent variables were obtained by impulse response, variance analysis was conducted on the model to further understand the impact proportion of shocks. The variance decomposition of VAR (3) model is carried out below, and the research period is set to 10 periods. The results are shown in Table 7.

Period	S.E	DRealized Volatility	DCSAD	DUncertainty Index
1	16736.08	99.98627	0.013732	0.000000
2	19528.17	99.95323	0.013063	0.033711
3	19547.87	99.94212	0.014485	0.043392
4	19721.84	99.83485	0.016406	0.148740
5	19797.34	99.81342	0.016287	0.170293
6	19800.66	99.79359	0.016959	0.189446
7	19806.84	99.75929	0.016994	0.223712
8	19808.25	99.75867	0.017195	0.224136
9	19809.31	99.74855	0.017303	0.234143
10	19809.76	99.74409	0.017324	0.238590

Table 7: Variance decomposition

According to the results in Table 6, the proportion of DRealized Volatility impact on self-disturbance gradually decreased from 99.98% in the 1st step to 99.74% in the 10th step, while the influence of DCSAD on DRealized Volatility rose from 0.013% in the 1st step to 0.017% in the 10th step, indicating that DCSAD has a certain short-term impact on DRealized Volatility. Similarly, the influence DUncertainty Index on DRealized Volatility increased from 0 liters in the first phase to 0.238% in the 10th phase, and DUncertainty Index also had a certain short-term influence on DRealized Volatility. Namely in a-share market fluctuations, the change of DCSAD on its probably at around 0.017%, and the impact of changes in the DUncertainty Index on its effect will be around 0.238%. By contrast, DUncertainty Index on the impact of Amman's a-share market fluctuations compared to the impact of the DCSAD will become stronger. But the explanation is limited, it may be that the reasons for the formation of fluctuations in Amman Stock Exchange (ASE) are quite complex.

8. Conclusion

This paper conducts empirical analysis based on quarterly data from the first quarter 1992 to the second quarter 2023. The model selects weighted index is used as the proxy for market indicator to estimate market returns with a quarterly frequency as the measure Amman Stock Exchange (ASE) to measure the volatility by the Realized Volatility, uncertainty index for Jordan from the FRED Economic DATA of St. Louis world to measure economic policy uncertainty (EPU). CSAD to measure herding behavior. The VAR model is constructed by EViews to better study the dynamic relationship between variables. Through computer simulation and calculation, the experimental results show that: Through correlation analysis and simple regression of variables, it is found that there isn't a regression relationship between the realized volatility and CSAD, and the uncertainty index. And there is an insignificant correlation between explained variables and explanatory variables.The original sequence of each variable is non-stationary under the significance of 5%, but their first-order difference is stationary. The results show that the equilibrium and stability of the relationship between realized volatility and CSAD, and the uncertainty index. under the significance of 5%, the Granger isn't cause between realized volatility and CSAD, and the uncertainty index in both directions.

Through impulse analysis and variance decomposition of the VAR (3) model, it can be concluded that the impact of the changes in Economic policy uncertainty on the volatility of Amman's stock market is stronger than that of changes in herding behavior. But the impacts of both are limited, it may be that the reasons for the formation of fluctuations in Amman Stock Exchange (ASE) are quite complex [28-36].

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